LAPORAN AKHIR PENELITIAN MULTI TAHUN

ID Proposal: 2a549c70-bb61-4a45-906d-b366f564289f
Laporan Akhir Penelitian: tahun ke-3 dari 3 tahun

1. IDENTITAS PENELITIAN

A. JUDUL PENELITIAN

Pengembangan Electronic-Nose Untuk Deteksi Kemurnian Daging Sapi

B. BIDANG, TEMA, TOPIK, DAN RUMPUN BIDANG ILMU

Bidang Fokus RIRN / Bidang Unggulan Perguruan Tinggi	Tema	Topik (jika ada)	Rumpun Bidang Ilmu
Kecerdasan Artifisial dan Teknologi Kesehatan	-	ICT dan Industri 4.0	Teknik Informatika

C. KATEGORI, SKEMA, SBK, TARGET TKT DAN LAMA PENELITIAN

Kategori (Kompetitif Nasional/ Desentralisasi/ Penugasan)	Skema Penelitian	Strata (Dasar/ Terapan/ Pengembangan)	SBK (Dasar, Terapan, Pengembangan)	Target Akhir TKT	Lama Penelitian (Tahun)
Penelitian Desentralisasi	Penelitian Terapan Unggulan Perguruan Tinggi	SBK Riset Terapan	SBK Riset Terapan	6	3

2. IDENTITAS PENGUSUL

Nama, Peran	Perguruan Tinggi/ Institusi	Program Studi/ Bagian	Bidang Tugas	ID Sinta	H-Index
RIYANARTO SARNO Ketua Pengusul	Institut Teknologi Sepuluh Nopember	Ilmu Komputer		29555	21
DWI SUNARYONO S.Kom., M.Kom Anggota Pengusul 1	Institut Teknologi Sepuluh Nopember	Teknik Informatika		6198766	5
Dr.Eng CHASTINE FATICHAH S.Kom, M.Kom Anggota Pengusul	Institut Teknologi Sepuluh Nopember	Teknik Informatika		5976088	10

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3. MITRA KERJASAMA PENELITIAN (JIKA ADA)

Pelaksanaan penelitian dapat melibatkan mitra kerjasama, yaitu mitra kerjasama dalam melaksanakan penelitian, mitra sebagai calon pengguna hasil penelitian, atau mitra investor

Mitra	Nama Mitra
Mitra Calon Pengguna	Ashananda Mustika Rahma

4. LUARAN DAN TARGET CAPAIAN

Luaran Wajib

Tahun Luaran	Jenis Luaran	Status target capaian (*accepted, published, terdaftar atau granted, atau status lainnya*)	Keterangan (*url dan nama jurnal, penerbit, url paten, keterangan sejenis lainnya*)
3	Dokumentasi hasil uji coba produk	Ada	-

Luaran Tambahan

Tahun Luaran	Jenis Luaran	Status target capaian (*accepted, published, terdaftar atau granted, atau status lainnya*)	Keterangan (*url dan nama jurnal, penerbit, url paten, keterangan sejenis lainnya*)
3	Publikasi Ilmiah Jurnal Internasional	accepted/published	Chemometrics and Intelligent Laboratory Systems - Journal - Elsevier
3	Prosiding dalam pertemuan ilmiah Internasional	sudah terbit/sudah dilaksanakan	Scopus Conferences

5. ANGGARAN

Rencana anggaran biaya penelitian mengacu pada PMK yang berlaku dengan besaran minimum dan maksimum sebagaimana diatur pada buku Panduan Penelitian dan Pengabdian kepada Masyarakat Edisi 12.

Total RAB 3 Tahun Rp. 139,000,000

Tahun 1 Total Rp. 0

Tahun 2 Total Rp. 0

Tahun 3 Total Rp. 139,000,000

Jenis Pembelanjaan	Item	Satuan	Vol.	Biaya Satuan	Total
Analisis Data	HR Pengolah Data	P (penelitian)	1	1,150,000	1,150,000
Analisis Data	HR Sekretariat/Administrasi Peneliti	OB	3	300,000	900,000
Bahan	ATK	Paket	1	95,000	95,000
Bahan	Bahan Penelitian (Habis Pakai)	Unit	5	6,000	30,000
Pelaporan, Luaran Wajib, dan Luaran Tambahan	Biaya pembuatan dokumen uji produk	Paket	1	2,150,000	2,150,000

Jenis Pembelanjaan	Item	Satuan	Vol.	Biaya Satuan	Total
Pelaporan, Luaran Wajib, dan Luaran Tambahan	HR Sekretariat/Administrasi Peneliti	OB	2	300,000	600,000
Pelaporan, Luaran Wajib, dan Luaran Tambahan	Publikasi artikel di Jurnal Internasional	Paket	2	15,937,500	31,875,000
Pelaporan, Luaran Wajib, dan Luaran Tambahan	Luaran KI (paten, hak cipta dll)	Paket	6	600,000	3,600,000
Pelaporan, Luaran Wajib, dan Luaran Tambahan	Biaya seminar internasional	Paket	17	1,000,000	17,000,000
Pengumpulan Data	HR Sekretariat/Administrasi Peneliti	OB	2	300,000	600,000
Pengumpulan Data	HR Pembantu Lapangan	OH	300	80,000	24,000,000
Pengumpulan Data	HR Pembantu Peneliti	OJ	560	25,000	14,000,000
Sewa Peralatan	Peralatan penelitian	Unit	10	4,300,000	43,000,000

6. HASIL PENELITIAN

A. RINGKASAN: Tuliskan secara ringkas latar belakang penelitian, tujuan dan tahapan metode penelitian, luaran yang ditargetkan, serta uraian TKT penelitian.

Sekarang ini makin banyak dijual daging sapi yang dicampur daging dengan daging hewan lain yang lebih murah untuk meraup keuntungan yang lebih. Sebagai contoh adalah pencampuran daging sapi dengan daging babi. Masyarakat pembeli sulit mengetahui kemurnian daging sapi, sehingga sering terjadi mengkonsumsi daging campuran yang tidak halal.

Dalam rangka mendukung unggulan penelitian di Institut Teknologi Sepuluh Nopember, maka peneliti mengembangkan keilmuan Internet of Things dengan mengajukan proposal tentang “Pengembangan Electronic Nose untuk Deteksi Kemurnian Daging Sapi”. Beberapa penelitian sebelumnya telah dilakukan untuk deteksi kemurnian daging sapi dengan menggunakan Electronic Nose (E-nose), akan tetapi penelitian ini akan berkontribusi dalam pengembangan metode preprosesing untuk signal denoising dan penentuan gas yang signifikan untuk mendeteksi kemurnian daging sapi. Electronic Nose untuk Deteksi Kemurnian Daging Sapi (ENOSIKA) yang diusulkan memiliki keuntungan 1) penyaringan noise yang tepat, 2) susunan sensor optimal, dan 3) parameter optimal dari support vector machine (SVM). Penelitian ini melakukan penyaringan noise yang tepat dilakukan dengan validasi silang dari mother wavelet yang berbeda, yaitu Haar, dmey, coiflet, symlet dan Daubechies. Array sensor dioptimalkan dengan mereduksi dimensi menggunakan principal component analysis (PCA). Penelitian ini akan mengusulkan algoritma optimasi parameter dari metode Support Vector Machine (SVM). Hasil dari Electronic Nose yang dibangun adalah tujuh kelas, yaitu (1) dan 100% daging babi; (2) 10% daging sapi dan 90% daging babi; (3) 25% daging sapi dan 75% daging babi; (4) 50% daging sapi dan 50% daging babi; (5) 75% daging sapi dan 25% daging babi; (6) 90% daging sapi dan 10% daging babi; dan (7) 100% daging sapi. Pada penelitian tahun kedua, dihasilkan publikasi ilmiah dan prototype Electronic Nose.

Pada tahun ketiga, penelitian ini akan melakukan peningkatan metode dan melakukan pengujian prototype Electronic Nose. Pengujian ini dilakukan untuk mengevaluasi Electronic Nose yang dibangun. Hasil dari tahun ketiga ini adalah prototype Electronic Nose untuk Deteksi Kemurnian Daging Sapi tahap alpha dan dokumen feasibility experiment (dokumen uji produk) sebagai bukti pengujian. Kedua hasil ini menjadi bukti dari pencapaian TKT yang akan dituju, yaitu TKT 6. Selain dua hasil tersebut, penelitian ini juga menjanjikan beberapa luaran tambahan, yaitu artikel ilmiah, hak cipta terkait dengan Electronic Nose dan dokumen business plan. Luaran yang sudah dicapai untuk pelaporan kemajuan adalah prototipe Electronic-Nose, dokumentasi awal uji coba, artikel ilmiah jurnal internasional terindeks Scopus yang berstatus published, dan prosiding dalam pertemuan ilmiah internasional berstatus accepted.

B. KATA KUNCI: Tuliskan maksimal 5 kata kunci.

Daging; Electronic Nose; Klasifikasi

Pengisian poin C sampai dengan poin H mengikuti template berikut dan tidak dibatasi jumlah kata atau halaman namun disarankan seringkas mungkin. Dilarang menghapus/memodifikasi template ataupun menghapus penjelasan di setiap poin.

C. HASIL PELAKSANAAN PENELITIAN: Tuliskan secara ringkas hasil pelaksanaan penelitian yang telah dicapai sesuai tahun pelaksanaan penelitian. Penyajian dapat berupa data, hasil analisis, dan capaian luaran (wajib dan atau tambahan). Seluruh hasil atau capaian yang dilaporkan harus berkaitan dengan tahapan pelaksanaan penelitian sebagaimana direncanakan pada proposal. Penyajian data dapat berupa gambar, tabel, grafik, dan sejenisnya, serta analisis didukung dengan sumber pustaka primer yang relevan dan terkini.

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C1. Luaran Wajib (Prototipe Electronic Nose dan Dokumen Uji Coba Produk)

Penelitian pada tahun ke tiga dilakukan dengan beberapa proses seperti pada Gambar 1. Hasil penelitian berupa pengembangan prototipe electronic nose [1]–[6] untuk deteksi kemurnian daging sapi dari tahun ke 2. Adapun langkah-langkah untuk mengembangkan prototipe e-nose dari hasil prototipe e-nose pada tahun ke 2 adalah sebagai berikut:

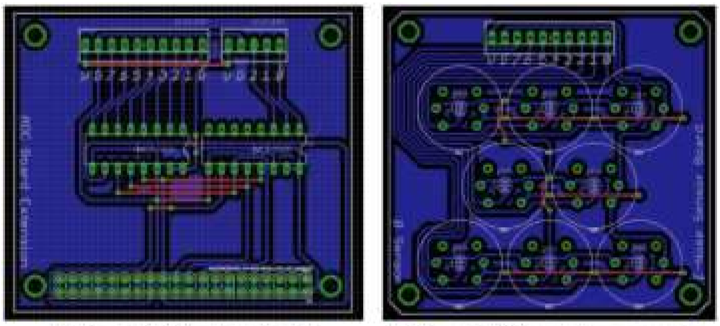
Gambar 1 Alur proses penelitian pada tahun ke tiga

A. Desain PCB

Pada tahun ke 2, proses desain PCB tidak dilakukan karena sensor yang digunakan adalah sensor yang sudah tertanam dengan modul, sehingga ukurannya lebih besar daripada sensor itu sendiri. Pada tahun ke tiga, untuk memperkecil ukuran dari prototipe electronic nose, desain PCB dilakukan sehingga alat e-nose lebih mudah dibawa. Desain PCB dibagi menjadi 2 yaitu PCB untuk pengganti modul sensor-sensor dan yang kedua adalah PCB untuk digital converter. PCB untuk modul-modul sensor didesain untuk 8 jenis sensor MQ yang digunakan adalah MQ 2, MQ 3, MQ 4, MQ 5, MQ 6, MQ 7, MQ 8, MQ 9. Masing-masing jenis sensor memiliki selektivitas masing-masing seperti yang dijelaskan pada Table xx.

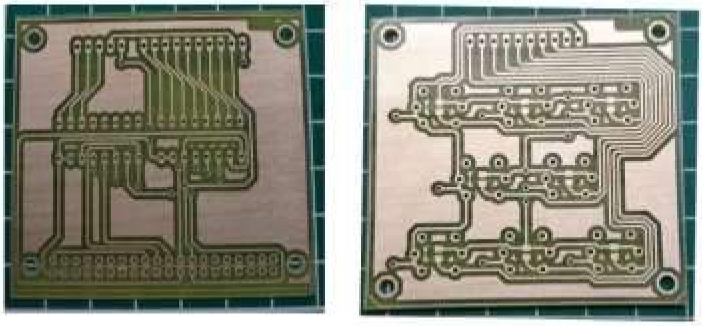
Tabel 1 Sensitivitas masing-masing Sensor terhadap volatile compound

No	Sensor	Initial	Compound Target
1	MQ 2	S1	LPG, i-butane, propane, methane, alcohol, Hydrogen, smoke
2	MQ 3	S2	Alcohol, Benzine, SH4, Hexane, LPG, CO
3	MQ 4	S3	Methane (CH_4), Natural gas
4	MQ 5	S4	H2, LPG, CH4, CO, Alcohol
5	MQ 6	S5	LPG, iso-butane, propane
6	MQ 7	S6	CO, H2, LPG, CH4, Alcohol
7	MQ 8	S7	H2, Alcoho, CO, CH4
8	MQ 9	S8	Methane, Propane and CO
9	DHT22	S9	Temperature & Humidity



(a) Desain PCB untuk Digital converter sensor dan Raspberry

(b) Desain PCB untuk penempatan sensor-sensor MQ

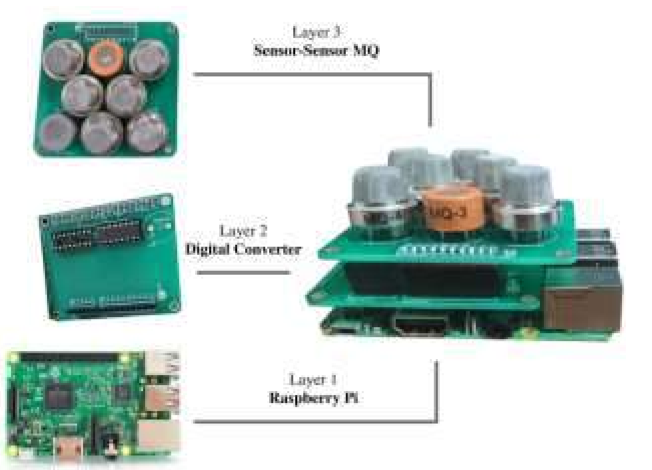


(c) Hasil PCB untuk Digital converter sensor dan Raspberry

(d) Hasil PCB untuk penempatan sensor-sensor MQ

Gambar 2 Desain dan hasil cetak PCB untuk digital converter dan sensor

Gambar 2 (a) adalah desain awal PCB yang akan digunakan untuk digital converter. Karena sensor yang digunakan 8 buah, maka digital converter yang digunakan 2 buah dan jenisnya MCP3008. Setiap converter terdiri dari 16 pin yaitu CH0 sampai CH8, DGND, CS/SHDN, DIN, DOUT, CLK, AGND, VREF, VDD. PCB yang kedua adalah PCB untuk sensor-sensor MQ. Terdapat 8 bulatan yang akan digunakan untuk memasang 8 sensor MQ, dan 8 pin output dan 2 pin untuk voltage dan GND. Gambar 2 (c) dan (d) adalah hasil PCB yang telah di cetak. Selanjutnya, PCB yang sudah dicetak dirangkai dengan susunan 3 layer. Layer 1 atau base layer adalah microcontroller yang digunakan untuk mengambil data. Microcontroller yang digunakan pada penelitian ini adalah Raspberry Pi. Microcontroller ini hanya menerima data digital. Karena output dari sensor MQ adalah nilai Analog, maka dibutuhkan converter analog to digital sehingga dapat terbaca oleh Raspberry Pi. Digital converter ini diletakkan pada layer 2 setelah Raspberry Pi. Layer yang paling atas adalah layer 3 yaitu PCB yang tertanam sensor-sensor MQ.



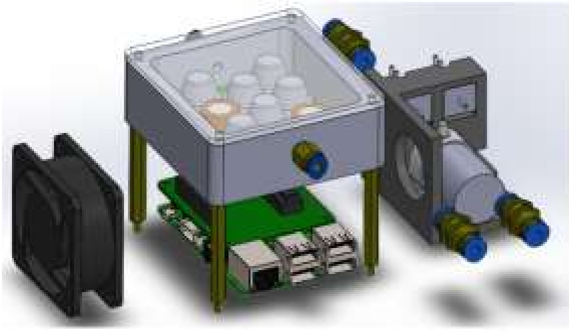
Gambar 3 Layering PCB dengan microcontroller

B. Desain Air-flow

Sistem airflow yang digunakan pada penelitian ini mengacu pada teknik Headspace yaitu salah satu teknik yang biasa digunakan untuk analisis kualitatif dan kuantitatif senyawa organik menguap (VOC) dari berbagai matriks. Sistem air-flow dibagi menjadi tiga proses yaitu:

- Delay
  ruang sensor dialiri oleh udara bebas menggunakan flash fan agar ruang sensor tidak lembab.
- Sampling
  Ruang sensor dialiri oleh udara dari ruang sample yang disedot menggunakan vacuum pump.
- Purging
  Ruang sensor dibersihkan dengan menggunakan flash fan sehingga pada saat pengambilan sampel selanjutnya tidak terpengaruh oleh residu gas dari pengambilan sampel sebelumnya.

Sistem air-flow menggunakan bantuan vacuum pump, valve, dan fan seperti pada Gambar xx.



Gambar 4 Desain dari sistem air-flow untuk prototipe electronic nose

C. Desain Box E-nose

Box didesain kotak mengikuti komponen-komponen yang ada seperti, ruang sensor, sistem air-flow, Raspberry dan PCB. Bagian atas box diberi layar LCD 7inch yang digunakan untuk memudahkan pengguna mengoperasikan prototipe e-nose.

D. Prototipe E-nose

Box untuk prototipe e-nose dicetak menggunakan printer 3D dengan filamen berwarna cream seperti pada Gambar 5. Terdapat menu power yang digunakan untuk menyalakan dan mematikan sistem Headspace.

(a) Desain BOX Prototipe Electronic Nose (b) Prototipe Electronic Nose tahun ke tiga

Gambar 5 Desain Box dan hasil prototipe electronic nose yang telah dirangkai

E. Uji Coba dan Evaluasi

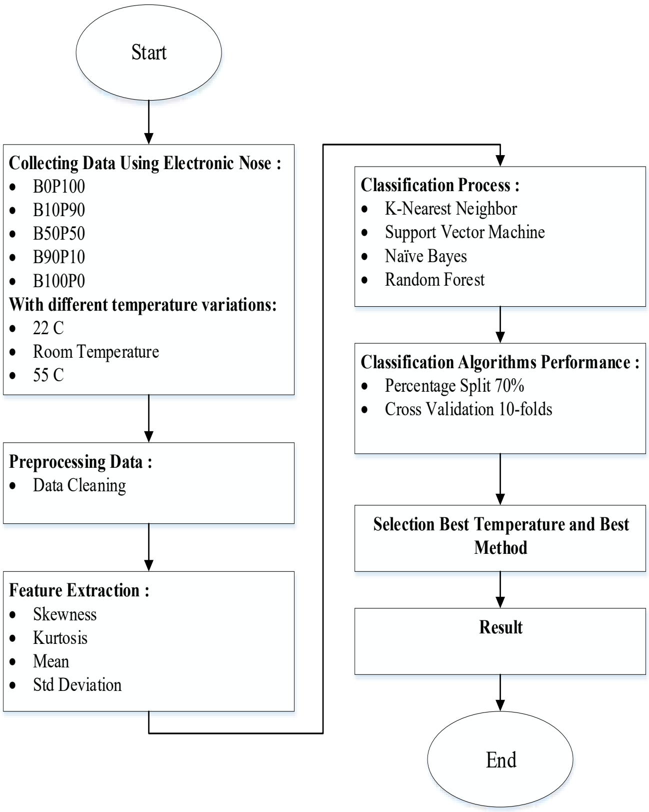
Sampel yang digunakan pada penelitian ini adalah daging sapi dan daging babi yang dibeli langsung di toko, hari, dan tanggal yang sama. Daging yang sudah disediakan kemudian dihaluskan atau diblender sehingga tekstur daging menjadi lebih halus dan pembagian prosentasi campuran daging oplosan menjadi lebih mudah. Data yang akan di test adalah 100 gram daging babi dan sapi dengan kombinasi porsentasi yang berbeda-beda. Penelitian ini menggunakan alat timbangan guna memastikan berat daging yang akan dicampur sudah sesuai. Masing-masing daging akan mempunyai masa yang sama yaitu 100 gram. Diagram blok dapat dilihat pada Gambar 3. Dijelaskan bahwa untuk kelas 1 diberikan daging sapi sebanyak 100 gram, kelas 2 daging sapi 90 gram di campur dengan daging babi 10 gram, kelas 3 daging sapi 75 gram dicampur dengan daging babi 25 gram, kelas 4 daging sapi dengan masa 50 gram dicampur dengan daging babi dengan masa 50 gram. Kelas 5 daging sapi 25 gram dicampur dengan daging babi 75 gram. Kelas 6 daging sapi 10 gram dicampur dengan daging babi 90 gram, dan yang terakhir daging babi 100 gram.

Langkah-langkah berikut digunakan untuk mengumpulkan sampel data:

1. e-nose dihidupkan dan sensor dihangatkan selama 15 menit (tentatif),
2. sampel ditempatkan di ruang sampel,
3. mengatur durasi waktu proses start, sensing, dan purging dalam hitungan menit,
4. proses pengambilan data dan transfer ke komputer menggunakan antarmuka USB atau Wi-Fi.

F. Hasil Analisis

Pada penelitian ini dilakukan analisis lebih lanjut dengan menggunakan algoritma untuk algoritma machine learning dengan 3 perbedaan temperatur pada masing-masing dari 5 variasi data sampel daging untuk menentukan hasil klasifikasi yang optimal. Suhu yang digunakan adalah suhu -22 ° C, Suhu Kamar dan 55 ° C, sedangkan variasi campuran daging yang digunakan adalah 0% Daging Sapi - 100% Daging Babi; Daging sapi 10% - Daging babi 90%; Daging sapi 50% - Daging babi 50%; Daging sapi 90% - Daging babi 10%; dan 100% Daging Sapi - 0% Daging Babi. Algoritma yang digunakan untuk pembelajaran mesin adalah k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Naïve Bayes, dan Random Forest.



Gambar 6 Alur scenario analisis data tahap I

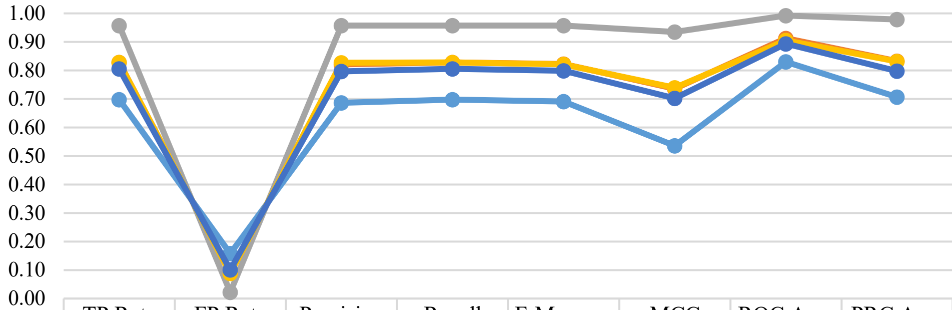
- Pengujian Skenario 1

Pada skenario pengujian ini dilakukan uji klasifikasi daging menggunakan metode k-Nearest Neighbor dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Pada pengujian skenario 1 dilakukan pemisahan data dari fungsi ekstraksi menjadi data latih dan data pengujian dengan rasio 30%, dan k = 3.

Tabel 2 Perbandingan variasi temperature dengan Skenario 1

	CODE	TEMPERATURE	PREDICTION		
			-22ºC	**Room Temp.**	**55ºC**
A C T U A L	**B0P100**	**-22ºC**	14	0	0
		Room Temp.	0	10	6
		55ºC	1	7	7
	B10P90	**-22ºC**	14	0	0
		Room Temp.	0	12	4
		55ºC	2	2	11
	B50P50	**-22ºC**	14	0	0
		Room Temp.	0	15	1
		55ºC	0	1	14
	B90P10	**-22ºC**	14	0	0
		Room Temp.	0	12	4
		55ºC	3	1	11
	B100P0	**-22ºC**	14	0	0
		Room Temp.	0	12	4
		55ºC	2	3	10

Detail Accuration using k-NN Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.70	0.16	0.69	0.70	0.69	0.54	0.83	0.71
B10P90	0.83	0.09	0.82	0.83	0.82	0.74	0.91	0.83
B50P50	0.96	0.02	0.96	0.96	0.96	0.93	0.99	0.98
B90P10	0.83	0.09	0.83	0.83	0.82	0.74	0.91	0.83
B100P0	0.81	0.10	0.80	0.81	0.80	0.70	0.89	0.80

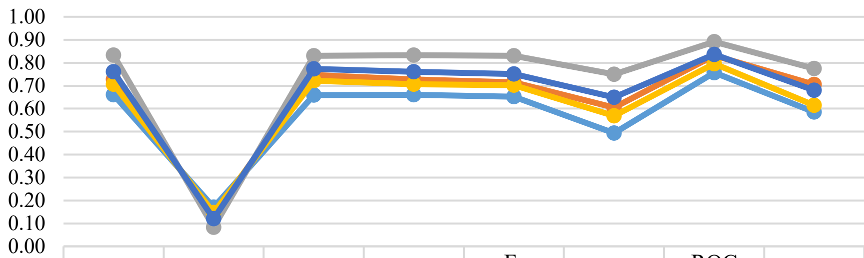
- Pengujian Skenario 2

Pada skenario pengujian ini dilakukan uji klasifikasi daging dengan menggunakan metode Support Vector Machine dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Dalam pengujian skenario 2, ini dilakukan dengan menggunakan k-fold cross-validation, dengan k = 10 untuk kernel RBF. Tujuan dari pengujian menggunakan k-fold cross-validation adalah untuk memilih parameter temperatur yang tepat sesuai dengan ketelitian tertinggi, sehingga ketepatan klasifikasi kemurnian SVM dapat ditingkatkan [21].

Tabel 3 Perbandingan variasi temperature dengan Skenario 2

	CODE	TEMPERATURE	PREDICTION		
			-22ºC	**Room Temp.**	**55ºC**
A C T U A L	**B0P100**	**-22ºC**	43	2	5
		Room Temp.	8	32	10
		55ºC	15	11	24
	B10P90	**-22ºC**	47	1	2
		Room Temp.	6	39	5
		55ºC	20	7	23
	B50P50	**-22ºC**	50	0	0
		Room Temp.	2	39	9
		55ºC	4	10	36
	B90P10	**-22ºC**	40	8	2
		Room Temp.	6	39	5
		55ºC	17	6	27
	B100P0	**-22ºC**	48	2	0
		Room Temp.	5	39	6
		55ºC	15	8	27

Detail Accuration using SVM Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.66	0.17	0.66	0.66	0.65	0.49	0.76	0.59
B10P90	0.73	0.14	0.75	0.73	0.71	0.60	0.83	0.70
B50P50	0.83	0.08	0.83	0.83	0.83	0.75	0.89	0.77
B90P10	0.71	0.15	0.72	0.71	0.70	0.57	0.80	0.61
B100P0	0.76	0.12	0.77	0.76	0.75	0.65	0.84	0.68

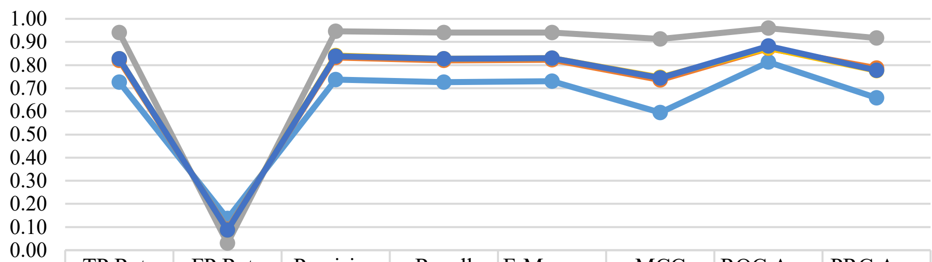
- Pengujian Skenario 3

Pada skenario pengujian ini, dilakukan uji klasifikasi daging dengan menggunakan metode Naïve Bayes dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Pada pengujian skenario 3 digunakan k-fold cross validation, dengan k = 10.

Tabel 4 Perbandingan variasi temperature dengan Skenario 3

	CODE	**TEMPERATURE**	**PREDICTION**		
			-22ºC	**Room Temp.**	**55ºC**
ACTUAL	**B0P100**	**-22ºC**	46	2	2
		Room Temp.	0	29	21
		55ºC	0	16	34
	B10P90	**-22ºC**	43	3	4
		Room Temp.	0	38	12
		55ºC	0	8	42
	B50P50	**-22ºC**	48	1	1
		Room Temp.	0	43	7
		55ºC	0	0	50
	B90P10	**-22ºC**	42	4	4
		Room Temp.	0	38	12
		55ºC	0	6	44
	B100P0	**-22ºC**	44	3	3
		Room Temp.	0	38	12
		55ºC	0	8	42

Detail Accuration using Naive Bayes Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.73	0.14	0.74	0.73	0.73	0.60	0.81	0.66
B10P90	0.82	0.09	0.83	0.82	0.82	0.74	0.87	0.79
B50P50	0.94	0.03	0.95	0.94	0.94	0.91	0.96	0.92
B90P10	0.83	0.09	0.84	0.83	0.83	0.75	0.87	0.78
B100P0	0.83	0.09	0.84	0.83	0.83	0.74	0.88	0.78

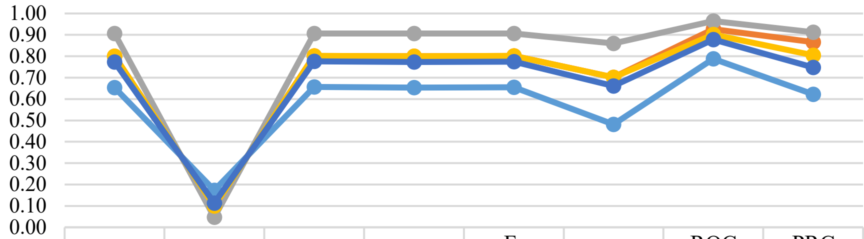
- Pengujian Skenario 4

Pada skenario pengujian ini dilakukan uji klasifikasi daging menggunakan metode random forest dengan 5 variasi daging dengan 3 variasi temperatur. Pada pengujian skenario ini digunakan k-fold cross validation, dengan k = 10.

Tabel 5 Perbandingan variasi temperature dengan Skenario 4

	CODE	TEMPERATURE	PREDICTION		
			-22ºC	Room Temp.	55ºC
ACTUAL	**B0P100**	**-22ºC**	49	1	0
		Room Temp.	0	26	24
		55ºC	0	27	23
	B10P90	**-22ºC**	49	0	1
		Room Temp.	0	35	15
		55ºC	0	14	36
	B50P50	**-22ºC**	50	0	0
		Room Temp.	0	44	6
		55ºC	0	6	42
	B90P10	**-22ºC**	49	1	0
		Room Temp.	0	35	15
		55ºC	0	14	36
	B100P0	**-22ºC**	49	1	0
		Room Temp.	0	33	17
		55ºC	0	16	34

Detail Accuration using Random Forest Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.65	0.17	0.66	0.65	0.65	0.48	0.79	0.62
B10P90	0.80	0.10	0.80	0.80	0.80	0.70	0.93	0.87
B50P50	0.91	0.05	0.91	0.91	0.91	0.86	0.96	0.91
B90P10	0.80	0.10	0.80	0.80	0.80	0.70	0.90	0.80
B100P0	0.77	0.11	0.78	0.77	0.77	0.66	0.88	0.75

Hasil Evaluasi menggunakan ROC

Untuk mengetahui suhu dan metode terbaik dalam percobaan ini, peneliti mengelompokkan nilai ROC terhadap metode dan suhu seperti pada tabel 6. Pada -22oC, metode yang memiliki akurasi tertinggi adalah metode random forest dengan nilai rata-rata ROC 1.000. Sedangkan metode yang memiliki akurasi tertinggi kedua adalah metode k-Nearest Neighbor dengan nilai rata-rata ROC 0,986. Metode naïve bayes menduduki peringkat ke-3 dengan nilai rata-rata ROC 0,971 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai rata-rata ROC 0,872. Pada suhu kamar, metode yang memiliki akurasi tertinggi adalah metode k-Nearest Neighbor dengan nilai rata-rata ROC 0.886. Sedangkan metode yang memiliki akurasi tinggi ke 2 adalah metode Naïve Bayes dengan nilai ROC rata-rata 0,856. Metode Random Forest menduduki peringkat ke-3 dengan nilai rata-rata ROC 0,839 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai ROC rata-rata 0,820. Pada suhu 55oC, metode yang memiliki akurasi tertinggi adalah metode Naïve Bayes dengan nilai ROC rata-rata 0,864. Sedangkan metode yang memiliki akurasi tertinggi kedua adalah metode K-Nearest Neighbor dengan nilai rata-rata ROC sebesar 0.848. Metode Random Forest menduduki peringkat ke-3 dengan nilai rata-rata ROC 0,836 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai rata-rata ROC 0,774

Berdasarkan hasil penelitian yang dilakukan oleh penulis maka diperoleh kesimpulan sebagai berikut:

1. Peneliti membagi percobaan menjadi 4 skenario dengan masing-masing komposisi 5 variasi daging (Beef 0%

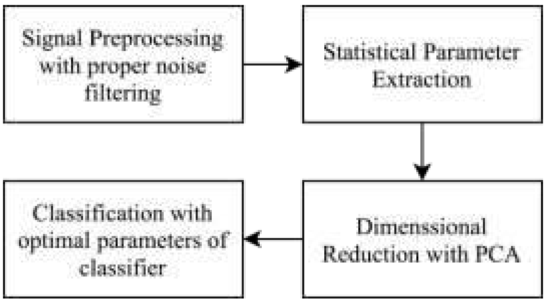
- Pork 100%, Beef 10% - Pork 90%, Beef 50% - Pork 50%, Beef 90% - Pork 10% dan Daging Sapi 100% - Daging Babi 0%) dengan 3 variasi suhu (-22oC, Suhu Kamar, dan 55oC), yaitu:

a. k-Metode Tetangga Terdekat
b. Mendukung Metode Mesin Vektor
c. Metode Bayer yang Naif
d. Metode Hutan Acak

2. Ada pengaruh temperatur terhadap peningkatan akurasi, yaitu pada -22oC. Karena semakin rendah suhunya semakin stabil nilai yang didapat oleh electronic nose.
3. Berikut adalah metode yang memiliki akurasi tinggi berdasarkan suhu:

a. Pada suhu -22oC urutan metode yang memiliki akurasi tertinggi sampai terendah adalah Random Forest dengan nilai rata-rata ROC 1,00; K-Nearest Neighbor dengan nilai rata-rata ROC 0.986; Naïve Bayes dengan nilai rata-rata ROC 0.971 dan Support Vector Machine dengan nilai rata-rata ROC 0.872.
b. Pada temperatur ruang urutan metode yang memiliki akurasi tertinggi sampai terendah yaitu K-Nearest Neighbor dengan nilai rata-rata ROC 0.886; Naïve Bayes dengan nilai rata-rata ROC 0.856; Random Forest dengan nilai rata-rata ROC 0.839 dan Support Vector Machine dengan nilai ROC rata-rata 0.821.
c. Pada suhu 55oC urutan metode yang memiliki akurasi tertinggi sampai terendah yaitu Naïve Bayes dengan nilai ROC rata-rata 0,864; K-Nearest Neighbor dengan nilai rata-rata ROC 0.848; Random Forest dengan nilai rata-rata ROC 0.836 dan Support Vector Machine dengan nilai rata-rata ROC 0.774.

Meningkatkan analisis data dengan menambakan pre-processing data seperti Gambar xx. Langkah pertama adalah pra-pemrosesan sinyal, yang membersihkan kebisingan dan menghasilkan keluaran dalam bentuk sinyal data yang direkonstruksi. Langkah selanjutnya adalah ekstraksi parameter statistik, yang memanfaatkan sinyal data yang direkonstruksi dan mengekstraknya untuk mendapatkan karakteristik sinyal. Langkah ketiga adalah reduksi dimensi, di mana sinyal yang diperoleh dianalisis untuk memilih hanya sensor yang memiliki pengaruh terbesar pada deteksi pemalsuan daging babi. Langkah terakhir adalah membangun model klasifikasi dari 7 kelas. Data yang diperoleh dari proses sebelumnya dibagi menjadi data pengujian (30%) dan data latih (70%) untuk dievaluasi dengan model klasifikasi. Data yang diperoleh dari e-nose diproses menggunakan komputer dengan scikit-learn oleh perangkat lunak pembelajaran mesin berbasis Python.



Gambar 7 Alur scenario meningkatkan hasil analisis data

1) PRA-PEMROSESAN DATA SINYAL

Pra-pemrosesan sinyal dilakukan untuk menghilangkan noise pada sinyal. Dalam penelitian ini kebisingan disebabkan oleh sensor internal, perubahan kondisi lingkungan seperti kelembaban dan suhu, serta perubahan kondisi kelistrikan seperti tegangan dan arus. Sinyal yang dihasilkan oleh e-nose biasanya non-stasioner, di mana sifat statistik sinyal berubah seiring waktu, membuat proses pengurangan noise menjadi lebih rumit. Penelitian ini menggunakan transformasi wavelet diskrit (DWT) kemudian membandingkan beberapa mother wavelet untuk menentukan mother wavelet yang paling sesuai untuk filter noise. Teknik ini mengidentifikasi data dari berbagai aspek analisis sinyal, tren, breakdown point, diskontinuitas, dan kesamaan. Data yang dihasilkan e-nose kemudian dibagi menjadi 7 kelas. Langkah pertama adalah melihat bentuk sinyal. Pada langkah kedua, jenis wavelet, yang disebut mother wavelet, ditentukan; ini sangat diperlukan karena bervariasi dan dikelompokkan berdasarkan fungsi dasar wavelet masing-masing. Jenis mother wavelet yang paling populer dalam pemrosesan sinyal adalah Haar, dmey, coiflet, symlet, dan Daubechies, yang semuanya dibandingkan dalam percobaan kami, dengan beberapa tingkat dekomposisi. Proses transformasi wavelet diskrit untuk sinyal yang diberikan x (t) dinyatakan dalam Persamaan 1.

$$dwt(m,n) = \left\langle x(t), w_{m,n}(t) \right\rangle = \frac{1}{\sqrt{2^m}} \int_{-\infty}^{\infty} x(t)\omega \times \left(\frac{t - n2^m}{2^m} \right) dt \tag{1}$$

dimana m, n, ω masing-masing mewakili parameter skala, parameter, dan wavelet induk. Penjelasan proses transformasi wavelet adalah sebagai berikut: langkah pertama adalah mentransformasikan data dengan Persamaan 2,

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\omega \times \left(\frac{t-b}{a} \right) dt \tag{2}$$

dimana $\omega \square(t)$ adalah analisis fungsi konjugasi kompleks wavelet, a adalah parameter dilatasi wavelet, dan b adalah lokasi atau posisi parameter. Fungsi wavelet dalam bentuk diskrit adalah sebagai berikut:

$$\omega_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} \omega \left(\frac{t - nb_0 a_0^m}{a_0^m} \right) \tag{3}$$

dimana m, n mewakili kontrol translasi dilatasi dan wavelet. a_0 adalah parameter dilatasi konstan dengan nilai lebih dari satu dan b_0 merupakan parameter lokasi, yang harus lebih dari 0. Jika $a_0 = 2$ dan $b_0 = 2$ disubstitusikan ke dalam Persamaan 2, grid diadik dari transformasi wavelet ditulis sebagai berikut:

$$\omega_{m,n}(t) = 2^{\frac{-m}{2}} \omega(2^{-m} t - n) \tag{4}$$

Dengan menggunakan fungsi wavelet diskrit ini, diperoleh transformasi diskrit:

$$T_{m,n} = \square_{-\times}^{\times} x(t)\omega_{m,n}(t)dt \tag{5}$$

$T_{m,n}$ dikenal sebagai koefisien detail wavelet dengan skala indeks m dan lokasi n. Wavelet diskrit terkait dengan fungsi penskalaan dan persamaan dilatasinya. Penggunaan fungsi penskalaan dimaksudkan untuk memperlancar sinyal. Hasil dari fungsi penskalaan berbelit-belit dengan sinyal, yang memberikan koefisien aproksimasi. Dalam percobaan ini, PyWavelets digunakan [47].

2) STATISTICAL PARAMETER EXTRACTION

Pada langkah ini, ekstraksi parameter dilakukan untuk mengekstrak nilai yang paling relevan dan informatif untuk merepresentasikan karakteristik respons sensor secara keseluruhan. Nilai pra-pemrosesan dari respons sensor dirata-ratakan untuk mendapatkan nilai tunggal [48]. Pada penelitian ini dilakukan beberapa metode ekstraksi parameter statistik (misalnya deviasi standar (ST), mean (M), kurtosis (K), dan skewness (SK). Penelitian ini juga membuat beberapa kombinasi metode ekstraksi parameter utama seperti sebagai mean dikombinasikan dengan deviasi standar (M + ST), mean dengan skewness (M + SK), mean dengan kurtosis (M + K), mean dengan deviasi standar dan skewness (M + ST. + SK), mean dengan deviasi standar dan kurtosis (M + ST + K), dan mean dengan semua ekstraksi parameter mayor (M + ST + SK + K) Ekstraksi parameter statistik menggunakan parameter M, rata-rata sinyal yang akan direkonstruksi diwakili oleh y (t). merekonstruksi sinyal menggunakan parameter mean, Persamaan 6 digunakan.

$$\overline{y(t)} = \frac{\square\, y(t)}{N} \tag{6}$$

adalah $\square\, y(t)$ jumlah hasil dari satu sensor, dan N merupakan jumlah data. Sedangkan jika menggunakan standar deviasi (ST) sebagai parameter statistik, digunakan Persamaan 7.

$$\sigma = \sqrt{\frac{1}{N} \square_{i=1}^{N} (x_i - \overline{y(t)})^2} \tag{7}$$

dimana x_i adalah setiap nilai dari populasi. Rumus rekonstruksi sinyal menggunakan skewness (ST) diwakili oleh Persamaan 8.

$$\alpha^3 = \frac{1}{N\sigma^3} \sum_{i=1}^{N} (x_i - \overline{y(t)})^3 \quad (8)$$

dimana σ adalah varians. Jika kita hanya menggunakan satu metode parameter statistik maka fitur yang dihasilkan adalah 10 fitur. Selanjutnya, jika kita menggunakan dua metode parameter statistik, 20 fitur yang dihasilkan, dan seterusnya.

3) DIMENSIONAL REDUCTION

Fitur yang dihasilkan dapat tersebar di berbagai dimensi; Oleh karena itu, reduksi dimensi digunakan untuk mengeliminasi variabel yang tidak memiliki peran signifikan dalam mendeteksi pemalsuan daging babi. Analisis komponen utama (PCA) adalah metode reduksi dimensi yang digunakan dalam penelitian ini. Vektor eigen digunakan untuk mempertimbangkan hubungan antar variabel. Dari hasil percobaan, keluaran digital dianggap sebagai variabel PCA. Langkah-langkah untuk melakukan analisis komponen utama adalah sebagai berikut:

a) calculate the covariance (Cov) using Equation 9, where x is the signal and y is the class target from the signal.

$$Cov(x, y) = \frac{\sum xy}{n} - (\bar{x})(\bar{y}) \quad (9)$$

b) calculate the eigenvalue using Equation 10.

$$(A - \lambda I) = (0) \quad (10)$$

where A, λ, I are square matrices of size *n x n*, scalar numbers, and identities, respectively.

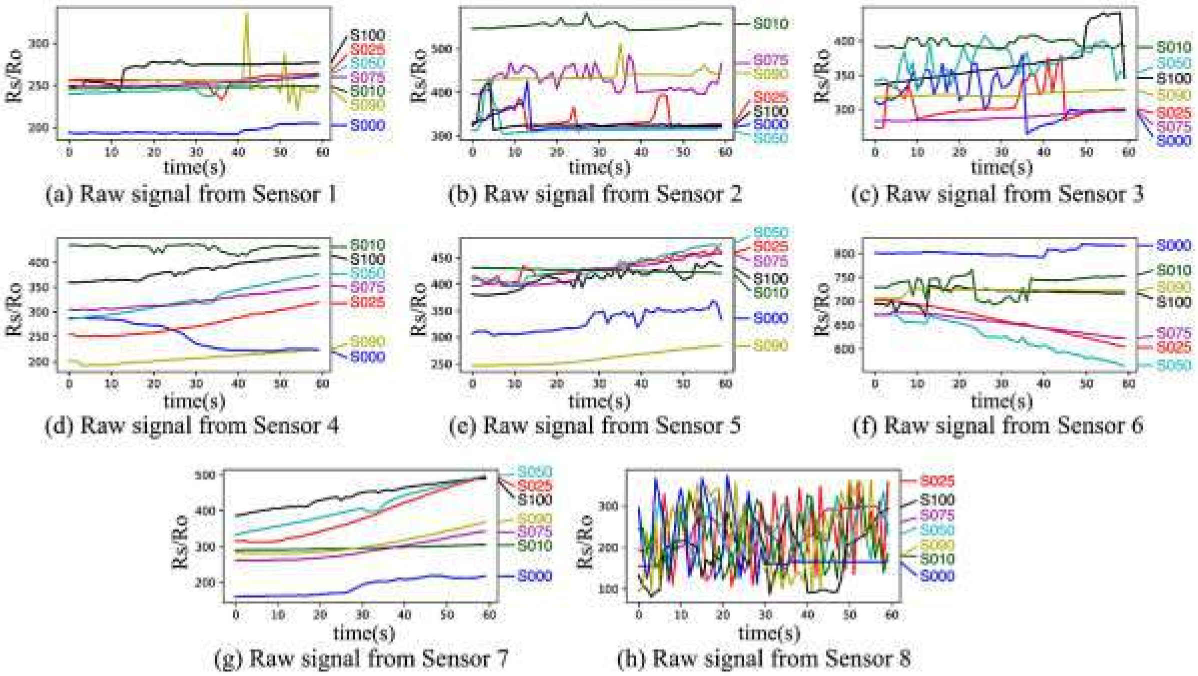
c) calculate the eigenvector using Equation 11.

$$[A - \lambda I][X] = [0] \quad (11)$$

d) determine the new variable (component) by multiplying the natural variable with the eigenvector.

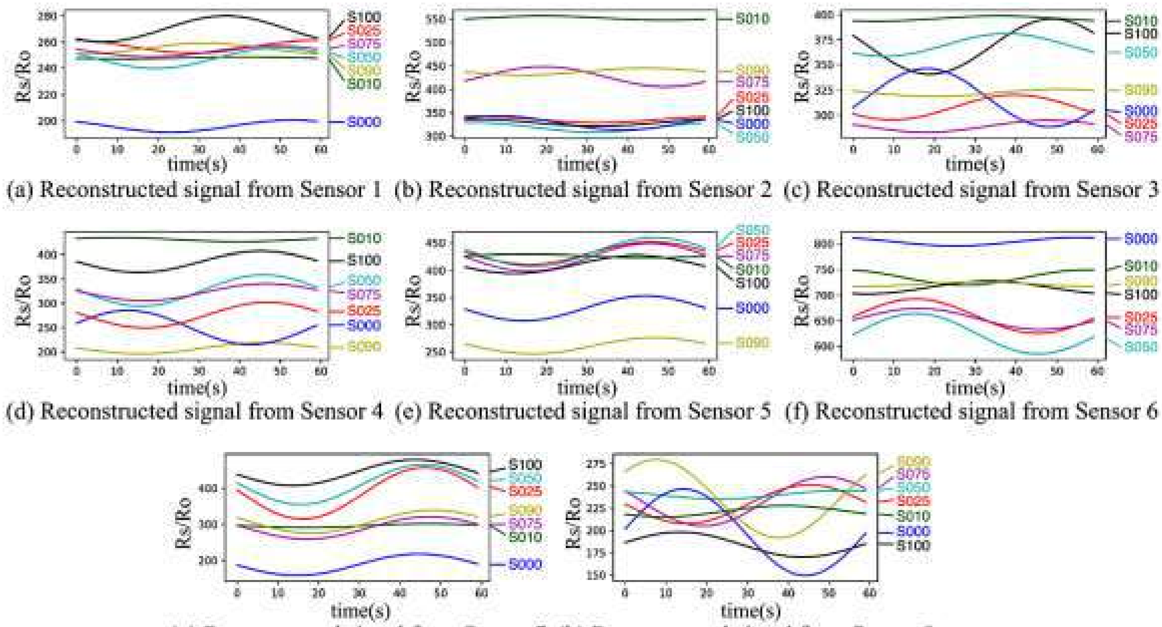
$$\rho I = \frac{\lambda_i}{\sum_{j=1}^{D} \lambda_i} \times 100\% \quad (12)$$

Jika nilai yang dihasilkan dari satu komponen yang digabungkan dengan komponen lainnya adalah 0, maka korelasi dianggap rendah dan dapat diartikan sebagai tidak ada hubungan [49]. Variabel yang memiliki nilai 0 dihapus. Setelah jumlah dimensi dikurangi, hasilnya distandarisasi agar nilainya tidak terlalu besar atau terlalu kecil. Metode yang digunakan untuk proses standardisasi adalah Standard Scaler. Metode ini memberikan ambang batas sesuai dengan data yang ada. Hasil dari keluaran electronic nose dapat dilihat pada gambar dibawah ini, terlihat hasilnya memiliki banyak gangguan yang menyebabkan hasil sinyal menjadi fluktuasi. Dengan metode signal processing menggunakan discrete wavelete transform maka gangguan dapat direduksi.



Gambar 8 Hasil grafik sinyal data electronic nose sebelum dilakukan pre-processing

Berikut adalah hasil dari penggunaan metode dwt pada sinyal electronic nose, terlihat perbedaan antara sebelum dan sesudah. Dalam gambar dibawah ini terlihat gangguan sudah direduksi dengan sangat baik.



Gambar 9 Hasil grafik sinyal data electronic nose sesudah dilakukan pre-processing

3) HASIL PARAMETER STATISTIK

Selain itu, dari delapan komponen yang dipilih, penelitian ini menentukan sensor n_komponen mana yang paling dominan. Tabel 7 menunjukkan bahwa pada komponen pertama faktor dominannya adalah S5 atau MQ 135. Faktor yang paling signifikan pada semua komponen adalah S1 atau MQ 2, yaitu pada komponen 8. Tabel 8 menunjukkan hasil reduksi dimensional dari kesepuluh parameter statistik ekstraksi kombinasi. Beberapa komponen dari hasil beberapa metode ekstraksi ciri dapat direduksi, seperti menggunakan metode statistik parameter M. Itu dapat mengurangi dimensi dari 10 menjadi 8 komponen menggunakan pengklasifikasi SVM. Metode statistik parameter M + ST dapat mereduksi dimensi menjadi 15 dari 20. Sedangkan metode statistik parameter M + SK menggunakan empat pengklasifikasi tidak mereduksi dimensi, namun tetap menggunakan 20 komponen. Metode parameter statistik yang menghasilkan fitur terbanyak adalah M + ST + SK + K, 40 fitur, yang dapat direduksi menggunakan pengklasifikasi JST. GAMBAR 5 menunjukkan data setelah reduksi dimensi menggunakan PCA. GAMBAR 5 a dan b menunjukkan data sebelum dan sesudah penskalaan fitur menggunakan normalisasi Standard Scaler (Z-score). Standarisasi digunakan untuk mengumpulkan data yang didistribusikan. Dari GAMBAR 5 dapat disimpulkan bahwa data dari kelas pertama menjadi lebih mengelompok dibandingkan dengan kelas lainnya.

3) KLASIFIKASI

Klasifikasi adalah proses pembagian variabel-variabel menjadi beberapa kelas. Pembagian kelas harus sesuai dengan hasil kenyataan dimana jika di kenyataan daging tersebut adalah daging sapi, maka dengan menggunakan electronic nose daging tersebut harus masuk dalam kelas daging sapi. Penelitian ini menggunakan metode klasifikasi Support Vector Classification (SVC) dengan parameter C =100 dan nilai gamma = 0,1. Parameter ini digunakan berdasarkan percobaan dengan memberikan rentang nilai antara 0,01 sampai dengan 1000 untuk parameter C dan rentang 0,01 sampai dengan 100 untk parameter gamma.

Tabel 6 Perbandingan hasil alurasi dari penggunaan parameter statistik dan machine learning

Classifier	Results	Statistical Parameter Method									
		ST	SK	K	M	M+ST	M+SK	M+K	M+ST+SK	M+ST+K	M+ST+SK+K
ANN	n component	10	10	10	10	17	20	20	25	27	40
	Accuracy without PCA (%)	70.48	50.00	42.86	94.52	95.48	93.10	92.14	94.76	93.57	93.57
	Accuracy optimization (%)	70.71	50.95	46.90	96.90	96.42	94.52	96.19	96.42	95.71	95.95
LDA	n component	10	10	10	9	17	20	20	23	30	17
	Accuracy without PCA (%)	66.90	36.19	38.57	89.29	92.86	89.29	90.00	93.10	90.71	93.10
	Accuracy optimization (%)	70.24	47.62	47.62	96.67	93.81	87.38	90.24	88.10	90.00	86.67
SVM	n component	10	10	10	8	17	20	20	27	30	35
	Accuracy without PCA (%)	66.90	47.86	40.71	95.24	96.19	90.24	89.52	93.10	87.86	91.90
	Accuracy optimization (%)	76.19	49.29	48.10	98.10	97.14	93.10	94.05	96.43	96.43	96.67
KNN	n component	10	10	10	9	15	20	20	30	29	40
	Accuracy without PCA (%)	65.48	44.29	38.10	94.52	91.90	84.76	86.90	87.38	89.05	84.29
	Accuracy optimization (%)	66.90	36.19	36.19	89.29	92.86	89.29	90.00	92.38	93.10	93.10

Algoritma untuk mencari parameter SVM yang optimal dari 420 data membutuhkan waktu eksekusi selama 16 detik. Data tersebut terbagi menjadi dua yaitu data latih dan data uji menggunakan validasi silang. Penelitian ini membandingkan tiga jenis validasi silang untuk mendapatkan hasil yang adil, yaitu 3 kali lipat, 5 kali lipat, dan 10 kali lipat. Nilai optimal yang ditemukan untuk parameter C dan γ adalah 100 dan 0,1, masing-masing, menggunakan validasi silang 10 kali lipat, seperti yang ditunjukkan pada TABEL 9. Pengujian dijalankan 20 kali untuk mengoptimalkan parameter. Langkah terakhir adalah klasifikasi menggunakan SVM. Pada GAMBAR 6 semua data dari Kelas 1, 6, dan 7 diprediksi dengan benar.

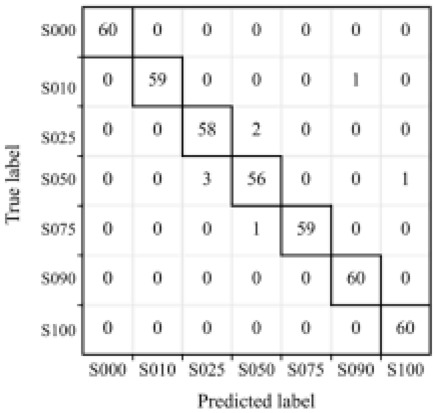
Tabel 7 Perbandingan evaluasi menggunakan cross-validation

Classifier	3 -fold cross-validation		5 -fold cross-validation		10-fold cross-validation	
	Train 280 data	Test 140 data	Train 336 data	Test 84 data	Train 378 data	Test 42 data
SVM		80.48%		93.31%		98.10%
LDA		75.95%		82.85%		96.67%
KNN		77.14%		88.57%		93.10%
ANN		73.33%		86.42%		95.48%

Tabel 8 Detail hasil evaluasi dari algoritma SVM

Class	Precision	Recall	F1-Score	Kappa Score	Avg Accuracy
1	1.00	1.00	1.00	97.78	98.10%
2	1.00	1.00	1.00		
3	0.98	0.98	0.98		
4	0.92	0.97	0.94		
5	1.00	0.98	0.99		
6	1.00	1.00	1.00		
7	0.97	0.93	0,95		

Sedangkan untuk Kelas 2, 59 data diprediksi dengan benar, dan 1 data salah prediksi; untuk Kelas 3, 58 data diprediksi dengan benar dan 2 data diprediksi salah; 4 data salah prediksi untuk Kelas 4, dan 1 data salah prediksi untuk Kelas 7, dan data 3 salah prediksi untuk Kelas 3. Terakhir, untuk Kelas 5, 59 data diprediksi dengan benar dan 1 data salah prediksi. Selain itu, TABEL 10 menunjukkan hasil evaluasi SVM dengan parameter optimal.



Gambar 10 Hasil confussion matrix dari hasil analisa

Selain itu, penelitian ini juga membandingkan beberapa metode klasifikasi, yaitu jaringan saraf tiruan (JST) [54], analisis diskriminan linier (LDA), K-nearest neighbours (KNN), dan SVM, tanpa menggunakan algoritma optimasi parameter 89%, 54 %, 87%, dan 91%, masing-masing. SVM dengan algoritma optimasi parameter yaitu C dan γ masing-masing adalah 100 dan 0.1, dan menghasilkan hasil terbaik (98.10%). Sebagai perbandingan, JST dengan algoritma optimasi parameter relu sebagai aktivasi menghasilkan 95,48%, KNN dengan algoritma optimasi parameter neighbour = 1 dan jarak sebagai bobot, memberikan 93,10%, dan LDA dengan algoritma optimasi parameter 92,86%. Hasil ini menunjukkan bahwa SVM yang dioptimalkan memiliki kinerja yang lebih unggul daripada yang lain. Optimalisasi pengaturan hyperparameter membuat batasan keputusan terbaik untuk mengklasifikasikan tujuh kelas campuran daging sapi dan babi.

C2. Luaran Tambahan (Artikel Ilmiah Jurnal Terindeks Scopus dan Artikel Ilmiah Seminar Terindeks Scopus)

Hasil dari penelitian tahun ketiga untuk Penelitian Pengembangan Electronic Nose untuk Deteksi Kemurnian Daging Sapi adalah **3 publikasi ilmiah jurnal internasional terindeks Scopus** dan **13 publikasi ilmiah seminar internasional terindeks Scopus**.

Judul-judul dari publikasi ilmiah jurnal internasional terindeks scopus:

1. Riyanarto Sarno, Kuwat Triyana, Shoffi Izza Sabilla, Dedy Rahman Wijaya, Dwi Sunaryono, Chastine Fatichah. Detecting Pork Adulteration in Beef for Halal Authentication using an Optimized Electronic Nose System. IEEE Access. *Accepted.*
2. Riyanarto Sarno, Shoffi Izza Sabilla, Dedy Rahman Wijaya, Dwi Sunaryono, Chastine Fatichah. Electronic nose dataset for pork adulteration in beef. Data in Brief, Vol. 32, October 2020, 106139. DOI:

10.1016/j.dib.2020.106139

3. Sinarring Azi Laga, Riyanarto Sarno. Temperature effect of electronic nose sampling for classifying mixture of beef and pork. Indonesian Journal of Electrical Engineering and Computer Science. Vol. 19, No. 3, 2020. DOI: 10.11591/ijeecs.v19.i3.pp 1626 -1634

Judul-judul dari publikasi ilmiah seminar internasional terindeks scopus:

1. Whilly Harsono, Recognition of Original Arabica Civet Coffee based on Odor using Electronic Nose and Machine Learning. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic). DOI: 10.1109/iSemantic50169.2020.9234234
2. Renny Sari Dewi. Software Effort Estimation Using Early COSMIC to Substitute Use Case Weight. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic). DOI: 10.1109/iSemantic50169.2020.9234227
3. Ilham Cahya Suherman. Implementation of Random Forest Regression for COCOMO II Effort Estimation. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic). DOI: 10.1109/iSemantic50169.2020.9234269
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5. Reza Hermansyah. Sentiment Analysis about Product and Service Evaluation of PT Telekomunikasi Indonesia Tbk from Tweets Using TextBlob, Naive Bayes & K-NN Method. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic). DOI: 10.1109/iSemantic50169.2020.9234238
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8. Desanty Ridzky. UTAUT2 model for Analyzing Factors Influencing User in using Online Travel Agent. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic). DOI: 10.1109/iSemantic50169.2020.9234258
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C3. Hak Kekayaan Intelektual

Hasil tambahan dari penelitian tahun ketiga ini berupa Hak Kekayaan Intelektual yang terdiri dari:

1. **HAK CIPTA PROGRAM KOMPUTER**
   Judul : MODUL VISUL WORKFLOW BERDASARKAN MODEL PROSES BISNIS UNTUK KASUS CRANIOSYNOSTOSIS
   Status : *Granted*

REPUBLIK INDONESIA
KEMENTERIAN HUKUM DAN HAK ASASI MANUSIA

SURAT PENCATATAN

CIPTAAN

Dalam rangka pelindungan ciptaan di bidang ilmu pengetahuan, seni dan sastra berdasarkan Undang-Undang Nomor 28 Tahun 2014 tentang Hak Cipta, dengan ini menerangkan:

Nomor dan tanggal permohonan	:	EC00202053925, 27 November 2020
Pencipta		
Nama	:	**Prof. Drs.Ec.Ir. Riyanarto Sarno, M.Sc.,Ph.D., Kelly Rossa Sungkono, S.Kom, M.Kom dkk**
Alamat	:	Jalan Tales 4/14 RT 003/ RW 010, Kelurahan Jagir, Kecamatan Wonokromo, Surabaya, JAWA TIMUR, 60244
Kewarganegaraan	:	Indonesia
Pemegang Hak Cipta		
Nama	:	**Prof. Drs.Ec.Ir. Riyanarto Sarno, M.Sc.,Ph.D., Kelly Rossa Sungkono, S.Kom, M.Kom dkk**
Alamat	:	Jalan Tales 4/14 RT 003/ RW 010, Kelurahan Jagir, Kecamatan Wonokromo, Surabaya, JAWA TIMUR, 60244
Kewarganegaraan	:	Indonesia
Jenis Ciptaan	:	**Program Komputer**
Judul Ciptaan	:	**MODUL VISUAL WORKFLOW BERDASARKAN MODEL PROSES BISNIS UNTUK KASUS CRANIOSYNOSTOSIS**
Tanggal dan tempat diumumkan untuk pertama kali di wilayah Indonesia atau di luar wilayah Indonesia	:	27 November 2020, di Surabaya
Jangka waktu pelindungan	:	Berlaku selama 50 (lima puluh) tahun sejak Ciptaan tersebut pertama kali dilakukan Pengumuman.
Nomor pencatatan	:	000222748

adalah benar berdasarkan keterangan yang diberikan oleh Pemohon.
Surat Pencatatan Hak Cipta atau produk Hak terkait ini sesuai dengan Pasal 72 Undang-Undang Nomor 28 Tahun 2014 tentang Hak Cipta.

a.n. MENTERI HUKUM DAN HAK ASASI MANUSIA
DIREKTUR JENDERAL KEKAYAAN INTELEKTUAL

Dr. Freddy Harris, S.H., LL.M., ACCS.
NIP. 196611181994031001

2. HAK CIPTA PROGRAM KOMPUTER

Judul : MODUL APLIKASI SIGNAL REPOSITORY UNTUK MENYIMPAN DATA SINYAL YANG DIPROSES DALAM ELECTRONIC NOSE

Status : *Terdaftar di KTT ITS*

MANUAL BOOK DAN LINK PROGRAM

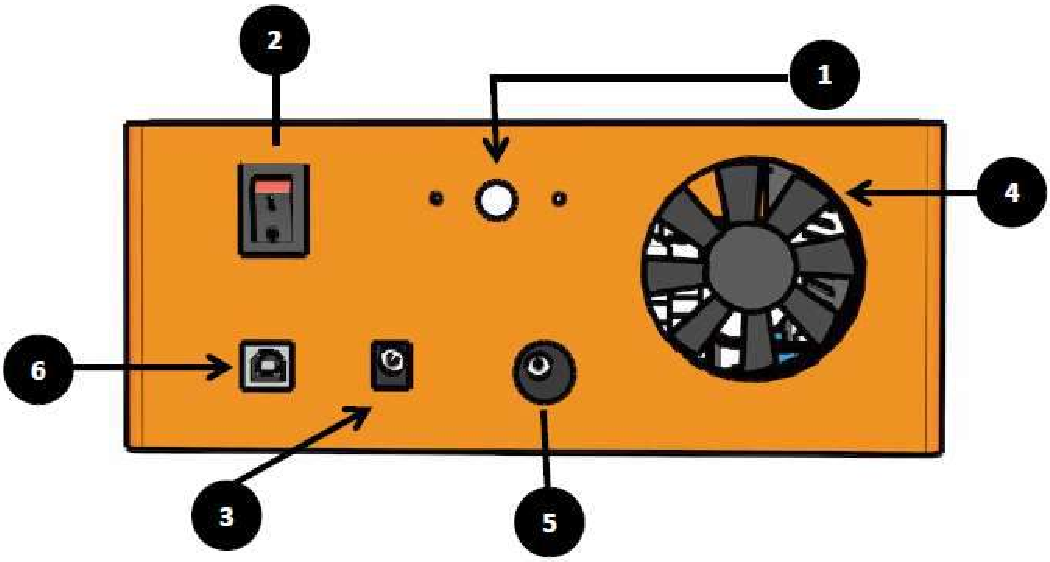
MODUL APLIKASI SIGNAL REPOSITORY UNTUK MENYIMPAN DATA SINYAL YANG DIPROSES DALAM ELECTRONIC NOSE

NAMA PENCIPTA (NIK):

Prof. Ir. Riyanarto Sarno, SE, M.Sc.,Ph.D.	(3578040308590002)
Dwi Sunaryono, S.Kom, M.Kom	(3578222805720002)
Dr. Eng. Chastine Fatichah S.Kom, M.Kom	(3578096012750004)
Shoffi Izza Sabilla, S.Kom	(3578225011940001)
Kelly Rossa Sungkono, S.Kom, M.Kom	(3507254906940001)

3. **DESAIN INDUSTRI**
Judul : BOX SISTEM ELECTRONIC NOSE
Status : *Terdaftar di KTT ITS*

Gambar 1 dari 7



Keterangan:

① KOMPONEN PNEUMATIC JENIS M5

② TOMBOL SAKLAR ON/OFF

③ LUBANG MASUKAN POWER SUPPLY MICRO-CONTROLLER

④ KIPAS KECIL

⑤ LUBANG MASUKAN POWER SUPPLY 12 V 5 A

⑥ LUBANG MASUKAN KABEL MICRO-CONTROLLER

4. PATEN

Judul : SISTEM ELECTRONIC NOSE UNTUK DETEKSI KEMURNIAN DAGING SAPI TERHADAP DAGING BABI

Status : *Terdaftar di KTT ITS*

Deskripsi

SISTEM *ELECTRONIC NOSE* UNTUK DETEKSI KEMURNIAN DAGING SAPI TERHADAP DAGING BABI

Bidang Teknik Invensi

Invensi ini mengenai Sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi, lebih khusus lagi, invensi ini berhubungan dengan alat untuk mendeteksi keberadaan campuran daging babi di dalam daging sapi berdasarkan persentase.

Latar Belakang Invensi

Salah satu cara untuk membedakan daging sapi dengan daging babi adalah dengan melihat warna dan teksturnya. Namun, untuk mendeteksi adanya daging sapi yang dicampur dengan daging babi, masyarakat masih kesulitan. Kementrian perdagangan melakukan uji laboratorium menggunakan *Enzyme-linked immunosorbent assay* (ELISA) dan tes DNA untuk mendeteksi daging sapi yang dicampur dengan daging babi. Namun pengujian ini dilakukan oleh orang-orang ahli dan membutuhkan waktu satu hari untuk satu sampel daging.

Invensi ini berkaitan dengan sistem deteksi kemurnian daging sapi yang di campur dengan daging babi berdasarkan aroma dari daging. Sampel pengujian untuk mendeteksi keberadaan daging babi di dalam daging sapi dengan campuran daging babi dengan klasifikasi persentase : kelas 1, persentase 0%-5%; kelas 2, persentase 6%-15%; kelas 3, persentase 16%-35%; kelas 4, persentase 36%-60%; kelas 5, persentase 61%-85%; kelas 5, persentase 86%-95%; dan kelas 6, persentase 96%-100% daging babi. Invensi ini berkaitan dengan beberapa artikel sebagai referensi, yaitu :

D. **STATUS LUARAN**: Tuliskan jenis, identitas dan status ketercapaian setiap luaran wajib dan luaran tambahan (jika ada) yang dijanjikan. Jenis luaran dapat berupa publikasi, perolehan kekayaan intelektual, hasil pengujian atau luaran lainnya yang telah dijanjikan pada proposal. Uraian status luaran harus didukung dengan bukti kemajuan ketercapaian luaran sesuai dengan luaran yang dijanjikan. Lengkapi isian jenis luaran yang dijanjikan serta mengunggah bukti dokumen ketercapaian luaran wajib dan luaran tambahan melalui Simlitabmas.

Tabel 9 Status Luaran Penelitian

Luaran	**Deskripsi Luaran**	**Status**
Wajib	Prototipe	Penjelasan di C1 bagian D
	Dokumentasi *Feasibility Study* (Pengujian Electronic Nose)	Penjelasan di C1 bagian E dan F
Tambahan	Artikel ilmiah dimuat di jurnal	Penjelasan di C2.
	Artikel ilmiah dimuat di prosiding	Penjelasan di C2.
	Hak Cipta	Penjelasan di C3
	Desain Industri	Penjelasan di C3
	Paten	Penjelasan di C3

E. **PERAN MITRA:** Tuliskan realisasi kerjasama dan kontribusi Mitra baik *in-kind* maupun *in-cash* (untuk Penelitian Terapan, Penelitian Pengembangan, PTUPT, PPUPT serta KRUPT). Bukti pendukung realisasi kerjasama dan realisasi kontribusi mitra dilaporkan sesuai dengan kondisi yang sebenarnya. Bukti dokumen realisasi kerjasama dengan Mitra diunggah melalui Simlitabmas.

Karena adanya kendala pandemi COVID-19, maka mitra pengguna berubah menjadi Arsenal Dissenlekal dengan PIC yaitu Pak Whilly, S.T., Kassubag Test Bench. Dokumentasi mengenai pertemuan dan testing sistem dengan mitra pengguna dapat dilihat pada gambar-gambar di bawah ini.

Gambar 11. Pengambilan Sampel tanggal 27 November 2020

Gambar 12. Uji Coba Prototipe di Lingkungan Mitra tanggal 27 November 2020

Gambar 13. Foto bersama Mitra tanggal 1 Desember 2020

F. **KENDALA PELAKSANAAN PENELITIAN**: Tuliskan kesulitan atau hambatan yang dihadapi selama melakukan penelitian dan mencapai luaran yang dijanjikan, termasuk penjelasan jika pelaksanaan penelitian dan luaran penelitian tidak sesuai dengan yang direncanakan atau dijanjikan.

Tidak ada kendala.

G. **RENCANA TAHAPAN SELANJUTNYA:** Tuliskan dan uraikan rencana penelitian di tahun berikutnya berdasarkan indikator luaran yang telah dicapai, rencana realisasi luaran wajib yang dijanjikan dan tambahan (jika ada) di tahun berikutnya serta *roadmap* penelitian keseluruhan. Pada bagian ini diperbolehkan untuk melengkapi penjelasan dari setiap tahapan dalam metoda yang akan direncanakan termasuk jadwal berkaitan dengan strategi untuk mencapai luaran seperti yang telah dijanjikan dalam proposal. Jika diperlukan, penjelasan dapat juga dilengkapi dengan gambar, tabel, diagram, serta pustaka yang relevan. Jika laporan kemajuan merupakan laporan pelaksanaan tahun terakhir, pada bagian ini dapat dituliskan rencana penyelesaian target yang belum tercapai.

Topik pengembangan e-nose untuk deteksi kemurnian daging sapi sesuai dengan roadmap penelitian yang dipaparkan pada Tabel 10.

Tabel 10 Riset Electronic Nose untuk Deteksi Kemurnian Daging Sapi (ENOSIKA)

Roadmap ENOSIKA	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**
TOPIK RISET PENGEMBANGAN (TKT 7-9)												
Pengembangan ENOSIKA untuk deteksi kesegaran daging												
Pengembangan ENOSIKA untuk deteksi kemurnian daging												
Pengembangan ENOSIKA untuk deteksi kesegaran buah												
Pengembangan Mobile ENOSIKA untuk deteksi kesegaran daging												
Pengembangan Mobile ENOSIKA untuk deteksi kemurnian daging												
Pengembangan Mobile ENOSIKA untuk deteksi kesegaran buah												
TOPIK RISET TERAPAN (TKT 4-6)												
Implementasi ENOSIKA untuk peningkatan *filtering* sinyal gas untuk deteksi kesegaran daging dan buah												
Implementasi ENOSIKA untuk peningkatan pemilihan gas gas untuk deteksi kesegaran daging dan buah												
Implementasi ENOSIKA untuk peningkatan klasifikasi gas gas untuk deteksi kesegaran daging dan buah												
Implementasi ENOSIKA untuk peningkatan *filtering* sinyal gas untuk deteksi kemurnian daging dan buah												
Implementasi ENOSIKA untuk peningkatan pemilihan gas gas untuk deteksi kemurnian daging dan buah												
Implementasi ENOSIKA untuk peningkatan klasifikasi gas gas untuk deteksi kemurnian daging dan buah												

Implementasi prototipe ENOSIKA												
TOPIK RISET DASAR (TKT 1-3)												
Optimasi *filtering* sinyal gas untuk deteksi kesegaran daging dan buah												
Optimasi pemilihan sinyal gas untuk deteksi kesegaran daging dan buah												
Optimasi klasifikasi sinyal gas untuk deteksi												
kesegaran daging dan buah												
Optimasi filtering sinyal gas untuk deteksi kesegaran daging												
Optimasi pemilihan sinyal gas untuk deteksi kesegaran daging												
Optimasi klasifikasi sinyal gas untuk deteksi kesegaran daging												

Roadmap rinci penelitian tahun pertama dan kedua dapat dilihat pada Tabel 11, sedangkan roadmap rinci tahun ketiga dapat dilihat pada Tabel 12. Berdasarkan rencana luaran pada Tabel 12, pencapaian luaran tahun ini (2020) adalah prototipe e- nose, dokumen feasibility experiment, artikel ilmiah dimuat di jurnal, artikel ilmiah dimuat di prosiding, dan hak kekayaan intelektual.

Tabel 11 Roadmap Penelitian Electronic-Nose untuk Deteksi Kemurnian Daging Sapi Tahun Sebelumnya

PENGEMBANGAN ELECTRONIC-NOSE UNTUK DETEKSI KEMURNIAN DAGING SAPI	**LUARAN**	**PENDANAAN**
Tahun I – TKT 4		
Pembentukan metode *de-noising* Penetapan metode Machine Learning untuk Deteksi Kemurnian Daging Sapi Perancangan Electronic-Nose untuk Deteksi Kemurnian Daging Sapi	1. 1 published artikel ilmiah dimuat di jurnal [5] 2. 5 published artikel ilmiah dimuat di prosiding [10], [15]– [18] 3. Rancangan prototipe Electronic Nose	Penelitian Terapan Unggulan Perguruan Tinggi (PTUPT)
Tahun II – TKT 5		
Peningkatan metode *de-noising* Penetapan metode Machine Learning untuk Deteksi Kemurnian Daging Sapi Pembentukan prototipe Electronic-Nose untuk Deteksi Kemurnian Daging Sapi Evaluasi prototipe Electronic-Nose untuk Deteksi Kemurnian Daging Sapi	1. Prototipe Electronic Nose 2. Dokumen pengujian awal 3. 8 published artikel ilmiah dimuat di jurnal [4], [16], [19]–[24] 4. 1 published artikel ilmiah di prosiding [25]	Penelitian Terapan Unggulan Perguruan Tinggi (PTUPT)

Tabel 12 Roadmap Penelitian Electronic-Nose untuk Deteksi Kemurnian Daging Sapi Tahun Sekarang (2020)

PENGEMBANGAN ELECTRONIC-NOSE UNTUK DETEKSI KEMURNIAN DAGING SAPI	**RENCANA LUARAN**	**PENDANAAN**
Tahun III – TKT 6		
Peningkatan prototipe Electronic-Nose untuk Deteksi Kemurnian Daging Sapi	Luaran wajib: 1. Pengembangan Prototipe Electronic Nose 2. Dokumen uji produk berupa *feasibility experiment* Luaran tambahan: 1. Artikel ilmiah dimuat di jurnal 2. Artikel ilmiah dimuat di prosiding 3. Hak Kekayaan Intelektual	Penelitian Terapan Unggulan Perguruan Tinggi (PTUPT)

H. DAFTAR PUSTAKA: Penyusunan Daftar Pustaka berdasarkan sistem nomor sesuai dengan urutan pengutipan. Hanya pustaka yang disitasi pada laporan kemajuan yang dicantumkan dalam Daftar Pustaka.

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on Information and Communications Technology, ICOIACT 2018, vol. 2018-Janua, pp. 489–494, 2018, doi: 10.1109/ICOIACT.2018.8350730.

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LAMPIRAN

LAMPIRAN I

PAPER JOURNAL SCOPUS 2020

1. Riyanarto Sarno, Kuwat Triyana, Shoffi Izza Sabilla, Dedy Rahman Wijaya, Dwi Sunaryono, Chastine Fatichah. Detecting Pork Adulteration in Beef for Halal Authentication using an Optimized Electronic Nose System. IEEE Access. *Accepted.*
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Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

Detecting Pork Adulteration in Beef for Halal Authentication using an Optimized Electronic Nose System

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ABSTRACT Recently, the issue of food authentication has gained attention, especially halal authentication, because of cases of pork adulteration in beef. Many studies have developed rapid detection for adulterated meat. However, these studies are not yet practical and economical methods and instruments and a faster analysis process. In this context, this paper proposes the Optimized Electronic Nose System (OENS) for more accurately detecting pork adulteration in beef. OENS has advantages such as proper noise filtering, an optimized sensor array, and optimized support vector machine (SVM) parameters. Noise filtering is carried out by cross-validation with different mother wavelets, i.e., Haar, dmey, coiflet, symlet, and Daubechies. The sensor array was optimized by dimension reduction using principal component analysis (PCA). An algorithm is proposed for the optimization of the SVM parameters. An experiment was conducted by analyzing seven classes of meat, comprising seven different mixtures of beef and pork. The first and seventh classes were 100% beef and 100% pork, respectively, while the second, third, fourth, fifth, and sixth classes contained 10%, 25%, 50%, 75%, and 90% of beef in a sample of 100 grams, respectively. Sample testing was carried out for 15 minutes for each sample. The classification test results to detect beef and pork had an accuracy of 98.10% using the optimized support vector machine. Thus, OENS has a favorable performance to detect pork adulteration in beef for halal authentication.

INDEX TERMS Electronic nose, beef, pork, adulteration, halal authentication, optimized SVM.

I. INTRODUCTION

The issue of food authentication has recently attracted the attention of consumers because of religious or lifestyle reasons [1]–[4]. Especially for Muslims, food authentication regarding halal food is essential [5]. Pork is food that Muslims cannot eat (The Holy Quran, 1:173; 5:3; 6:145; 16:115). However, pork adulteration in beef has been discovered in the market [3], [6]. The practice of mixing beef with pork is sometimes done for economic reasons [7], [8]; the seller adulterates pork in beef because pork is cheaper than beef [9].

Recent research has discussed meat authentication using visual detection. The procedure includes DNA isolation from fresh meat samples, amplification of specific DNA sequences, and detection using lateral flow assays. This research can authenticate horse meat and pork meat with high selectivity and reproducibility values. However, this process still takes quite a long time, namely, 25-30 minutes [10]. Another recent study used lateral flow sensing (LFS) and polymerase chain reaction (PCR) for the rapid visual detection of adulterated meat [11]. The samples used in this study were the adulterated beef samples prepared by mixing with duck meat in a series of proportions of 0%, 0.01%, 0.05%, 0.1%, 0.5%, 1%, 5%, 10%, 50%, and 100%. This research took less than 2 hours to process. Various scientific methods have been developed to identify mixed meats, including gas chromatography (GC) and mass spectrometry (MS) [12], high-performance liquid chromatography (HPLC), nuclear magnetic resonance (NMR) spectroscopy [13], and Fourier transform infrared (FTIR) spectroscopy [14]. However, several things have to be considered when using these tools, such as cost, time, and experience [15], [16]. The price of GC-MS instrument is around USD 120,000 in 2017 [17], while the cost of testing a sample is

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Data Article

Electronic nose dataset for pork adulteration in beef

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A B S T R A C T

This article provides a dataset of several weight combinations from the adulteration of pork in beef using an electronic nose (e-nose). Seven combinations mixtures have been built, they were 100% pure beef, 10% mixed with pork, 25% mixed with pork, 50% mixed with pork, 75% mixed with pork, 90% mixed with pork, and 100% pure pork. By using this combination, a minimum of 10% of a mixture of pork or beef can be detected. In each experiment cycle, data were collected for 120 s using an e-nose. The availability of this dataset can enable further research about meat adulteration, Halal authentication, etc. For several cases, food adulteration is one of the main concerns in food science, for example, due to economic, religious reasons, etc. This dataset can also be utilized as the data source for several interesting topics such as signal processing, sensor selection, e-nose development, machine learning algorithms, etc.

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Temperature effect of electronic nose sampling for classifying mixture of beef and pork

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ABSTRACT

Strong demand and strong price of raw foodstuffs like beef was commonly used in conventional markets by beef dealers to commit fraud in order to gain larger income. The fraud has been in the form of combining beef and pork. In Indonesia, this has been a issue of food health in recent years. Via scent, some food safety concerns can be expected. By using electronic nose that is equipped with electrochemical and air sensors such as temperature sensors, strain, and humidity to find the pure beef or mixed beef. According to its selectivity, the sensor can detect gas to make small icurrents that are the result of chemical sensor and gas interactions with oxygen. In this study, the classification method k-NN, SVM, Naïve Bayes, and Random Forest was used in 5 different meat variations with a ratio of 0%, 10%, 50%, 90% and 100% with temperatures of -22° C, Room Temp., And 55° C. The results showed the effect of temperature on increasing the accuracy, which is at a temperature of -22° C. The lower the temperature, the more stable the value obtained by electronic nose. At a temperature of -22° C, the method that produces the highest accuracy is the Random Forest method.

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1. INTRODUCTION

Strong demand and strong price of raw foodstuffs like beef was commonly used in conventional markets by beef dealers committing deception to gain more income. The fraud took the form of combining beef and pork [1]. In Indonesia, this has been a issue of food health in recent years. Via scent, some food safety concerns can be expected. By using electronic nose that is equipped with electrochemical and air sensors such as temperature sensors, strain, and humidity to find the pure beef or mixed beef. Food protection and insurance cover a variety of things like nutrition, sanitation and legality [2]. The creation of blending beef and pork is often practiced in fresh state. It occurs because pork is an inexpensive animal protein source, and is readily available on the market, making it beef scam more lucrative for the rogue seller. The case of this mixed beef poses significant questions, given that Indonesia is the world's largest nation with a Muslim majority. However, certain classes of people are hypersensitive, too or aversion to pork [3]. Their scent can discern certain food safety issues.

By using electronic nose that is equipped with electrochemical and air sensors such as temperature sensors, strain, and humidity to find the pure beef or mixed beef [4]. Depending on its selectivity, the sensor can detect gas by generating low currents which result from chemical sensor reations and gas between oxygen [5]. In this research, further analyzes using algorithms for machine learning algorithms with 3 temperature differences in each of the 5 variations of sample meat data was applied to determine optimum classification result. The temperature used were the temperature of -22° C, Room Temp And 55° C, while the variation of the meat mixture used were 0% Beef - 100% Pork; Beef 10% - Pork 90%; Beef 50% - Pork 50%;

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Recognition of Original Arabica Civet Coffee based on Odor using Electronic Nose and Machine Learning

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***Abstract*—Many studies have used an electronic nose (E-nose) to detect several types of coffee. To the best of our knowledge, none of the studies have tried to detect odors from a mixture of several types of coffee. Therefore, this research proposes E-nose which can be used to recognize original Arabica civet coffee. The mixture of Arabica civet coffee and Robusta coffee (non-civet coffee) is used as the object of this research. Nine combinations of mixture are prepared in this study. Those combinations are referred to as classes. After collecting the data, a statistical calculation would be determined to obtain parameter statistics. Moreover, the classification method used in this study is to recognize original Arabica civet coffee and original Robusta coffee. Several classifications had been compared, namely Logistic Regression (LR), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN). The best result is the KNN method with an accuracy value of 97.7% for nine classes.**

Keywords*—*E-nose, Classification, Sensors, Arabica Coffee, Robusta Coffee, Civet Coffee.

I. Introduction

Traditionally, the aroma of coffee has been used to differentiate the originality of coffee. The aroma of coffee contains gas which is obtained by determining the gas content. During the roasting, temperature increases, and the biological process occurs. Then, coffee releases a robust aroma [1]. New compounds formed by physical and chemical reactions evaporate. E-nose has the ability to simulate the work of the human sense of smell. An electronic nose is made to catch the gas and recognize odors by using sensors [2]. The database of aroma produced by coffee is a pattern of odor, one of which functions to develop the system that can recognize a pattern, so it can be classified and be inspected [3].

In 2016, a study was conducted to classify coffee using a backpropagation neural network. The result showed that backpropagation neural network is capable of determining the differences [4] between Arabica and Robusta with a success rate of 40%.

Another E-nose study attained an accuracy of 71% for the Support Vector Machine (SVM) method and 57% for the Perceptron method. The study tried to classify the aroma of Arabica coffee and the aroma of Robusta coffee. The SVM method could recognize Arabica coffee and Robusta coffee with better results than the Perceptron method [5]. However, the research had a weakness in the classification method. The result of the classification has a lesser percentage of accuracy. Moreover, there was not any statistical calculation that could be used for preprocessing before classifying the data.

Therefore, this study aims to improve the weaknesses of the previous studies. E-nose used in this study has different characteristics to identify the odor and aroma of the gas because it consists of various types of sensors [6]. Then, the preprocessing stage using statistical calculations can obtain the characteristics from each signal response. This study has three values from a combination of statistical calculations; there are the values of average and standard deviation, the values between the minimum and maximum, and the values between average, standard deviation, and minimum and maximum values. After preprocessing stage, the calculation continues with the classification phase. Confusion matrix [7] is used in this study to evaluate the classification method.

Besides, we try to use other classification methods, so the results can be compared. Other classification methods that we use in this study are Logistic Regression (LR), Linear Discriminant Analysis (LDA) [8], and K-Nearest Neighbors (KNN). Comparing the result generated from three classification methods use the confusion matrix, and the best accuracy is chosen for the purpose of this study.

II. Related Research

A. *E-nose using Backpropagation Neural Network*

This study uses a system that puts several sets of gas sensors and receives input signals from TGS 2610, TGS 2611, TGS 2602, TGS 2620, and TGS 822 [4]. The resistance of the sensor results in a change of voltage when the sensor detects the presence of gaseous elements from the aroma of coffee. This signal is operated by a signal conditioning circuit to be delivered to the analog-digital converter (ADC) circuit and to change over into digital form. The process continues when the digital signal transmitted to the Personal Computer (PC) and to be processed using backpropagation NN (Neural Network). Backpropagation NN used is built with

Software Effort Estimation Using Early COSMIC to Substitute Use Case Weight

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Abstract—**In the size estimation software, there are many methods that have proven their reliability. One of them is Use Case Points (UCP). UCP has a well-known advantage based on the use case scenario which is a reformation of the user story in the software requirements specification (SRS) document. However, UCP also has several weaknesses, including the use case is a summary of the user story. User stories often do not reveal detailed data. Therefore, the potential ambiguity of the use case must be watched by a business/system analyst. On the other hand, there is an international association called COSMIC, which has developed a global standard for calculating the size of the software namely ISO/IEC 19761. The COSMIC model begins with a user story which is then carried out cascade to sequence diagrams to make an engagement between process/method flow and data. The purpose of this study is to substitute the use case weight of the pure UCP method, to become a COSMIC functional size unit (Cfsu). Then, the estimation results of the two are compared with the actual effort. The case study used as a comparison of the COSMIC and UCP methods is the Hair Salon Online Booking Application. From this study the results obtained are the deviation between the results of the original UCP estimate (keep use case weight) of the actual effort is 76.85 percent. As for software effort estimation using early COSMIC is 92.67 percent against the actual effort.**

Keywords—COSMIC, use case points, use case weight, software estimation, software measurement

I. Introduction

In the 21st century, there are various modern ways of developing software. Generally, there are 3 phases in software development namely planning, implementation, and evaluation. At all stages, many professionals and researchers have published international standards. One of them is the international standard related to software size estimation in the planning phase.

Starting from 1979, A.J. Albrecht published the first time a method for measuring the scale of software called Function Points (FP) [1]. Through the International Function Points User Group (IFPUG), the FP method is upgraded to ISO/IEC 20926:2009 standard [2]. The FP method revolution also made various other global standards such as ISO/IEC 20968:2002 Mk II FPA [3].

In addition to the FP method, Cost Constructive Model (COCOMO) I and II have also been tested by previous researchers. Since it was first published by Barry W. Boehm [4], COCOMO II received a lot of welcome from many researchers to test the accuracy of its estimated value compared to other methods, as Sarno et al [5] [6] [7] [8].

At the end of 2019, the Common Software Measurement International Consortium (COSMI) launched a version version 4.02 to calculate the estimated software development effort. The COSMIC model approaches 4 types of transactions, Entry (E), eXit (X), Read (R), and Write (W). COSMIC is often used by researchers by describing the Unified Modeling Language (UML) sequence diagrams [9].

Use Case Points (UCP) is one method of calculating software size estimates that was discovered by Gustav Karner in 1993 [10]. UCP has applied various professional cost / size estimators for their accuracy in actual effort. There is a different point of view between the COSMIC and UCP methods. The COSMIC model is a hybrid of FP methods.

As is well known, FP has been standardized by international associations with various types of practical tests in thousands of industries and also algorithmically [11] [12]. Therefore, COSMIC as a respectable association, made another standard, COSMIC Full Function Points (FFP) with ISO / IEC 19761: 2003 version 4.02 [13] and simplified to version 5.0 [14].

While UCP also has the advantage of input parameters based on the description of use cases and actors involved in the system. But for the COSMIC model, the advantage is that it can be clearly described the involvement of data in each process / method flow through sequence diagrams in UML approach [9].

II. Statement of the Problem

A. Research Problem

The above description becomes the background of the writer to describe the formulation of the problem as follows:

RP1: Can the use case weight in the UCP method be replaced by early COSMIC?

RP2: What percentage of accuracy is generated at the estimated effort based on the early COSMIC method with UCP?

The two problems above aim to find out more whether changing the use case weight to a COSMIC functional size unit in the UCP method affects the level of accuracy of the real project effort.

B. Research Limitation

The limitations of this research are the case studies used by the authors. The case study specified is a Hair Salon Online Booking application development project. This application is done by 1 advanced programmer plus database designer, 1 layout designer also as a project leader. Work on this application for 12 days according to client's request. The software development life cycle method used is agile programming until the application testing period is complete.

III. Previous Works

A. Modifying UCP Method

The original UCP method by Karner [10] was illustrated in Fig. 1.

Implementation of Random Forest Regression for COCOMO II Effort Estimation

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Abstract—**One of Project Manager early activity is to estimate time, and cost based on given scope, which can help project manager to plan schedule and used resources. Estimation is very important in project management because a bad result of estimation will result in bad management of project and may cause failure. There are methods that can be used to estimate software development effort; COCOMO II is one method that commonly used. Many researcher before have been used algorithm, such as Bat, Bee Colony, or MOPSO to increase COCOMO II estimation accuracy. However, as the technology advanced, there are a lot more options that can be used to predict software effort estimation based on COCOMO, such as machine learning. In this paper, we compare machine learning algorithm with tuning parameter method to know whether tuning parameter estimation is better than machine learning estimation or vice versa. In this paper, we use Random Forest Regression as machine learning algorithm to estimate the effort. We also compare it with another machine learning algorithm, Support Vector Regression, and Bee Colony Method as parameter tuning method. The results of experiment is evaluated by their error rate. The results show that Random Forest Regression is better than Support Vector Regression and Bee Colony Method.**

Keywords—effort estimation, COCOMO II, Random Forest Regression

I. Introduction

Project Manager (PM) is a role that has responsibilities to maintain project management process groups such as initiating, planning, executing, monitoring, controlling, and closing the project according to PMBOK [1]. One of PM early activity is to estimate time, and cost based on given scope, which can help project manager to plan timeline and used resources. In software development industry, the challenge of project manager is to make sure that the high quality software can be achieved with resources as few as possible. Estimation is very important in project management because a bad result of estimation will result in bad management of project and may cause failure. Based on [2], about 65% failed projects are caused by Management factors; one of it is poor estimation method.

One of methods that commonly used to estimate software development effort is Constructive Cost Model (COCOMO) II. COCOMO II [3] rely on Kilo Line of Code (KLOC) multiplied by constants, Effort Multipliers, and Scale Factors [3].

Many previous researches used algorithm, such as Fuzzy Logic Model [4], Bat Algorithm [5], MOPSO [6], and Bee Colony [7], to optimize COCOMO parameters in order to increase estimation accuracy. However, as the technology advanced, there are a lot more options that can be used to predict software effort estimation based on COCOMO, such as machine learning.

Therefore, this research aims to study whether tuning the constant parameter of COCOMO II is a better method than using machine learning algorithm to predict the estimation of software development effort or vice versa. Support Vector Regression and Random Forest Regression are machine learning algorithm that used in this research with the help of programming language, Python.

In this paper, we provide the study of the implementation of machine learning algorithms, Support Vector Regression and Random Forest Regression, as the comparison to parameter tuning method for COCOMO II effort estimation. In Section 2, related work about software development estimation method and steps of the working methodology of the research will be discussed. In Section 3, the result and the analysis of the research will be presented. In the last section, the research is concluded, whether tuning constant parameter of COCOMO II is a better method than using machine learning algorithm or vice versa.

II. Related Work

Various studies have been conducted to optimize COCOMO II estimation results. Some studies used statistical models to predict time and effort. Various studies also used statistical models, but those models are used to change parameter values in the COCOMO formula, and some studies use machine learning algorithm to improve the COCOMO model in estimating time and effort in software development. There are also studies that comparing several methods or algorithms in order to find out, which method or algorithm that has the best accuracy and small error when used for COCOMO effort and time estimation.

Langsari et al. [6], [8], [9] have done several studies about optimizing COCOMO II parameter in order to increase its estimation accuracy. In [6] they applied Fuzzy Multi-Objective Particle Swarm Optimization (Fuzzy MOPSO) to optimize time and effort parameters of COCOMO II on NASA93 dataset. They optimized COCOMO II time and effort by using MATLAB to calibrate COCOMO II coefficients, A, B, C, and D. In the end, they found new parameters ($A = 4.852$, $B = 0.2830$, $C = 2.802$, $D = 0.3615$) and able to reduce MRE and MMRE significantly, and make the estimation close to its actual time and effort.

Sarno et al. [10] applied different neural network architectures to adjust the parameters of COCOMO effort estimation with the help of Backpropagation algorithm to

Android Application for Presence Recognition based on Face and Geofencing

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Abstract—**The Attendance system, especially in companies is needed to help assess the attendance and discipline of employees. Some attendance systems that have been made based on the detection of biometrics, barcodes, and QR Codes have not been able to simplify the attendance process where employees still have to queue in front of the attendance machine. This paper aims to design an attendance system that flexible which can simplify and speed up the process by using a mobile application based on geofencing and face recognition so the company does not need to expend the extra cost to buy dedicated machine. The system is using a mobile application as a device to presence. Each of the employees has their own geofencing area which worked as a location virtual boundary. The employee face images are sent to the server from mobile application for the attendance process which includes a recognition process using k-Nearest Neighbours (k-NN) and Principal Component Analysis (PCA). The results obtained are using face recognition k-NN and PCA obtained a 90% accuracy rate with a processing time of 1.5 seconds. The fastest time to do a complete presence is 3.4s which include a geofencing authentication and face recognition process.**

Keywords—: mobile-based presences system, geofencing, face recognition, k-Nearest Neighbours, principal component analysis

I. Introduction

The technology is currently developing very fast wherein the industrial era 4.0 all activities can be connected and accessed by using the internet and smartphone. The attendance system is also growing to make it easier for employees to use and facilitate the monitoring of employees. Companies that have branches in various locations, data synchronization is the main thing. The system is demanded to accommodate each employee could make a presence at each branch. Currently, many of the attendance systems used in companies use presence machines located at a particular location where each employee must take turns to make absences both using biometric recognition such as fingerprints, Qr Code and by using face recognition on the machine.

Some companies have locations that are difficult to reach or often have obstacles for their employees to reach the work location. Other companies have employees who works outside the office so the static attendance system is not feasible [1]. One of them is at a port company located in Indonesia where the company's location is at the end of the island and access to that location often results in traffic jams due to the accumulation of container trucks. Therefore the use of a static presence system is less efficient to use

Mohammed et al [2] proposed an RFID based multimodal student attendance management system (MSAMS) and also face recognition. In the paper, face recognition was using a haar cascade and also using PCA for feature extraction to classify the image. The results obtained were 98% accuracy for face recognition. But in this system requires students to be in a certain room to do the absence and a long recognition process.

Sunaryono, Siswantoro, and Anggoro [3] used Android, QrCode and also face recognition on the attendance system. The QrCode was used so that students could be absent from the available classes where the QrCode was placed in each class and displayed on the raspberry pi screen. In terms of face recognition using LDA, k-NN and also regression for classification. The results obtained 97% accuracy using LDA and 93% with the additional use of k-NN classification

Lodha, Gupta, Jain, and Narula [4] used a Bluetooth system on the attendance system where they used Bluetooth BLE placed on a student ID card. The drawback of this attendance system was it could not be verified whether the presence is the student owner of the card.

Hameed, Saquib, and Hassan [5] applied RFID based attendance system where they use an arduino microcontroller as the processing module to get a low cost system. This system is placed in various selected location and the user must queue to take a presence so the system is cannot handle the user outside the office. This research was similar to Pireva, K. R., Siqeca, J., and Berisha, S [6] which used a RFID as the identity of the user. The drawback of RFID system is not being able to ascertain whether the user detected is the owner of the actual card.

Raghuwanshi and Swami [7] proposed an attendance system using video and face recognition. The system used a camera placed in various classroom in order to detect student automatically. This system simplified the attendance process but it required a high cost to operate. If it is used in a company which has a various location the companies must provide a large number of cameras. Nowadays, the use of smartphones both Android and IOS is growing rapidly. Almost every employee who works at a company uses a smartphone to communicate. Based on that, the use of an application on a smartphone can be a solution to help the attendance process. The system needs to have a mechanism to be able to minimize employee fraud in absences where the location of absences and verification of absent system users is valid.

This paper proposes a mobile-based attendance system using Geofencing and face recognition. The use of Geofencing in the system is intended to provide a location boundary where employees can make presence and face recognition for validation of employees to minimize the occurrence of fraud in absences. In this system, every employee is required to have a logon password and register a

Sentiment Analysis about Product and Service Evaluation of PT Telekomunikasi Indonesia Tbk from Tweets Using TextBlob, Naive Bayes & K-NN Method

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Abstract—**Online reviews are very important for any business that wants to control its online reputation. This allows businesses to have active and positive participation from consumers. As an information and communication company in Indonesia PT Telekomunikasi Indonesia Tbk commonly called Telkom require a customer's perspective or review to maintain the relevance of their digital products on the market. One method often used to analyze online reviews is sentiment analysis. Sentiment Analysis is used to gain an understanding of the opinions, attitudes, and emotions expressed in the mention of online by determining the emotional tone behind a series of words.**

This research tries to compare classifications in sentiment analysis of Telkom's product from consumer reviews written in the form of tweets on Twitter. Each tweet about Telkom digital products such as Indihome, UseeTV, and Wifi.id will be collected as data. The use of classification types will be compared to help with the accuracy of sentiment analysis based on three types of methods TextBlob, Naïve Bayes & K-NN (K-Nearest Neighbor).

The best result of this research is the K-NN algorithm with an accuracy score of 75% followed by Naïve Bayes 69.44% and the last is TextBolb with 54.67%.

Keywords : Online Review, Customer's Experience, Sentiment Analysis, TextBlob, Naïve Bayes, K-NN

I. INTRODUCTION

Intense competition in digital products in Indonesia requires every company that involved to keep improving its products. One way to improve the product by knowing reviews from consumers through social media. In this era, Twitter is one of the most frequently used microblogging and social networking service in expressing people's opinions.

Consumer satisfaction is important for both customers and businesses [1]. Customer satisfaction is used to measure the value of a brand to a product, service, or experience [2]. If Telkom provides their customers with an astonishing customer service, they will stand out from the digital business competition in Indonesia. One method often used to analyze customer satisfaction is sentiment analysis [3]. Sentiment analysis is widely used because of its ability to gain rich insight into the details and the reason for otherwise opaque market trends.

Customer reviews written on the social media are type unstructured data, so they need appropriate techniques to be able to analyze them [4]. In this research, we choose TextBlob, Naïve Bayes & K-NN as classification methods because of ease the algorithm dan its implementation for sentiment analysis. Each tweet data will go through pre-processing such as punctuation removal, trimming, and stopword removal [5], [6] then classifying using TextBlob, Naïve Bayes & K-NN. The output of sentiment analysis in this research will be categories into two different emotions Positive or Negative [7].

This research showed how sentiment analysis of customer opinion determines customer satisfaction index and compares which classification the best used as a basis for corporate decision making for their products.

II. LITERATURE REVIEW

Sentiment analysis is a type of data mining that deals with people's opinions through Natural Language Processing, computational linguistics, and text analysis [8]. In recent years, sentiment analysis is a great tool in social media to select up an outline of widespread public opinion at a precise subject. A lot of research has been done in the field of sentiment from hotel review [9] to movie review [10] which aims to extract opinions about topics, trends, etc.

Bayhaqy et al [11] used Decision Tree, K-Nearest Neighbor, and Naïve Bayes to classified tweets about E-Commerce. In their research K-NN algorithm gave the best result with data accuracy of around 88.50% compared to Decision Tree with 77% and Naïve Bayes approach with 64%.

Raut et al [12] classified sentiment from tweets using Optimized Feature Set to compare it with KNN and SVM. Their

Event Classification in Surabaya on Twitter with Support Vector Machine

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***Abstract*— Twitter is a social media that is often used by many people in the world. The information is spread and obtained through social media. For example, there is a company that is organizing a new event that many people need to know. This allows the creation of a system that supports the presentation of user information by detecting certain events from Twitter's social media data. In this study, tweet data will be retrieved using Twitter API and stored in JSON format. Furthermore, there will be a pre-processing which includes the deletion of characters, number, URL, stemming, and lower case. Furthermore, feature extraction is performed using Global Vector for Word Representation. we will classify into four classes, which are Competitions, Seminars, Festivals, and Other events. The classification is using SVM to predict the type of event. There are three experimental methods used, there is SVM C, SVM linear, and SVM Nu. SVM Nu was conducted with changes in the SVC parameters in the form of kernel and Nu to produce the best accuracy. Based on the experiments we have done, the best results are obtained with an accuracy of 85.2% by classification using the NuSVC method with an RBF kernel and nu parameter of 0.2.**

***Keywords*—SVM, Twitter, Text Classification**

I. Introduction

One of the important characteristics of Twitter is its simple service and is known as a fairly popular news distribution media[1]. Twitter is a social media that is still trending among the people with a total of 321 million active users[2]. The main feature of Twitter is the tweet where users can communicate with other users and tell whatever they want[3]. Social media is a place for users to say something that can be seen by people around the world[4]. So as more and more accounts are trying to make interesting tweets in order to get a lot of accounts that follow or are called followers. The popularity of Twitter causes this social media has been used for a variety of covert purposes, for example as individual protests, opinions, events, activities, distribution of information media.

Twitter is often used as a medium for sharing information among the public. This has caused several communities and individuals who have finally created Twitter accounts to deliver news about events to be held around them. Events can be in the form of information about a competition, seminar, workshop, festival event and others. Twitter is flexible so it makes Twitter is an ideal medium to be used for various event detection. The tweet data obtained can be processed into a basis for detecting an event that occurred in Surabaya. To facilitate the representation of information in Twitter, we can classify and classify each tweet in Surabaya. for example, when we need information for a competition or seminar that is held in Surabaya.

In this paper, it discusses the identification of local events that occurred in Surabaya based on tweet data. Tweets are taken from the Twitter API and saved in JSON format. then proceed with pre-processing which includes the elimination of special characters, casefolding, stemming and stopword removal. In addition, labeling is also done to determine the class of the tweet. Then feature extraction is performed using NLP Standford and for classification, we use Support Vector Machine method.

II. Related Work

A. Support Vector Machine

Nowadays SVM has succeeded in solving real world problems, and providing better solutions compared to conventional methods such as artificial neural networks. besides that many researchers use SVM as a reference method. That's why we try to explore using SVM in this study. SVM works well for unstructured and semi-structured data such as images and text. And changes to the kernel also greatly affect the power of SVM, so here the kernel and some parameters are available for testing data accuracy. We use three methods from SVM to find the best accuracy for our Twitter data.

The SVM concept can help find the best hyperplane that works as a separator for two classes in the input space[5]. The problem that can be discussed is the effort to find a line that addresses the two groups. SVM is one of the best classification methods for unseen data samples.

In this paper, classification uses the SVM multiclass, a middle class separated by more than two classes[7]. SVM tries to find the best hyperplane in the input space. The basic method of SVM is a linear, and subsequently developed so that it can be used in non-linear problems[8]. by incorporating the concept of kernel tricks in high-dimensional workspaces[9]. This development has stimulated research interest in the area of pattern recognition for the full investigation of the potential capabilities of the SVM in terms of application.

Analysis of E-Commerce (Bukalapak, Shopee, and Tokopedia) Acceptance Models Using TAM2 Method

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***Abstract*—The high level of public satisfaction with the sale and purchase transactions is a measure of the success of various business programs. Therefore, companies as the main actors in business processes must be supported by the existence of an information technology. The use of E-Commerce which is digitally able to facilitate buying and selling online but it is still considered difficult, so the company that runs e-commerce needs to know what factors can affect individual interest in using online transactions to improve the existing system to make it better. Based on this, the authors conducted a study to find out what factors could influence the user interest in using e-commerce. The author also makes comparisons of three e-commerce sites, namely Shopee, Tokopedia, and Bukalapak using TAM2 method. The conclusions are drawn using SEM with PLS as a tool for data analysis. The results of this study are to show that measurement evaluation model has been valid and reliable. Then, obtained structural evaluation model shows the aspects which impacts usage behavior and intention of the users. The evaluation results can provide recommendations of the requirement which have to be considered so that could be developed in further research.**

***Keywords*—E-commerce; User Acceptance; TAM 2; SEM-PLS**

I. Introduction

In this modern era, technology has a very important role in life. The use and adoption of Information technology becomes the main concern of many research [1]. It has influenced many aspects as economic, governments, organization, education, industry, and many other things. From scientific side, Information Technology has led the branches of science in the future. The key to reach the success in global competition is an accurate information [2]. With the increasing development of internet usage, user can create an opportunity to build a good impact to organizations [3]. Information Technology has an important role to interact with customers in order to achieve a valuable performance [4]. One of them is through the use of Electronic Commerce (E-Commerce). It influences the business industry beliefs [5]. So that's why E-commerce being one of an important information technology as a result of information technology growth and developments.

This study aims to give a prediction and help modelling the user acceptance of e-commerce in Indonesia. The authors conducted a study by focusing on comparing three E-commerce sites namely Shopee, Tokopedia, and Bukalapak as it becomes the most monthly web visit in Indonesia at Quartal IV in 2019. This study wants to find out based on the customers perspective and to know what factors could influence the interest of buyers in using e-commerce to conduct online trading transactions. The method used is TAM 2 (Technology Acceptance Model 2), as well as drawing conclusions using SEM (Structural Equation Model) with PLS (Partial Least Square) as a tool for data analysis. SEM is considered good in collecting the evidence through questionnaires. The way it collected is effective and efficient and it also easy to understand [6]. Kim Gye Soo (2016) defined that PLS-SEM is fit for conducting an analysis. It is capable to deal with data inadequacies such as an abnormal data and accommodates formally measured constructions [7].

II. Literature Review

A. E-Commerce

E-commerce become possible in 1991 when the internet began to be used to commercial use. Its initial form of commercial transactions begins in the late 1970s. E-commerce refers to describe the activity of trading in products or services using computer networks [8]. Electronic Commerce is a place to share a good deal of information about business and a place to conduct a business transaction through telecommunications networks. E-commerce refers to all aspect in transaction of goods and services between business to business as well as business to consumer [9].

B. Technology Acceptance Model 2 (TAM 2)

TAM is one of the largest popular concepts that is often used to measure user acceptance of a technology. Much research have been done to make some improvements from the originally model [10]. Venkatesh and Davis (2000) did the research and declared a modified TAM model called TAM2 which gives several additional variables to the previous model

UTAUT2 model for analyzing factors influencing user in using Online Travel Agent

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Abstract- Technology development in Indonesia has increasingly progressed and provided business opportunities for businesses to meet customer's needs. The presence of e-commerce that have been widely spread in Indonesia is one of the examples of the technological progress. Indonesia already has an e-commerce online travel agent that prioritized user's needs to make it easier for the user to make an online reservation more efficient and effective. Traveloka and Tiket.com are an e-commerce online travel agents with many downloader in Indonesia, in choosing an online travel agent, users are certainly influenced by several factors identify by using UTAUT2 model. The results of this study indicate the use of Traveloka for users is influenced by perceived security, price value, and habit factors, while Tiket.com is influenced by facilitating conditions, performance expectancy, and habit. Companies could focus on these factors in terms of increasing the desire of users to use online travel agents.

Keywords: Online Travel Agent, UTAUT 2

I. Introduction

In this digital era, the number of internet users in Indonesia is around 30% or reaching 82 million people from the total population providing business opportunities for companies in the e-commerce sector [1]. The Statistics in Indonesia in 2019 stated that online sales transactions reached 23.82 million transactions and obtained operating revenues of 17.21 trillion[2]. A large number of transactions in e-commerce are encouraging tourism companies to create an Online Travel Agent. Nowadays, users are more interested in using an online travel agent because the accessibility is more effective, more product choices are provided, the available services are more extensive and affordable [3]. Providing and maintaining customer satisfaction to meet user's needs is the biggest challenge for e-commerce[4]. Indonesia has several well-known e-commerce online travel agents such as Traveloka and Tiket.com. Traveloka and Tiket.com occupy the top level as online travel agents in Indonesia which could meet customer's needs, this is proven by both of these online travel agents is the most downloaded application with more than 10 million smartphone users. Based on this data, there are internal and external behavioral factors that motivate users to use each of the applications. The purpose of this study is to examine the factors that influence users in using Traveloka and Tiket.com by adopting the UTAUT2 model. The UTAUT2 model can provide knowledge to companies in forming appropriate marketing strategies according to user behavior specifications [5]. Venkatesh et.al [6] stated that the behavior related to technology acceptance, several indicators influence such as performance expectancy, facilitating condition, hedonic motivation, effort expectancy, social influence, habit, and price value factors. These factors aim to improve the quality service and can attract users acceptance of the technology.

II. Previous Research

Before the UTAUT 2 and UTAUT, other models have been widely used in various studies in acceptance of information technology. UTAUT was formed from the development of eight acceptance theories. UTAUT had four constructs, there are effort expectancy, performance expectancy, social influence and facilitating conditions with four moderating variables were identified gender, experience, age and voluntariness of use[7]. Based on Venkatesh et.al [6], UTAUT model developed to be UTAUT2 focus on measuring actual user behavioral intentions by adding several factors and eliminating constructs on the moderating voluntariness of use variable in the previous theory. The UTAUT2 model has also been used in various studies. In previous studies, the UTAUT2 model analyzing customer acceptance of applications that adopt electronic payments[8] and online ticket reservations[7,8]. Users are influenced by factors in using Online Travel Agent in previous studies are performance expectancy, social influence, facilitating conditions, hedonic motivation, and habit in good categories while for effort expectancy in very good categories. The moderation effect in the study did not affect the independent and dependent variables[11].

III. The Proposed Method

This study using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model. The UTAUT2 is a development model of the UTAUT model. Figure 1 model of UTAUT2 were grown produce seven variables there are performance expectancy (PE), effort expectancy (EE) , social influence (SI), facilitating condition (FC), hedonic motivation (HM), price value (PV), habit (HB), perceived security (PS) that affect the behavior intention (BI) and use behavior (UB).

Hexagonal Patch Microstrip Antenna with Parasitic Element for Vehicle Communication

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Abstract—**In this paper, a compact conformal antenna is proposed for vehicle to X (V2X) communication applications. The Hexagonal-shaped geometry is applied in the design to attain desired band in the vehicular communication spectrum. The proposed dimension antenna is 50mm x 50mm x 1.6 mm. By loading the hexagonal patch and annular slot with different sizes at each angle, it realizes to enhance bandwidth and increase the gain. This article explains how we found that tuning and overlapping of resonant frequency was mainly achieved by hexagonal parasitic element. The prototype antenna had been design using Ansys HFSS v.15. The simulation result shows that the antenna had resonant frequency at 5.9 GHz with return loss value of 32.95 dB. The antenna had VSWR value of 1.0189. This microstrip antenna had thickness of 1.6 mm, so it should be easy to fit up hidden in front of a vehicle for vehicular communication.**

Keywords: Hexagonal Patch, Microstrip Antenna, Vehicle Communication, Wireless Communication.

I. Introduction

The wireless communication are one of advanced technology of our time. In the present days, wireless communication becomes an essential part of various types of wireless communication devices. There are many devices, as it allows users to interact with others. Wireless communication technologies are widely used for transmission of data or information from one place to another. It should bring great convenience for the activities of people. For example, cellular communication such as GSM, LTE, and 5G can make interpersonal communication more convenient and makes people connecting faster [1]. Not only used as wireless communication, it can also be used to manage vehicles; for instance, it can support system to provide information about real time traffic on the roadway to effectively help drivers from traffic congestion and traffic accident [2].

Nowadays, the population of vehicles remains increasing, be it for public transportation and personal transportation. Each year the number of vehicles on the road has grown faster than the roadway capacity. It is not comparable with the existing road segments. Thus, the level of traffic congestion has also increased significantly in every year.

In addition, the traffic accident can also lead to traffic congestion on the road. Therefore, it takes a system that can help a driver who is able to give information about the speed, position, direction and traffic situation when driving the vehicle. For this reason, the 5.9 GHz has allocated for the dedicated short-range communication (DSRC) system. DSRC is communication technologies which help the various communications between vehicles and infrastructure [3]. DSRC uses the IEEE 802.11p wireless access for vehicle environments (WAVE) standard which modified of the IEEE 802.11 Wi-Fi standard. The bandwidth allocation for DSRC is 75 MHz from 5.85 to 5.925 GHz. It has applied for the DSRC system which includes the vehicle to vehicle (V2V) communication and the vehicle to infrastructure (V2I) communication [4].

Among many antenna technologies existing in the recent years, ones which are widely used and can be implemented on the vehicles are Monopoles Antenna, Patch Antenna, On-Glass Antenna, Glued Foil Antenna, and Fractal Antenna [5]. But, the patch antenna is more popular in the automotive industry than others. Because it is unobtrusively flat and easily implemented into the vehicles component; for example behind a bumper, fender, roof or trunk cover.

Most of vehicle antenna are designed for low frequency application; for example, frequency and amplitude modulation on radio broadcasting at 30-300 MHz, GSM spectrum frequency at 800-900 MHz, GPS at 1.23 – 1.57 GHz, and Bluetooth transmission, often known to be connected to radio on the

Canny Edge and Hough Circle Transformation for Detecting Computer Answer Sheets

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***Abstract*— The use of the computer answer sheet media as a medium for writing answers has now become a necessity, this is because the computer answer sheet media is considered to be very easy and fast in the correction process. Some research and implementation applied in solving cases of correction computer answer sheet with various methods, but the use of inappropriate methods will affect the results that are less than the maximum in detecting. Some use the detection of circles which are not precise so that it has the potential to detect answers that should not be detected with clearly. This study propose Canny and Hough circle transformation method for enhanced by calculating the distance between answers to increase accuracy by 95.75%. This can be used as a basic method in making detection devices.**

Keywords*— *Computer answer sheet, Edge detection, Canny, Hough circle transformation.

I. Introduction

The use of computer answer sheet media is a breakthrough for the implementation in the exam or questionnaire that has touched technology inside that aims to facilitate implementation. Recently, Computer Answer Sheet almost applied in various educational institutions and agencies in the process of determining the results of selection or examinations. This is can increasingly proving that technology evolved, especially in education world. Detection of an image is inseparable from the edge detection method as an initial detection when processing images to the next level, choosing the right method and technique is certainly very important because it will affect the expected results.

From some of the explanations above, this study propose the use of Canny and Hough Circle Transformation as a perfect collaboration for circle detecting of Computer Answer Sheet. On the other hand, the application of the Canny and Hough Circles Transformation methods has been applied in other studies with different cases, namely the detection of plug trays for planting seeds automatically which results in an average seedling evaluation of up to 89%[1]. Image is a continuous function of two dimensions intensity. Sources of light illuminate objects, the object reflects a portion of the beam of light. This reflection of light was later captured by optical instruments like human eyes, camera, scanner, etc., so the image of the object called the imagery is captured on film. An image is stored in the pixel to be computer processing. Pixels are square grates that provide a continuous function of brightness and color imagery information[2]. From an image can be processed to be developed into various forms of application according to their needs, including it uses image processing in determining an answer selected in a computer answer sheet. Of course, there are many media and tools that have developed the tracking of answers from computer answer sheet based on image processing, but the combination of Canny and Hough Circle Transformation is of course still interesting to apply and test in an image detection process. This study will be explained how the flow and process carried out when a computer answer sheet answer detection application will be built using the Canny and Hough Circle Transformation methods.

II. Related Theory

A. Detection of Circle Objects without Canny and Hough Circle Transformation

In previous studies, the detection of circular objects without combination of canny and hough produces less than optimal results. In a case described an Optical Mark Reader (OMR) sheet detection using the edge detection method looks good, but the process after edge detection uses Median Filtered Image as the final process, which is considered inappropriate to capture an object like a circle[3]. Another case that also applies Canny as edge detection processes for the detection of circle objects using thresh image, which results in the detection of circle objects being numerous so that it has the potential to process circles that should not need to be corrected, because circle detection that should be corrected only focuses on the circle which is should be the answer[4].

B. Computer answer sheet

Compared to the charging system of the exam, registrations and online records from hundreds to millions of participants, the use of Computer Answer Sheet is still more optimal because it saves computer supply requirements. With the online system, you have to available 1 computer for 1 respondence or participants in exam, as for the system offline, only 1 computer answer sheet for 1 respondence or

Item Analysis for Examination Test in the Postgraduate Student's Selection with Classical Test Theory and Rasch Measurement Model

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Abstract*— University entrance exams are conducted to ensure applicants' qualifications are placed into the program of their choice. Test results have important and significant value in making the right decision about the suitability of the applicant; the validity of the exam is significant to achieve the objectives set. The purpose of this study is to provide empirical evidence of the validity of the new construct in developing the Academic and English Test Exams using the Classical Test Theory and the Rasch Measurement Model. Admission Test for postgraduate entrance examination consisting of 120 multiple choice items with five answers/option choices (A-E) and has been developed and assessed by experts who are competent in their fields and questions are given to 409 postgraduate entrance exam participants. Software applications used for CTT and Rasch Model are ITEMAN version 3 and JMETRIK version 4 windows, where the application is free of licenses. The software automatically generates parameter estimation recommendations for assessing the quality of test items. The CTT results identified 39 questionable items using difficulty and index discrimination. Rasch's results show that the statistics of people (Separation 2.55> 2.00 and reliability 0.87> 0.80) and item statistics (Separation 9.4> 3.0 and reliability 0.99> 0.8) are excellent person and item reliability. Overall, using the Rasch model obtained 68 constructs that incorrectly matched items, as well as irrelevant identified, are suggested to be removed. While CTT provides limited information on two parameters, Rasch's results provide very detailed information about the quality of the items being tested. Thus the two models can be integrated to produce sufficient evidence of validity and reliability items in the development of standardized tests. Even from the second approach, the model produced 28 items in common as problem items. These results indicate that more items are recommended for removal by the Rash model than the CTT can be linked to the procedure followed by two frameworks in determining the quality of test items.

***Keywords*— C.T.T., Rash Model, Item Analysis**

I. Introduction

To get high-quality question instruments, in addition to theoretical analysis (item review), empirical analysis is also necessary. This practical item analysis can be divided into two, namely: with the classical test theory approach and item response theory (IRT) [1] The test is a measurement technique designed as a systematic procedure for studying the behaviour of individuals or groups of individuals [2]. In this description, two analytical methods that are generally used in developing tests, namely traditional or standard item analysis in classical experiments or Classical Test Theory (CTT) and modern interpretation, are based on item response theory (IRT). These processes generally follow the identification of the objectives of the test and the preparation of a pool of items in the test preparation process. To produce tests in educational measurements, the criteria and guidelines that have been established for the development of valid and reliable tests must be followed adequately. This provides accurate information in the use of tests and construction [1]

Analysis of test instruments in education can be done through two approaches. The first approach is the most common and is widely applied in education to date, especially in research, namely the classical test theory (CTT). This statement is following the report [3] in his study entitled "the accuracy of the results of item analysis according to classical test theory and item response theory in terms of sample size," that classical test theory (CTT) is a popular analytical technique. It is used in stock in this century. The conventional test theory developed by Charles Spearman in 1904 can be used to predict the results of an exam. In classical test theory, the aspects that largely determine the quality of the items are the level of difficulty and the distinguishing features of the questions. However, the characteristics of items produced by classical test theories are inconsistent (changing) depending on the ability of test-takers. According to [4], measurement errors in classical test theory can only be sought for groups, not individuals. A second approach is a modern approach with the Rasch model coined by Dr Georg Rasch is a Danish mathematician. Rasch modelling exists to overcome

ANALYSING PUBLIC INTEREST IN SHARIA BANKING USING UTAUT2 METHOD

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Abstract— **The majority of Indonesia's population are Muslim, hence, the market for Sharia banking should be more dominant than conventional banking. However, the market share of Sharia banking in Indonesia is still relatively small, i.e. less than 8% of the total population. Some studies have found that awareness of Sharia banking among Muslims is high but the importance of using the product is low. The purpose of the present study is to find out potential user interest in Sharia banks, more specifically the Sharia Bank, by investigating the relationship between behavioral intention and two control variables as well as a number of latent variables that are affected most. These variables describe behavioral intention and use behavior. The result shows that high significant variables to be influential of behavioral intention for the age groups 21-30 years, 31-40 years and >40 years are perceived trust and perceived risk. Women aged >40 years are more interested than other age groups. The results obtained can help Sharia banks in Indonesia to improve strategies in the market share.**

Keywords— UTAUT2, GeSCA, Sharia Bank

I. INTRODUCTION

In the modern era, technology develops very quickly, which is critical for future growth. The rapid development of information technology constitutes a huge challenge in many sectors, for example the banking sector, in terms of data management and financial innovation [1, 2]. On the banking world competing products and facilities are continuously being developed to provide public services. In Indonesia there are two types of banking, i.e. Sharia banking and conventional banking. The fundamental difference between Sharia banking and conventional banking is that Sharia banking does not apply interest [3]. Interest is considered haram by Islam, so instead profit sharing is applied. The total population of Indonesia was around 269.6 million people in the 2020 census data from the Central Bureau of Statistics Indonesia [4]. The majority of the population was Muslim (87.18%). In the 2015 inter-census population survey data, the population aged 15-64 years is categorized as productive, at 68.7%, or ±183.36 million people. Seen from the size of the productive Muslim population, the market share of Sharia banks should be growing very fast. In practice, compared to the market share of conventional banking, the use of Sharia banking is relatively low, at around 5.95% of the total population [5].

The public interest among the Muslim majority towards Sharia banking is still relatively small. This study aimed to determine the potential public interest in Sharia banking in Indonesia using the Unified Theory of Acceptance and the Use of Technology 2 (UTAUT2) method. The business performance of Sharia bank has steadily improved in recent years. This is evidenced by the Sharia Bank's financial statements for 2017 and 2018, where assets increased from 440,256 to 492,345 billion, net income increased from 7,201 to 9,789 billion, and financing increased from 277,589 to 310,708 billion. In 2018 and 2019, assets increased from 492,345 to 524,144 billion. Net income increased from 9,789 to 14,021 billion, and financing increased from 310,708 to 339,461 billion [6]. The overall performance of the Sharia Bank has shown an upward trend in Indonesia. Thus, public interest in Sharia Bank products is an interesting topic of study.

This study attempted to examine the effect of two control variables, age and gender, on behavioral intention. The method used, UTAUT2, is a development of the original UTAUT method by adding three variables to the existing variables, namely: price value, hedonic motivation, and habit [7]. Thus, the variables used in this study were: performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, price value, experiences, perceived risk, and perceived trust. The products of the Sharia Bank that were examined were: banking, Hasanah Personal (information application about products of the Sharia Bank), internet banking, and Wakaf Hasanah (conducting application for endowments online). Data collection was done by conducting a questionnaire using a 1-5 Likert scale. The data were analyzed and grouped based on age and gender. The software used for the analysis to know which variables were dominant in describing behavioral intention was Generalized Structured Component Analysis (GeSCA).

II. LITERATURE VIEW

A. Relationship between customer and Sharia banking

Veysel Yilmaz et al (2018) [8] examined the relationship between students' perceptions about the level of satisfaction and the level of service provided to banks. The model used was Structral Equation Modeling (SEM). Data collection was based on a Likert scale questionnaire. The model in this research was based on the SERVQUAL scale using the

Application Methods Backpropagation in Identification of Functions Kidney Organ by Iris Image

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Abstract—In the world of medical or health identification early kidney function is something that can not be underestimated. Special attention is needed on this matter. In determining the function of the kidneys can be seen through the internal organs can be seen is the iris. Through iris ophthalmologist can determine a person's kidney function along with several other supporting data. The steps in this research is to analyze the needs, system design, and implementation. In making this program do classification backpropagation in this research is to analyze the needs, system design, and implementation. In making this program do classification backpropagation to classify iris organ normal kidney function normal, acute, and chronic. Someone identified organ normal kidney function when iris regular pattern, while for acute and chronic can be identified if the iris is irregular and had a basin deeper than people who have normal kidney function. The outcome of this study to identify and classify the function of the kidneys by iris of the eye to determine the normal kidney, acute and chronic. Accuracy of this application is to reach 100 percent.

Keywords— health, kidney, eye iris, backpropogation

I. Introduction

COVID-19 in addition to attacking the lungs, COVID-19 can also attack the kidneys, but many people are unaware, especially Americans. In the 2020 National Kidney Foundation-Harris Poll Survey on COVID-19 and findings on Kidney Health showed very low awareness of the risk of developing acute kidney injury due to COVID-19, in the long-term it has an impact on kidney health. Few of Americans are aware of COVID-19 can cause acute injury to the kidneys, only 1 in 5 people are aware of it. Acute kidney injury (AKI) occurs in about 15% of the total coronavirus patients who have been treated, now many of these patients require dialysis [1].

Kidneys are the organs which must be protected and treated early. So we have to know the science of studying it in order not mistaken in treating kidney. Iridology is scientific knowledge that analyzes the composition of the iris. Iridology is the science that can detect declining kidney function based on the detection edge of the iris of the human eye. It can be used to perform diagnostic guidelines for kidney disease. Advances in science and technology in particular processing digital image could be applied to assist the classification and identification of an object. Image processing technology (Image processing) can be applied to recognize and identify the function of the kidney. One of research has neural networks to identify the Retinoblastoma using algorithms backpropagation by generating value 90% accuracy.

In this study, the authors identify based on some previous research methods Algorithms backpropagtion based backpropagtion a controlled type of training (supervised) using weighting adjustment patterns to achieve the minimum error between the output value of the prediction results with real output [2]. By using the algorithm, it can be expected to facilitate the process of identifying the function of the kidney with good accuracy.

Based on the description above, conducted research entitled "Application Methods Backpropagation in Identification of Functions Kidney Organ by Iris Image".

II. Previous Research

Retinoblastoma is eye cancer and it occurs in children. This disease attacks the thin nerve tissue behind the eyes (the part that is sensitive to light). Retinoblastoma attacks one or both eyes of the patient, the disease is a type of disease that can be caused by a genetic mutation called Retinoblastoma1 (RB1). This disease can cause blindness, even cause death.

The method used in this research is Backpropagation Artificial Neural Network using input of the retinal fundus image. Steps in overcoming retinoblastoma are image management (resizing, gray scaling, morphological closure surgery, and optical disk elimination), methods using the backpropagation nervous system and the Co-Gray Level Matrix for feature extraction in the system testing in this study, the method used This use reaches 90% accuracy [3]–[5].

Dokumen pendukung luaran Wajib #1

Luaran dijanjikan: Dokumentasi hasil uji coba produk

Target: Ada
Dicapai: Tersedia

Dokumen wajib diunggah:
1. Dokumentasi (foto) Pengujian Produk
2. Dokumen Deskripsi dan Spesifikasi Produk
3. Dokumen Hasil Uji Coba Produk

Dokumen sudah diunggah:
1. Dokumen Deskripsi dan Spesifikasi Produk
2. Dokumen Hasil Uji Coba Produk
3. Dokumentasi (foto) Pengujian Produk

Dokumen belum diunggah:
- Sudah lengkap

Nama Produk: SISTEM ELECTRONIC NOSE UNTUK DETEKSI KEMURNIAN DAGING SAPI TERHADAP DAGING BABI
Tgl. Pengujian: 4 Desember 2020
Link Dokumentasi: 0

Deskripsi

SISTEM *ELECTRONIC NOSE* UNTUK DETEKSI KEMURNIAN DAGING SAPI TERHADAP DAGING BABI

Bidang Teknik Invensi

Invensi ini mengenai Sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi, lebih khusus lagi, invensi ini berhubungan dengan alat untuk mendeteksi keberadaan campuran daging babi di dalam daging sapi berdasarkan persentase.

Latar Belakang Invensi

Salah satu cara untuk membedakan daging sapi dengan daging babi adalah dengan melihat warna dan teksturnya. Namun, untuk mendeteksi adanya daging sapi yang dicampur dengan daging babi, masyarakat masih kesulitan. Kementrian perdagangan melakukan uji laboratorium menggunakan *Enzyme-linked immunosorbent assay* (ELISA) dan tes DNA untuk mendeteksi daging sapi yang dicampur dengan daging babi. Namun pengujian ini dilakukan oleh orang-orang ahli dan membutuhkan waktu satu hari untuk satu sampel daging.

Invensi ini berkaitan dengan sistem deteksi kemurnian daging sapi yang di campur dengan daging babi berdasarkan aroma dari daging. Sampel pengujian untuk mendeteksi keberadaan daging babi di dalam daging sapi dengan campuran daging babi dengan klasifikasi persentase : kelas 1, persentase 0%-5%; kelas 2, persentase 6%-15%; kelas 3, persentase 16%-35%; kelas 4, persentase 36%-60%; kelas 5, persentase 61%-85%; kelas 5, persentase 86%-95%; dan kelas 6, persentase 96%-100% daging babi. Invensi ini berkaitan dengan beberapa artikel sebagai referensi, yaitu :

1. *Electronic nose for classifying beef and pork using Naïve Bayes*, 2017 International Seminar on Sensors, Instrumentation, Measurement and Metrology (ISSIMM) (Wijaya et al., 2017);

2. *Temperature effect of electronic nose sampling for classifying mixture of beef and pork*, Indonesian Journal of Electrical Engineering and Computer Science. Vol. 19, No 3, 2020 (Sinarring Azi, Laga; Riyanarto, 2020).

Terkait dengan jurnal-jurnal tersebut, belum ditemukan PATEN yang terkait dengan invensi ini. Paten yang sudah ada mengenai *Electronic Nose* untuk monitoring kesegaran daging yang dalam Paten Nomor WO2015150880A1 dengan judul *Electronic nose for determination of meat freshness*. Namun demikian, invensi tersebut masih mempunyai kelemahan-kelemahan dan keterbatasan yang antara lain adalah (1) hanya digunakan untuk monitoring kesegaran daging; (2) daging yang digunakan untuk percobaan pada Paten ini adalah daging ayam bagian dada dan paha; (3) Paten ini menggunakan rangkaian dari empat jenis gas sensor.

Karena belum ditemukannya Paten yang terkait dengan deteksi kemurnian daging sapi terhadap daging babi menggunakan *Electronic Nose*, untuk itu invensi ini diajukan. Invensi ini terdiri dari (a) Sistem Hardware; dan (2) Software aplikasi. Data pengujian yang di ambil menggunakan invensi ini telah di publikasikan untuk melihat keefektifan keakuratan dari invensi ini. Data tersebut dapat diakses pada jurnal yang berjudul *Electronic nose dataset for pork adulteration in beef*, Data in Brief (Sarno et al., 2020).

Ringkasan Invensi

Invensi yang diusulkan ini adalah untuk mendeteksi kemurnian daging sapi terhadap daging babi menggunakan sistem *Electronic Nose.* Invensi yang diusulkan terdiri dari (a) Sistem hardware yang dicirikan dengan kombinasi sensor yang digunakan, ruang sensor array, kotak atau *box* sistem *Electronic Nose*; dan (b) Software aplikasi yang dicirikan dengan metode parameter statistik dan metode klasifikasi.

Kombinasi sensor yang digunakan pada invensi ini terdiri dari 10 sensor gas seri Metal Oxide Sensor (MOS) yang disusun secara berurutan dengan 2 posisi, 5 sensor di sisi atas dan 5 sensor di sisi bawah. Kombinasi sensor ini diletakkan di ruang sensor array dimana bagian tengah ujung kanan dan kiri terdapat lubang selang yang di aliri oleh udara. Jika lubang ujung kanan digunakan untuk udara masuk, maka lubang ujung kiri digunakan udara keluar dari ruang sensor array. Lubang ini dibuat untuk meminimalisir kondisi ruang sensor array menjadi lembab sehingga dapat mempengaruhi hasil pembacaan sensor. Rangkaian komponen seperti micro-controller, alat penghisap udara, kipas kecil, *step-down*, *breadboard*, dan ruang sensor array di susun di dalam *box* sistem *Electronic Nose*. Software aplikasi dipasang atau di *install* di komputer atau laptop yang tersambung dengan sistem *Electronic Nose*. Software tersebut berisi beberapa menu seperti Home, Add Sample, Reports, Parameter Statistic, dan Classification.

Tujuan lain dari invensi ini adalah membantu masyarakat khususnya Muslim untuk mendeteksi keberadaan campuran daging babi di dalam daging sapi dengan cara yang mudah, yaitu melalui aromanya. Tujuan dan manfaat-manfaat yang lain serta pengertian yang lebih lengkap dari invensi berikut ini sebagai perwujudan yang lebih disukai dan akan dijelaskan dengan mengacu pada gambar-gambar yang menyertainya.

Uraian Singkat Gambar

Untuk memudahkan pemahaman mengenai inti invensi ini, selanjutnya akan diuraikan perwujudan invensi melalui gambar-gambar terlampir.

Gambar 1, adalah gambar blok diagram Sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi.

Gambar 2, adalah gambar tampak atas dari Sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi.

- Gambar 2a, adalah sisi bagian belakang sistem hardware.
- Gambar 2b, adalah penyambung *pneumatic* dengan kotak.
- Gambar 2c, adalah dinding samping kanan.
- Gambar 2d, adalah tabung sensor.
- Gambar 2e, adalah *Valve matic* dengan tegangan 12V DC.
- Gambar 2f, adalah Lubang angin.
- Gambar 2g, adalah Pompa angin penyedot.
- Gambar 2h, adalah *Stepdown* tegangan.
- Gambar 2i, adalah breadboard.
- Gambar 2j, adalah micro-controller.
- Gambar 2k, adalah dinding sisi samping kiri.
- Gambar 2l, adalah dinding sisi depan.
- Gambar 2m, adalah penyambung *pneumatic* berbahan akrilik.
- Gambar 2n, adalah kipas angin kecil (*mini fan)*.
- Gambar 2o, adalah saklar on/off.

- Gambar 2p, adalah *Pneumatic* M5.
- Gambar 2q, adalah dinding sisi bawah.
- Gambar 2r, adalah selang PU Tube.
- Gambar 2s, adalah lubang baut M3.
- Gambar 2t, adalah rangkaian untuk memasukkan adaptor.

Gambar 3, adalah Ruang sensor

- Gambar 2d1, adalah lapisan pertama dari ruang sensor.
  - Gambar 2d1a, adalah jenis sensor gas ke 1
  - Gambar 2d1b, adalah jenis sensor gas ke 2
  - Gambar 2d1c, adalah jenis sensor gas ke 3
  - Gambar 2d1d, adalah jenis sensor gas ke 4
  - Gambar 2d1e, adalah jenis sensor gas ke 5
  - Gambar 2d1f, adalah jenis sensor gas ke 6
- Gambar 2d2, adalah lapisan kedua dari ruang sensor.
- Gambar 2d3, adalah lapisan ketiga dari ruang sensor.
- Gambar 2d4, adalah lapisan keempat dari ruang sensor.
- Gambar 2d5, adalah lapisan kelima dari ruang sensor.
- Gambar 2d6, adalah lapisan keenam dari ruang sensor.
  - Gambar 2d1a, adalah jenis sensor gas ke 7
  - Gambar 2d1b, adalah jenis sensor gas ke 8
  - Gambar 2d1c, adalah jenis sensor gas ke 9
  - Gambar 2d1d, adalah jenis sensor gas ke 10
  - Gambar 2d1e, adalah jenis sensor gas ke 11
  - Gambar 2d1f, adalah jenis sensor gas ke 12

Gambar 4, adalah gambar ruang sensor array sebelum dirangkai menjadi satu kesatuan.

- Gambar 2d1g, adalah lubang sensor untuk sensor gas ke 1
- Gambar 2d1h, adalah lubang sensor untuk sensor gas ke 2
- Gambar 2d1i, adalah lubang sensor untuk sensor gas ke 3
- Gambar 2d1j, adalah lubang sensor untuk sensor gas ke 4
- Gambar 2d1k, adalah lubang sensor untuk sensor gas ke 5
- Gambar 2d1l, adalah lubang sensor untuk sensor gas ke 6
- Gambar 2d2a, adalah dinding tabung sensor 2d lapisan urutan 2d2.
- Gambar 2d3a, adalah dinding tabung sensor 2d lapisan urutan 2d3.
- Gambar 2d4a, adalah dinding tabung sensor 2d lapisan urutan 2d4.

- Gambar 2d5a, adalah dinding tabung sensor 2d lapisan urutan 2d5.
- Gambar 2d6g, adalah lubang sensor untuk sensor gas ke 7
- Gambar 2d6h, adalah lubang sensor untuk sensor gas ke 8
- Gambar 2d6i, adalah lubang sensor untuk sensor gas ke 9
- Gambar 2d6j, adalah lubang sensor untuk sensor gas ke 10
- Gambar 2d6k, adalah lubang sensor untuk sensor gas ke 11
- Gambar 2d6l, adalah lubang sensor untuk sensor gas ke 12

Gambar 5, adalah diagram alir (*flowchart*) dari aplikasi software untuk deteksi kemurnian daging sapi terhadap daging babi.

Gambar 6, adalah tampilan software deteksi kemurnian daging sapi terhadap daging babi untuk menu klasifikasi data sinyal

Uraian Lengkap Invensi

Sebagaimana telah dikemukan pada latar belakang invensi, bahwa belum ada invensi mengenai sistem *electronic nose* untuk mendeteksi kemurnian daging sapi terhadap daging babi serta pengujian laboratorium yang membutuhkan tenaga ahli dan proses yang lama, maka invensi ini diusulkan. Invensi ini akan secara lengkap diuraikan dengan mengacu kepada gambar-gambar yang menyertainya.

(a) Sistem Hardware

Mengacu pada Gambar 1, yang menampilkan gambar blok diagram secara lengkap sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi, diawali dengan sampel daging yang akan diuji. Sampel daging dimasukkan ke dalam ruang pengujian. Invensi ini akan mendeteksi aroma dari sampel daging menggunakan selang polymer tube (PU) ukuran 4mm yang akan di teruskan ke dalam ruang sensor. Terdapat micro-controller di dalam rangkaian *Electronic Nose* yang digunakan sebagai pengumpul data. Micro-controller ini terhubung dengan sensor-sensor yang ada di ruang sensor. Ketika aroma sampel daging masuk ke ruang sensor, maka sensor akan mengirimkan data analog yang diterima oleh micro-controller dan diteruskan ke software aplikasi yang tertanam di laptop atau komputer.

Mengacu pada Gambar 2, terdapat beberapa rangkaian untuk membangun Sistem hardware dari *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi. Gambar 2a merupakan sisi bagian belakang sistem hardware dengan ukuran 20cm x 8cm dan ketebalan dinding 5mm. Sisi bagian belakang ini berbahan filamen PLA dan di cetak menggunakan 3D printer. Sisi bagian belakang ini terdapat sambungan *pneumatic* seperti Gambar 2b dengan kotak sisi bagian belakang berbahan akrilik dengan ukuran 7cm x 2cm dan ketebalan dinding 10mm. Gambar 2b memiliki 3 lubang yang digunakan untuk memasang Gambar 2p di sisi bagian dalam sistem hardware. Sedangkan Gambar 2c merupakan dinding samping kanan berbahan akrilik dengan ukuran 24cm x 7cm dan ketebalan dinding 5mm. Terdapat lubang angin-angin seperti Gambar 2f yang digunakan sebagai sirkulasi udara. Tujuan diberikan sirkulasi guna menjaga suhu ruangan agar tetap stabil. Gambar 2k, adalah dinding sisi samping kiri sistem hardware berbahan akrilik dengan ukuran 24cm x 7cm dan ketebalan dinding adalah 5mm. Terdapat lubang angin-angin seperti Gambar 2f yang digunakan sebagai sirkulasi udara. Gambar 2l, adalah dinding sisi depan dengan ukuran 20cm x 8cm, ketebalan dinding 5mm. Sisi bagian depan ini berbahan filamen PLA dan di cetak menggunakan 3D printer. Gambar 2q merupakan sisi bawah sistem hardware berbahan akrilik dengan ukuran 24cm x 18cm dan ketebalan dinding 5mm. Gambar 2d merupakan tabung sensor dengan ukuran 20cm x 4cm dan ketebalan 3cm. Tabung sensor ini terdiri dari 6 lapisan berbahan akrilik yang akan dijelaskan pada Gambar 3 dan Gambar 4.

Sistem hardware mengggunakan Gambar 2e yaitu *Valve matic* dengan tegangan 12V DC sebagai pengatur udara yang masuk ke ruang sensor. *Valve matic* ini mengatur udara sampel atau udara bebas (*free air*) yang masuk ke dalam ruang sensor. Gambar 2e memiliki 3 buah lubang yaitu 2 buah lubang *input* dan 1 buah lubang *output*. Lubang input digunakan sebagai lubang untuk udara masuk melalui selang PU Tube berukuran 4mm. Lubang output digunakan sebagai udara keluar melalui selang PU Tube atau Gambar 2r yang berukuran 4mm menuju ke ruang sensor atau Gambar 2d. Mekanisme Gambar 2e dibantu dengan Gambar 2g yaitu pompa angin penyedot untuk menyedot angin menuju ke ruang sensor. Pompa angin memiliki 2 lubang yaitu lubang input dan output dengan tegangan 3,3 V. Selang PU tube atau Gambar 2r dengan ukuran 4mm dimasukkan ke lubang *input* dan *output* pada pompa angin penyedot.

Gambar 2h adalah *Stepdown* tegangan dengan *input* 12V DC dan *output* 5V DC. Gambar 2i merupakan breadboard untuk mengatur voltage (+/-) dari setiap sensor. Gambar 2j atau *Micro-controller* digunakan sebagai pembaca data sensor analog. Untuk dapat membaca data dari sensor, maka diperlukan program yang dijalankan di komputer atau laptop dan tersabung dengan Gambar 2j. Gambar 2n merupakan kipas angin kecil dengan ukuran 6cm x 6cm dan ketebalan 1,5cm. Kipas ini digunakan untuk menjaga suhu sistem hardware agar tetap stabil. Gambar 2o pada sisi depan merupakan tombol on/off untuk menyalakan dan mematikan sistem hardware. Sedangkan Gambar 2o pada sisi belakang digunakan untuk menyalakan dan mematikan *Valve matic*. Gambar 2t komponen yang digunakan untuk lubang masukan untuk memasang *Power supply* 12V DC. Gambar 2m merupakan penyambung *pneumatic* berbahan akrilik 4cm x 2cm dan ketebalan dinding 10mm. Gambar 2m digunakan untuk memasang 1 buah Gambar 2p di sisi dalam sistem hardware.

Mengacu pada Gambar 3 dan Gambar 4, merupakan rangkaian untuk membuat ruang sensor. Pada Gambar 3 terdapat 6 lapisan dinding untuk membangun ruang sensor agar kedap dari udara bebas. Ruang sensor dibuat kedap untuk meminimalisir udara sampel terkontaminasi dengan udara bebas atau udara di sekitar lingkungan. Lapisan pertama ruang sensor dapat dilihat pada Gambar 2d1. Lapisan pertama merupakan dinding ruang sensor dengan ukuran 4cm x 19cm dan ketebalan dinding 5mm. Pada lapisan pertama ini digunakan untuk meletakkan 6 jenis sensor gas Metal Oxide Semi-conductor (MOS). Gambar 2d1a untuk sensor gas jenis ke 1, Gambar 2d1b untuk sensor gas jenis ke 2, Gambar 2d1c untuk sensor gas jenis ke 3, Gambar 2d1d untuk sensor gas jenis ke 4, Gambar 2d1e untuk sensor gas jenis ke 5, dan Gambar 2d1f untuk sensor gas jenis ke 6. Selain itu, pada lapisan pertama terdapat 6 lubang lingkaran dengan ukuran masing-masing lingkaran 3cm x 17cm. Gambar 2d1g merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 1 atau Gambar 2d1a. Gambar 2d1h merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 2 atau Gambar 2d1b. Gambar 2d1i merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 3 atau Gambar 2d1c. Gambar 2d1j merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 4 atau Gambar 2d1d. Gambar 2d1k merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 5 atau Gambar 2d1e. Gambar 2d1l merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 6 atau Gambar 2d1f.

Mengacu pada Gambar 4, tabung sensor bagian tengah ini dibuat sampai 4 kali agar sensor yang tersusun di posisi atas tidak bertabrakan dengan sensor yang tersusun di posisi bagian bawah. Gambar 2d2 merupakan lapisan kedua ruang sensor dengan ukuran 4cm x 19cm dan ketebalan dinding 5mm. Bagian tengah lapisan atau Gambar 2d2a ini dilubangi dengan ukuran 3cm x 17cm. Gambar 2d3 merupakan lapisan ketiga ruang sensor dengan ukuran 4cm x 19cm dan ketebalan dinding 5mm. Bagian tengah lapisan atau Gambar 2d3a ini dilubangi dengan ukuran 3cm x 17cm. Gambar 2d4 merupakan lapisan keempat ruang sensor dengan ukuran 4cm x 19cm dan ketebalan dinding 5mm. Bagian tengah lapisan atau Gambar 2d4a ini dilubangi dengan ukuran 3cm x 17cm. Gambar 2d5 merupakan lapisan kelima ruang sensor dengan ukuran 4cm x 19cm dan ketebalan dinding 5mm. Bagian tengah lapisan atau Gambar 2d5a ini dilubangi dengan ukuran 3cm x 17cm.

Gambar 2d6 merupakan lapisan keenam ruang sensor dengan ukuran 4cm x 19cm dan ketebalan dinding 5mm. Lapisan keenam digunakan untuk meletakkan 6 jenis sensor gas lanjutan dari lapisan pertama ruang sensor yaitu Gambar 2d1. Gambar 2d6a untuk sensor gas jenis ke 7, Gambar 2d6b untuk sensor gas jenis ke 8, Gambar 2d6c untuk sensor gas jenis ke 9, Gambar 2d6d untuk sensor gas jenis ke 10, Gambar 2d6e untuk sensor gas jenis ke 11, dan Gambar 2d6f untuk sensor gas jenis ke 12. Selain itu, pada lapisan keenam terdapat 6 lubang lingkaran dengan ukuran masing-masing lingkaran 3cm x 17cm pada lapisan keenam ruang sensor. Gambar 2d6g merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 1 atau Gambar 2d6a. Gambar 2d6h merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 2 atau Gambar 2d6b. Gambar 2d6i merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 3 atau Gambar 2d6c. Gambar 2d6j merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 4 atau Gambar 2d6d. Gambar 2d6k merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 5 atau Gambar 2d6e. Gambar 2d6l merupakan lubang lingkaran yang digunakan untuk menempelkan sensor gas jenis ke 6 atau Gambar 2d6f.

Untuk merakit ruang sensor maka Gambar 2d1, Gambar 2d2, Gambar 2d3, Gambar 2d4, Gambar 2d5, dan Gambar 2d6 ditumpuk sesuai urutannya lalu di rapatkan menggunakan Gambar 2s atau baut ukuran M3.

(b) Sistem Software

Mengacu pada Gambar 5 hingga Gambar 6 merupakan alur diagram untuk membaca data, mengambil data, mengolah data, dan menampilkan ke dalam software aplikasi Sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi. Proses pertama adalah data signal yang diambil dari hasil pembacaan sensor di micro-controller dengan menggunakan perhitungan Formula (1) hingga Formula (4). *Output* yang dihasilkan oleh sensor gas seri MOS adalah *analog to digital conversion* (ADC). Untuk menghitung resistansi sensor (Rs) menggunakan Formula (1) dimana Vc adalah tegangan pada micro-controller dan RL adalah beban sensor resistensi yang diukur menggunakan Ω meter.

$$\boldsymbol{Rs = \frac{Vc - VRL}{VRL}\ x\ RL} \tag{1}$$

Untuk menghitung tegangan output rangkaian (VRL) menggunakan Formula (2) dimana ADC di kalikan dengan nilai Vc dan dibagi dengan 1023 bit.

$$\boldsymbol{VRL = \frac{ADC\ x\ Vc}{1023}} \tag{2}$$

$$\boldsymbol{C = \gamma \left[\frac{R_s}{R_o}\right]^{\tau}\ ,\ \gamma, \tau\ \epsilon\ R^{+}} \tag{3}$$

$$\boldsymbol{C = 10^{\frac{\log\left(\frac{\frac{Rs}{Ro} - \gamma}{\alpha}\right)}{\beta}}} \tag{4}$$

Untuk mencari konsentrasi gas (C), diturunkan rumus dari datasheet masing-masing sensor dengan parameter nilai resistansi sensor sebenarnya (Rs) dan nilai resistansi sensor pada udara bersih (RO). Formula (3) dan Formula (4) digunakan untuk mengukur kosentrasi gas berdasar resistansi sensor

Selanjutnya adalah proses perhitungan Parameter statistical menggunakna nilai rata-rata (average) dan standar deviasi dari satu sinyal respon sensor yang dijelaskan pada Formula (5) dan Formula (6).

$$\boldsymbol{\mu = \frac{1}{n}\ x\ \sum_{t=0}^{n} y(t)} \tag{5}$$

$$\boldsymbol{\sigma = \sqrt{\frac{1}{N}\ x\ \sum_{t=0}^{N} (y(t) - \mu)^2}} \tag{6}$$

μ adalah nilai rata-rata sinyal dalam satu periode waktu, n adalah panjang sinyal dan *y(t)* adalah nilai sinyal (respon sensor dalam ppm) terhadap waktu *(t)*. σ adalah nilai standar deviasai sinyal y, N adalah panjang sinyal, *y(t)* adalah nilai sinyal terhadap waktu *(t)* dan adalah nilai rata-rata sinyal y. Selanjutnya adalah proses Classification dengan menggunakan Formula (7).

$$\boldsymbol{d_{CAD}(x,y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i| + |y_i|}} \quad (7)$$

d_CAD adalah hasil perhitungan jarak Canberra vektor x terhadap vektor y, n adalah panjang vektor atribut, x adalah vektor atribut data sedangkan y adalah vector atribut training set. Jarak Canberra merupakan weighted manhattan distance. Selanjutnya adalah proses Evaluasi dengan menggunakan Formula (8).

$$\boldsymbol{Akurasi = \frac{TruePositif + TrueNegative}{TruePositif + FalsePositif + FalseNegative + TrueNegative}} \quad (8)$$

Mengacu pada Gambar 1 hingga Gambar 6, hasil dari invensi ini adalah persentase campuran daging babi dengan akurat yaitu 94,20%. Dari uraian di atas jelas bahwa hasil dari invensi ini dapat memberi manfaat bagi masyarakat untuk mendeteksi daging babi di dalam daging sapi secara praktis yaitu hanya dengan aromanya saja.

Klaim

1. Suatu sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi dengan klasifikasi persentase: kelas 1, persentase 0%-5%; kelas 2, persentase 6%-15%; kelas 3, persentase 16%-35%; kelas 4, persentase 36%-60%; kelas 5, persentase 61%-85%; kelas 5, persentase 86%-95%; dan kelas 6, persentase 96%-100% daging babi.
2. Suatu sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi sesuai klaim 1, terdiri dari:
   (a) suatu sistem hardware yang memiliki Modul Rangkaian Sistem *Electronic Nose* dengan tata letak komponen yang disusun sedemikian rupa. Rangkaian ini memiliki 1 buah komponen micro-controller, 2 buah pembagi tegangan, 1 buah breadboard, 1 buah kipas kecil, 12 buah jenis sensor gas MOS, 1 buah ruang sensor, dan 1 buah box sistem *Electronic Nose*.
   (b) Suatu software aplikasi yang memiliki beberapa menu seperti Home, Add Sample, Reports, Parameter Statistic, dan Classification.
3. Suatu sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi sesuai dengan klaim 1 dan 2, dimana kombinasi sensor disusun di dalam ruang sensor dengan posisi 6 buah sensor gas di posisi atas dan 6 buah sensor gas di posisi bawah dan berhadap-hadapan.
4. Suatu sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi sesuai dengan klaim 1 sampai 3, dimana di ruang sensor terdapat 1 buah lubang di ujung tengah sisi kanan dan 1 buah lubang di ujung tengah sisi kiri. Lubang di sisi kanan digunakan sebagai aliran udara masuk ke ruang sensor array, sedangkan lubang di sisi kiri digunakan sebagai aliran udara yang keluar dari ruang sensor.
5. Suatu sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi sesuai klaim 1 dan 2, dimana menu Add Sampel adalah menu yang digunakan untuk mengambil data dari sistem hardware menggunakan program.
6. Suatu sistem *Electronic Nose* untuk deteksi kemurnian daging sapi terhadap daging babi sesuai dengan klaim 1, klaim 2, dan klaim 5, dimana menu Parameter Statistic adalah menu yang

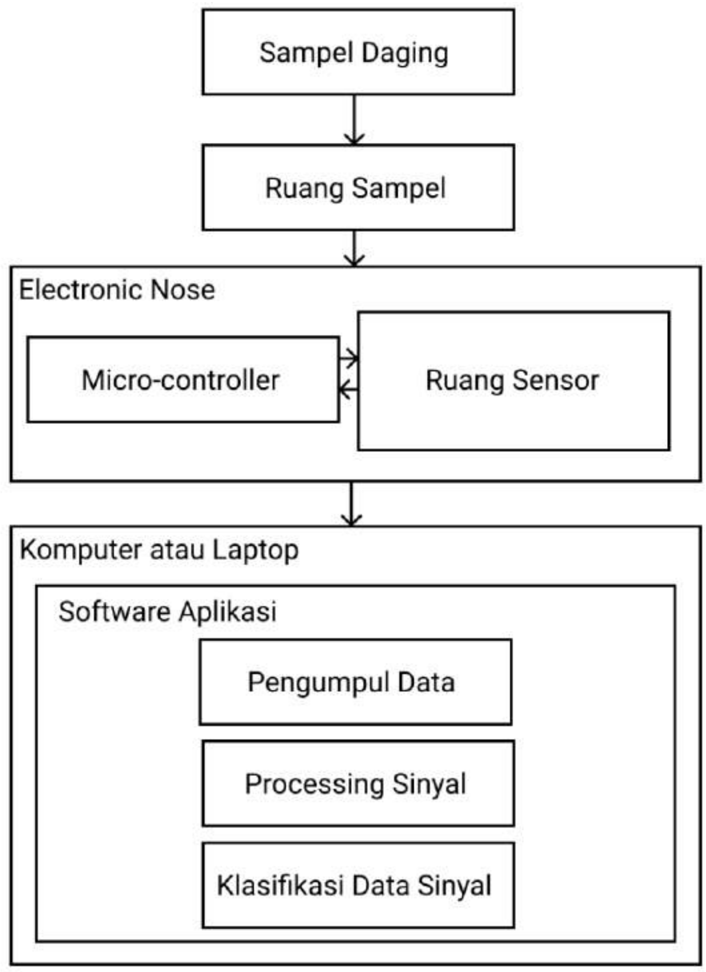
digunakan untuk mengolah data sinyal. Menu Classification adalah menu kasifikasi data sinyal menggunakan program, dan tingkat akurasinya mencapai 94,20%.

Abstrak

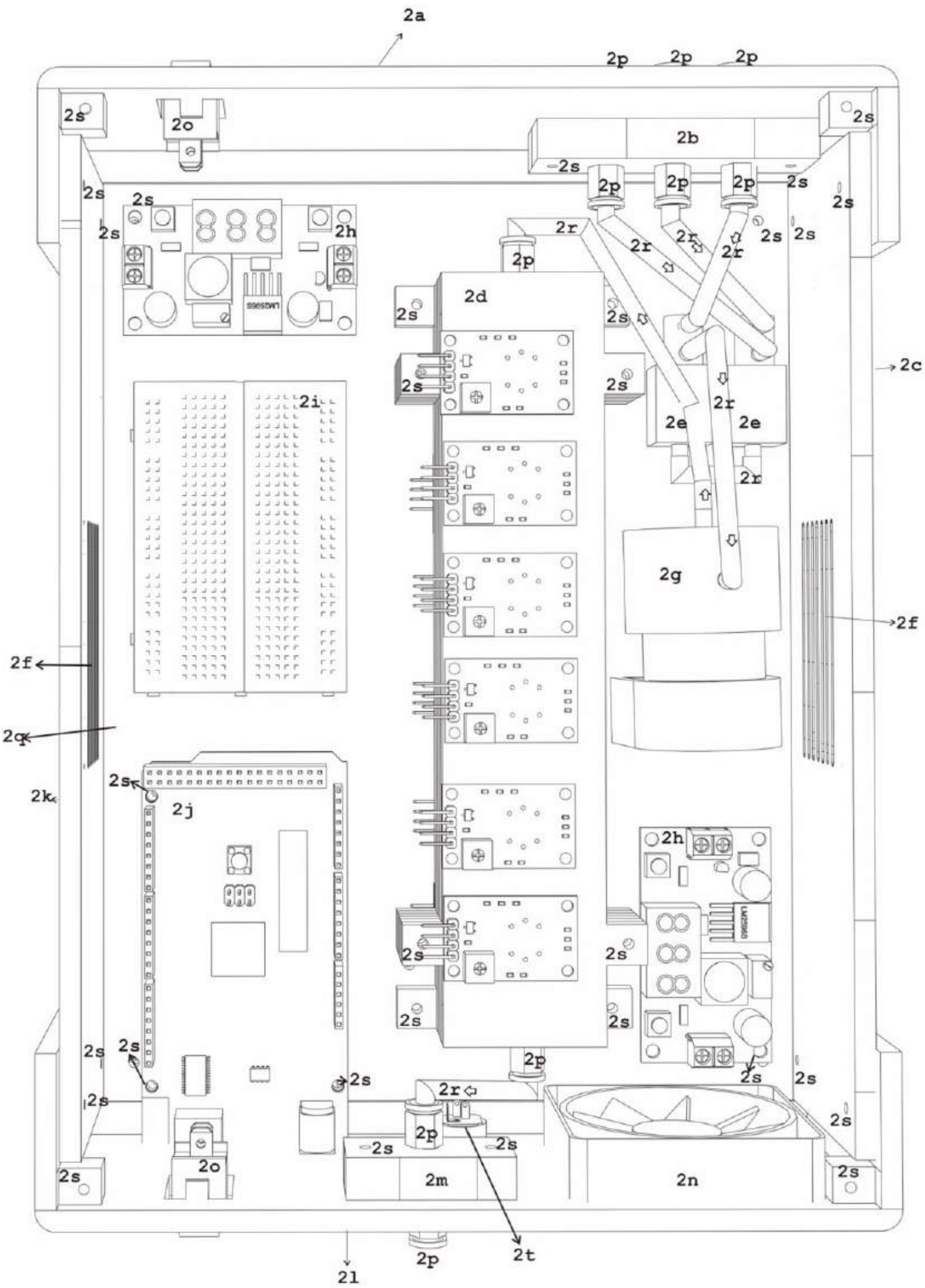
SISTEM *ELECTRONIC NOSE* UNTUK DETEKSI KEMURNIAN DAGING SAPI TERHADAP DAGING BABI

Invensi yang diusulkan ini adalah solusi dari permasalahan di atas yang dapat membantu masyarakat khususnya muslim. Hasil dari invensi ini dapat mendeteksi kemurnian daging sapi yang di campur dengan daging babi dengan klasifikasi persentase: kelas 1, persentase 0%-5%; kelas 2, persentase 6%-15%; kelas 3, persentase 16%-35%; kelas 4, persentase 36%-60%; kelas 5, persentase 61%-85%; kelas 5, persentase 86%-95%; dan kelas 6, persentase 96%-100% daging babi. Penggunaan micro-controller yang digunakan sebagai pengumpul data dari sensor *electronic nose*, lalu data disimpan di dalam file dengan format *Comma Separated Value* (csv). Data tersebut kemudian diproses dan dilakukan klasifikasi menggunakan software aplikasi deteksi kemurnian daging sapi terhadap daging babi. Hasil luaran dari software aplikasi ini adalah kelas persentase campuran daging berdasarkan data sinyal *electronic nose.*

Dengan proses perwujudan invensi ini, masyarakat dapat mendeteksi adanya daging babi di dalam daging sapi melalui aromanya dengan hasil yang akurat yaitu 94,20%.


Sampel Daging
Ruang Sampel
Electronic Nose
Micro-controller
Ruang Sensor
Komputer atau Laptop
Software Aplikasi
Pengumpul Data
Processing Sinyal
Klasifikasi Data Sinyal

Gambar 1


2a
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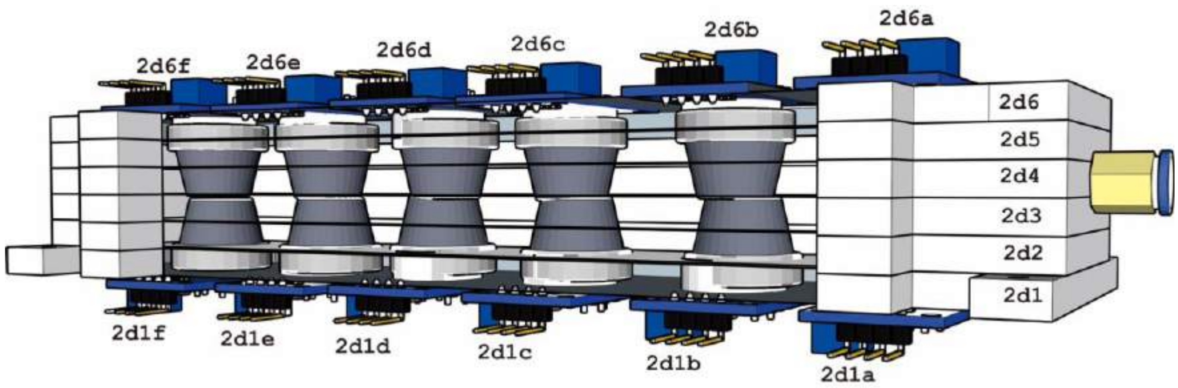
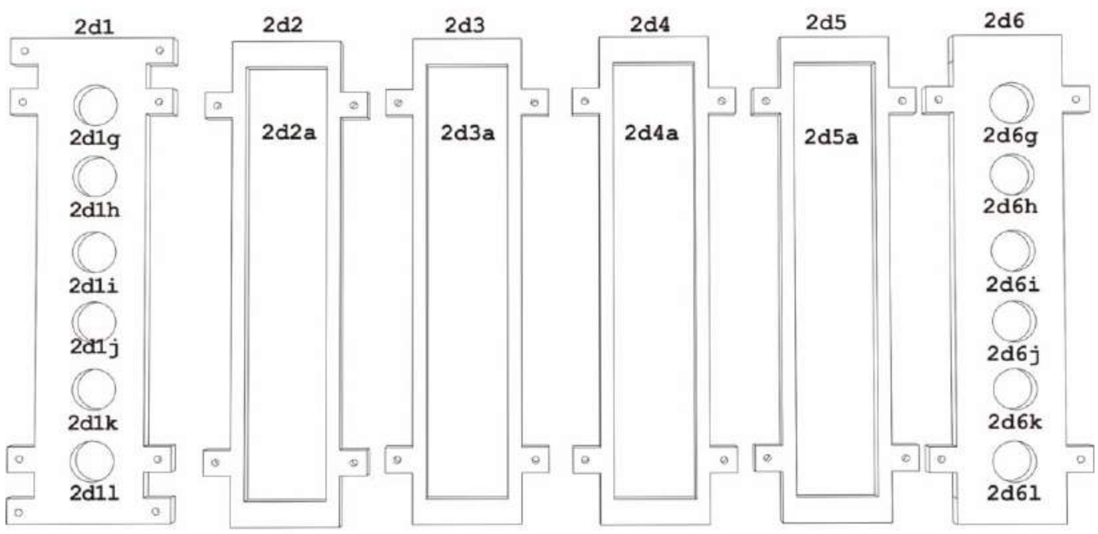
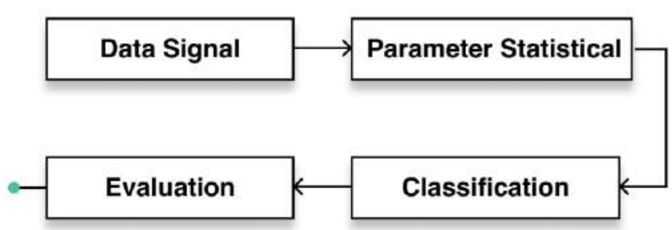
Gambar 2



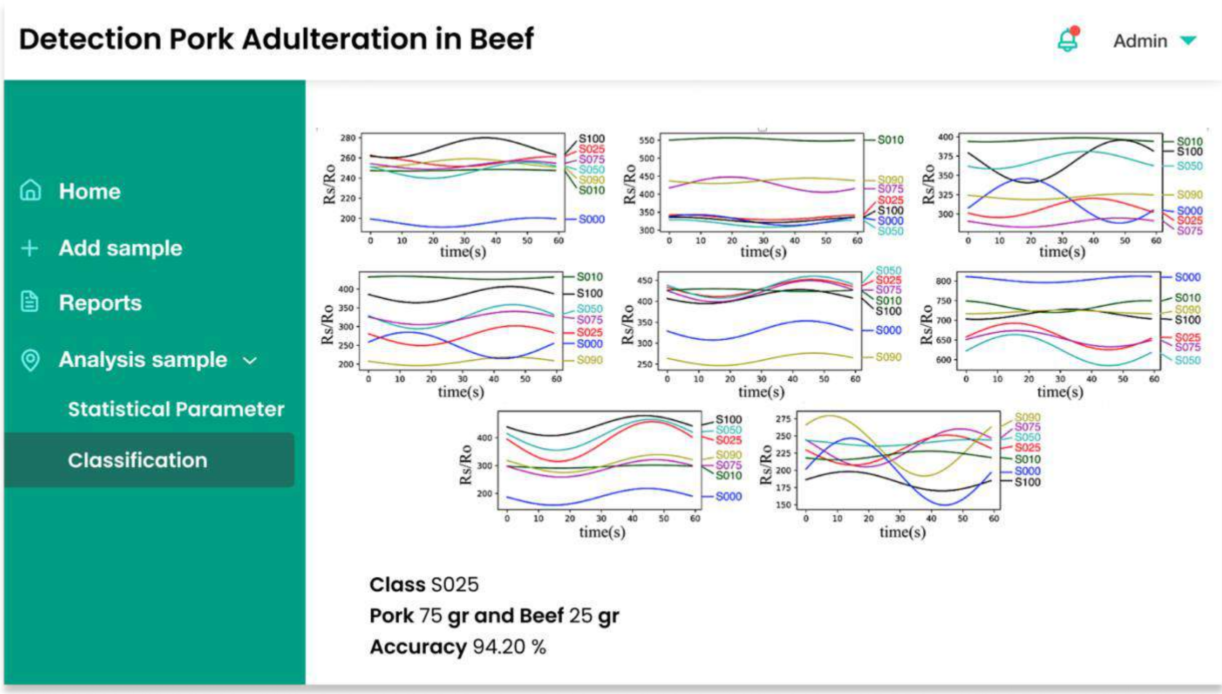
Gambar 3



Gambar 4



Gambar 5


Detection Pork Adulteration in Beef
Admin
Home
Add sample
Reports
Analysis sample
Statistical Parameter
Classification
Rs/Ro
time(s)
Class S025
Pork 75 gr and Beef 25 gr
Accuracy 94.20 %

Gambar 6

DOKUMENTASI HASIL UJI COBA PRODUK
LAPORAN AKHIR

PENGEMBANGAN ELECTRONIC-NOSE UNTUK DETEKSI KEMURNIAN DAGING SAPI

Tim Peneliti:

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Dibiayai oleh :
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Kementerian Riset, Teknologi, dan Pendidikan Tinggi
Sesuai dengan Perjanjian Penelitian
Nomor : 1360/PKS/ITS/2020
Tanggal 20 Maret 2020

LEMBAGA PENELITIAN DAN PENGABDIAN KEPADA MASYARAKAT
INSTITUT TEKNOLOGI SEPULUH NOPEMBER
SURABAYA 2020

A. Uji Coba dan Evaluasi

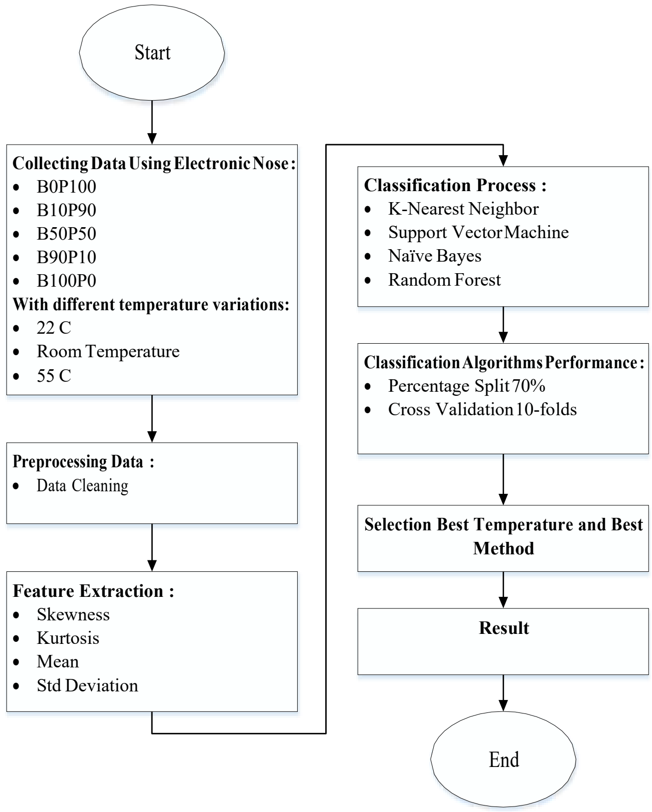
Sampel yang digunakan pada penelitian ini adalah daging sapi dan daging babi yang dibeli langsung di toko pada hari dan tanggal yang sama. Daging yang sudah disediakan kemudian dihaluskan atau diblender sehingga tekstur daging menjadi lebih halus dan pembagian prosentasi campuran daging oplosan menjadi lebih mudah. Data yang akan di test adalah 100 gram daging babi dan sapi dengan kombinasi porsentasi yang berbeda-beda. Penelitian ini menggunakan alat timbangan guna memastikan berat daging yang akan dicampur sudah sesuai. Masing-masing daging akan mempunyai masa yang sama yaitu 100 gram. Diagram blok dapat dilihat pada Gambar 3. Dijelaskan bahwa untuk kelas 1 diberikan daging sapi sebanyak 100 gram, kelas 2 daging sapi 90 gram di campur dengan daging babi 10 gram, kelas 3 daging sapi 75 gram dicampur dengan daging babi 25 gram, kelas 4 daging sapi dengan masa 50 gram dicampur dengan daging babi dengan masa 50 gram. Kelas 5 daging sapi 25 gram dicampur dengan daging babi 75 gram. Kelas 6 daging sapi 10 gram dicampur dengan daging babi 90 gram, dan yang terakhir daging babi 100 gram.

Langkah-langkah berikut digunakan untuk mengumpulkan sampel data:

1. e-nose dihidupkan dan sensor dihangatkan selama 15 menit (tentatif),
2. sampel ditempatkan di ruang sampel,
3. mengatur durasi waktu proses start, sensing, dan purging dalam hitungan menit,
4. proses pengambilan data dan transfer ke komputer menggunakan antarmuka USB atau Wi-Fi.

B. Hasil Analisis

Pada penelitian ini dilakukan analisis lebih lanjut dengan menggunakan algoritma untuk algoritma machine learning [2], [9], [10] dengan 3 perbedaan temperatur pada masing-masing dari 5 variasi data sampel daging untuk menentukan hasil klasifikasi yang optimal. Suhu yang digunakan adalah suhu -22 ° C, Suhu Kamar dan 55 ° C, sedangkan variasi campuran daging yang digunakan adalah 0% Daging Sapi - 100% Daging Babi; Daging sapi 10% - Daging babi 90%; Daging sapi 50% - Daging babi 50%; Daging sapi 90% - Daging babi 10%; dan 100% Daging Sapi - 0% Daging Babi. Algoritma yang digunakan untuk pembelajaran mesin adalah k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Naïve Bayes, dan Random Forest.



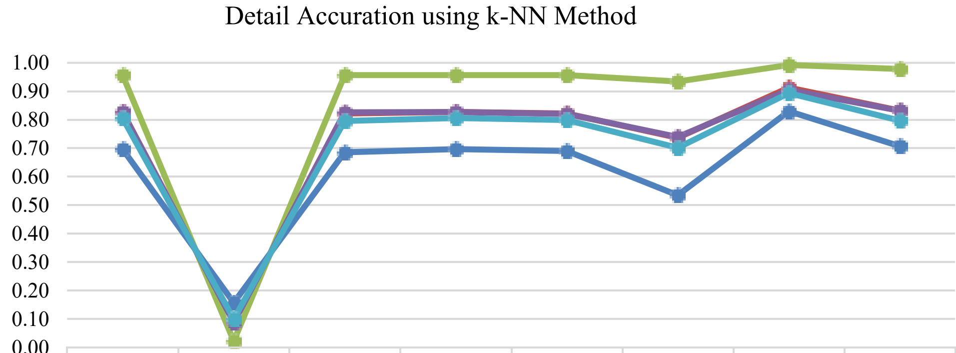
Gambar 1 Alur Metode

- Pengujian Skenario 1

Pada skenario pengujian ini dilakukan uji klasifikasi daging menggunakan metode k-Nearest Neighbor dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Pada pengujian skenario 1 dilakukan pemisahan data dari fungsi ekstraksi menjadi data latih dan data pengujian dengan rasio 30%, dan k = 3.

Tabel 1 Perbandingan variasi temperature dengan Skenario 1

	CODE	**TEMPERATURE**	**PREDICTION**		
			-22^{o}C	**Room Temp.**	**55^{o}C**
	B0P100	**-22^{o}C**	14	0	0
		Room Temp.	0	10	6
		55^{o}C	1	7	7
	B10P90	**-22^{o}C**	14	0	0
		Room Temp.	0	12	4
		55^{o}C	2	2	11
	B50P50	**-22^{o}C**	14	0	0
		Room Temp.	0	15	1
		55^{o}C	0	1	14
	B90P10	**-22^{o}C**	14	0	0
		Room Temp.	0	12	4
		55^{o}C	3	1	11
	B100P0	**-22^{o}C**	14	0	0
		Room Temp.	0	12	4
ACTUAL		**55^{o}C**	2	3	10



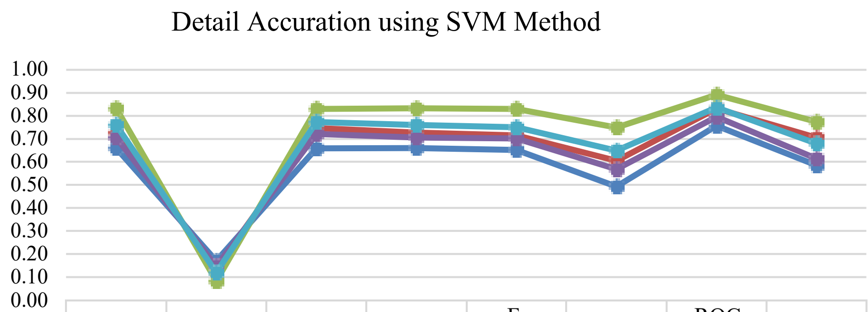
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.70	0.16	0.69	0.70	0.69	0.54	0.83	0.71
B10P90	0.83	0.09	0.82	0.83	0.82	0.74	0.91	0.83
B50P50	0.96	0.02	0.96	0.96	0.96	0.93	0.99	0.98
B90P10	0.83	0.09	0.83	0.83	0.82	0.74	0.91	0.83
B100P0	0.81	0.10	0.80	0.81	0.80	0.70	0.89	0.80

- Pengujian Skenario 2

Pada skenario pengujian ini dilakukan uji klasifikasi daging dengan menggunakan metode Support Vector Machine dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Dalam pengujian skenario 2, ini dilakukan dengan menggunakan k-fold cross-validation, dengan k = 10 untuk kernel RBF. Tujuan dari pengujian menggunakan k-fold cross-validation adalah untuk memilih parameter temperatur yang tepat sesuai dengan ketelitian tertinggi, sehingga ketepatan klasifikasi kemurnian SVM dapat ditingkatkan.

Tabel 2 Perbandingan variasi temperature dengan Skenario 2

	CODE	**TEMPERATURE**	**PREDICTION**		
			-22°C	**Room Temp.**	**55°C**
ACTUAL	**B0P100**	**-22°C**	43	2	5
		Room Temp.	8	32	10
		55°C	15	11	24
	B10P90	**-22°C**	47	1	2
		Room Temp.	6	39	5
		55°C	20	7	23
	B50P50	**-22°C**	50	0	0
		Room Temp.	2	39	9
		55°C	4	10	36
	B90P10	**-22°C**	40	8	2
		Room Temp.	6	39	5
		55°C	17	6	27
	B100P0	**-22°C**	48	2	0
		Room Temp.	5	39	6
		55°C	15	8	27



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.66	0.17	0.66	0.66	0.65	0.49	0.76	0.59
B10P90	0.73	0.14	0.75	0.73	0.71	0.60	0.83	0.70
B50P50	0.83	0.08	0.83	0.83	0.83	0.75	0.89	0.77
B90P10	0.71	0.15	0.72	0.71	0.70	0.57	0.80	0.61
B100P0	0.76	0.12	0.77	0.76	0.75	0.65	0.84	0.68

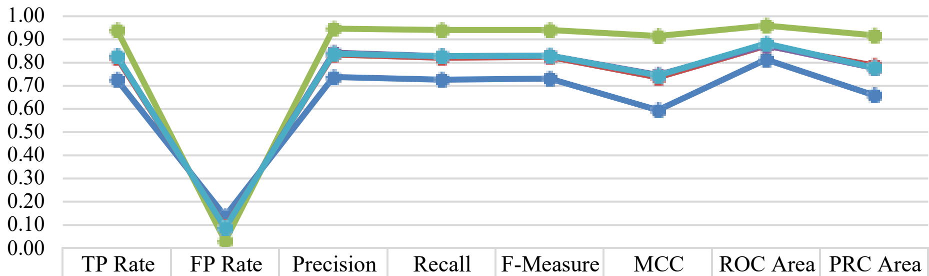
- Pengujian Skenario 3

Pada skenario pengujian ini, dilakukan uji klasifikasi daging dengan menggunakan metode Naïve Bayes dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Pada pengujian skenario 3 digunakan k-fold cross validation, dengan k = 10.

Tabel 3 Perbandingan variasi temperature dengan Skenario 3

	CODE	TEMPERATURE	PREDICTION		
			-22ºC	**Room Temp.**	**55ºC**
ACTUAL	**B0P100**	**-22ºC**	46	2	2
		Room Temp.	0	29	21
		55ºC	0	16	34
	B10P90	**-22ºC**	43	3	4
		Room Temp.	0	38	12
		55ºC	0	8	42
	B50P50	**-22ºC**	48	1	1
		Room Temp.	0	43	7
		55ºC	0	0	50
	B90P10	**-22ºC**	42	4	4
		Room Temp.	0	38	12
		55ºC	0	6	44
	B100P0	**-22ºC**	44	3	3
		Room Temp.	0	38	12
		55ºC	0	8	42

Detail Accuration using Naive Bayes Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.73	0.14	0.74	0.73	0.73	0.60	0.81	0.66
B10P90	0.82	0.09	0.83	0.82	0.82	0.74	0.87	0.79
B50P50	0.94	0.03	0.95	0.94	0.94	0.91	0.96	0.92
B90P10	0.83	0.09	0.84	0.83	0.83	0.75	0.87	0.78
B100P0	0.83	0.09	0.84	0.83	0.83	0.74	0.88	0.78

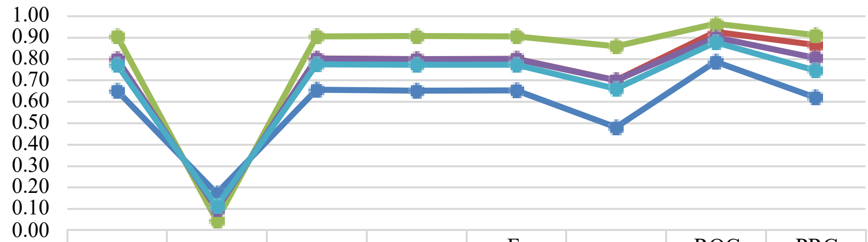
- Pengujian Skenario 4

Pada skenario pengujian ini dilakukan uji klasifikasi daging menggunakan metode random forest dengan 5 variasi daging dengan 3 variasi temperatur. Pada pengujian skenario ini digunakan k-fold cross validation, dengan k = 10.

Tabel 4 Perbandingan variasi temperature dengan Skenario 4

	CODE	TEMPERATURE	PREDICTION		
			-22ºC	**Room Temp.**	**55ºC**
A C T U A L	**B0P100**	**-22ºC**	49	1	0
		Room Temp.	0	26	24
		55ºC	0	27	23
	B10P90	**-22ºC**	49	0	1
		Room Temp.	0	35	15
		55ºC	0	14	36
	B50P50	**-22ºC**	50	0	0
		Room Temp.	0	44	6
		55ºC	0	6	42
	B90P10	**-22ºC**	49	1	0
		Room Temp.	0	35	15
		55ºC	0	14	36
	B100P0	**-22ºC**	49	1	0
		Room Temp.	0	33	17
		55ºC	0	16	34

Detail Accuration using Random Forest Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.65	0.17	0.66	0.65	0.65	0.48	0.79	0.62
B10P90	0.80	0.10	0.80	0.80	0.80	0.70	0.93	0.87
B50P50	0.91	0.05	0.91	0.91	0.91	0.86	0.96	0.91
B90P10	0.80	0.10	0.80	0.80	0.80	0.70	0.90	0.80
B100P0	0.77	0.11	0.78	0.77	0.77	0.66	0.88	0.75

Hasil Evaluasi menggunakan ROC

Untuk mengetahui suhu dan metode terbaik dalam percobaan ini, peneliti mengelompokkan nilai ROC terhadap metode dan suhu seperti pada tabel 6. Pada -22oC, metode yang memiliki akurasi tertinggi adalah metode random forest dengan nilai rata-rata ROC 1.000. Sedangkan metode yang memiliki akurasi tertinggi kedua adalah metode k-Nearest Neighbor dengan nilai rata-rata ROC 0.986. Metode naïve bayes menduduki peringkat ke-3 dengan nilai rata-rata ROC 0.971 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai rata-rata ROC 0.872. Pada suhu kamar, metode yang memiliki akurasi tertinggi adalah metode k-Nearest Neighbor dengan nilai rata-rata ROC 0.886. Sedangkan metode yang memiliki akurasi tinggi ke 2 adalah metode Naïve Bayes dengan nilai ROC rata-rata 0.856. Metode Random Forest menduduki peringkat ke-3 dengan nilai rata-rata ROC 0.839 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai ROC rata-rata 0.820. Pada suhu 55oC, metode yang memiliki akurasi tertinggi adalah metode Naïve Bayes dengan nilai ROC rata-rata 0.864. Sedangkan metode yang memiliki akurasi tertinggi kedua adalah metode K-Nearest Neighbor dengan nilai rata-rata ROC sebesar 0.848. Metode Random Forest menduduki peringkat ke-3 dengan nilai rata-rata ROC 0.836 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai rata-rata ROC 0.774

Berdasarkan hasil penelitian yang dilakukan oleh penulis maka diperoleh kesimpulan sebagai berikut:

1. Peneliti membagi percobaan menjadi 4 skenario dengan masing-masing komposisi 5 variasi daging (Beef 0% - Pork 100%, Beef 10% - Pork 90%, Beef 50% - Pork 50%, Beef 90% - Pork 10% dan Daging Sapi 100% - Daging Babi 0%) dengan 3 variasi suhu (-22oC, Suhu Kamar, dan 55oC), yaitu:
   a. k-Metode Tetangga Terdekat
   b. Mendukung Metode Mesin Vektor
   c. Metode Bayer yang Naif
   d. Metode Hutan Acak
2. Ada pengaruh temperatur terhadap peningkatan akurasi, yaitu pada -22oC. Karena semakin rendah suhunya semakin stabil nilai yang didapat oleh electronic nose.
3. Berikut adalah metode yang memiliki akurasi tinggi berdasarkan suhu:
   a. Pada suhu -22oC urutan metode yang memiliki akurasi tertinggi sampai terendah adalah Random Forest dengan nilai rata-rata ROC 1,00; K-Nearest Neighbor dengan nilai rata-rata ROC 0.986; Naïve Bayes dengan nilai rata-rata ROC 0.971 dan Support Vector Machine dengan nilai rata-rata ROC 0.872.

b. Pada temperatur ruang urutan metode yang memiliki akurasi tertinggi sampai terendah yaitu K-Nearest Neighbor dengan nilai rata-rata ROC 0.886; Naïve Bayes dengan nilai rata-rata ROC 0.856; Random Forest dengan nilai rata-rata ROC 0.839 dan Support Vector Machine dengan nilai ROC rata-rata 0.821.
c. Pada suhu 55oC urutan metode yang memiliki akurasi tertinggi sampai terendah yaitu Naïve Bayes dengan nilai ROC rata-rata 0.864; K-Nearest Neighbor dengan nilai rata-rata ROC 0.848; Random Forest dengan nilai rata-rata ROC 0.836 dan Support Vector Machine dengan nilai rata-rata ROC 0.774.

DOKUMENTASI HASIL UJI COBA PRODUK
LAPORAN AKHIR

PENGEMBANGAN ELECTRONIC-NOSE UNTUK DETEKSI KEMURNIAN DAGING SAPI

Tim Peneliti:

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Sesuai dengan Perjanjian Penelitian
Nomor : 1360/PKS/ITS/2020
Tanggal 20 Maret 2020

LEMBAGA PENELITIAN DAN PENGABDIAN KEPADA MASYARAKAT
INSTITUT TEKNOLOGI SEPULUH NOPEMBER
SURABAYA 2020

A. Uji Coba dan Evaluasi

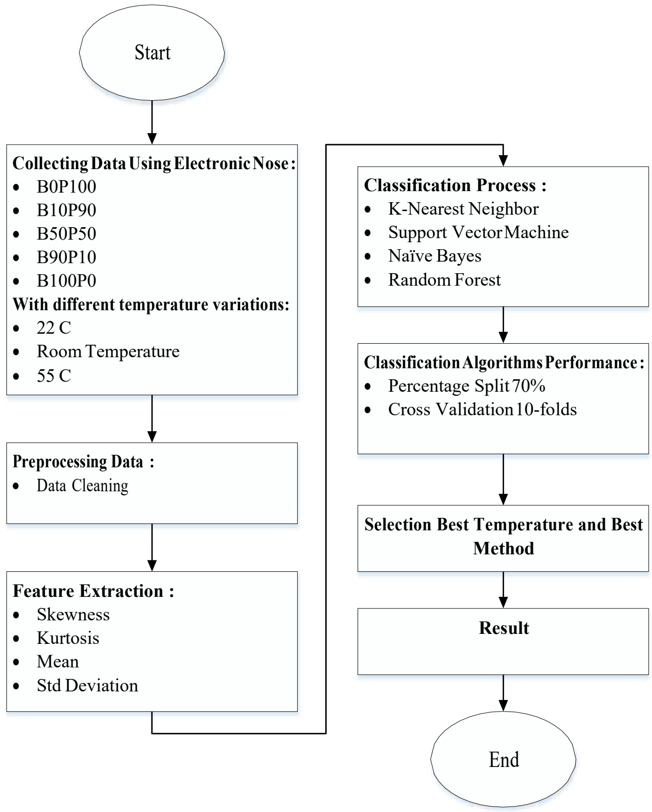
Sampel yang digunakan pada penelitian ini adalah daging sapi dan daging babi yang dibeli langsung di toko pada hari dan tanggal yang sama. Daging yang sudah disediakan kemudian dihaluskan atau diblender sehingga tekstur daging menjadi lebih halus dan pembagian prosentasi campuran daging oplosan menjadi lebih mudah. Data yang akan di test adalah 100 gram daging babi dan sapi dengan kombinasi porsentasi yang berbeda-beda. Penelitian ini menggunakan alat timbangan guna memastikan berat daging yang akan dicampur sudah sesuai. Masing-masing daging akan mempunyai masa yang sama yaitu 100 gram. Diagram blok dapat dilihat pada Gambar 3. Dijelaskan bahwa untuk kelas 1 diberikan daging sapi sebanyak 100 gram, kelas 2 daging sapi 90 gram di campur dengan daging babi 10 gram, kelas 3 daging sapi 75 gram dicampur dengan daging babi 25 gram, kelas 4 daging sapi dengan masa 50 gram dicampur dengan daging babi dengan masa 50 gram. Kelas 5 daging sapi 25 gram dicampur dengan daging babi 75 gram. Kelas 6 daging sapi 10 gram dicampur dengan daging babi 90 gram, dan yang terakhir daging babi 100 gram.

Langkah-langkah berikut digunakan untuk mengumpulkan sampel data:

1. e-nose dihidupkan dan sensor dihangatkan selama 15 menit (tentatif),
2. sampel ditempatkan di ruang sampel,
3. mengatur durasi waktu proses start, sensing, dan purging dalam hitungan menit,
4. proses pengambilan data dan transfer ke komputer menggunakan antarmuka USB atau Wi-Fi.

B. Hasil Analisis

Pada penelitian ini dilakukan analisis lebih lanjut dengan menggunakan algoritma untuk algoritma machine learning [2], [9], [10] dengan 3 perbedaan temperatur pada masing-masing dari 5 variasi data sampel daging untuk menentukan hasil klasifikasi yang optimal. Suhu yang digunakan adalah suhu -22 ° C, Suhu Kamar dan 55 ° C, sedangkan variasi campuran daging yang digunakan adalah 0% Daging Sapi - 100% Daging Babi; Daging sapi 10% - Daging babi 90%; Daging sapi 50% - Daging babi 50%; Daging sapi 90% - Daging babi 10%; dan 100% Daging Sapi - 0% Daging Babi. Algoritma yang digunakan untuk pembelajaran mesin adalah k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Naïve Bayes, dan Random Forest.



Gambar 1 Alur Metode

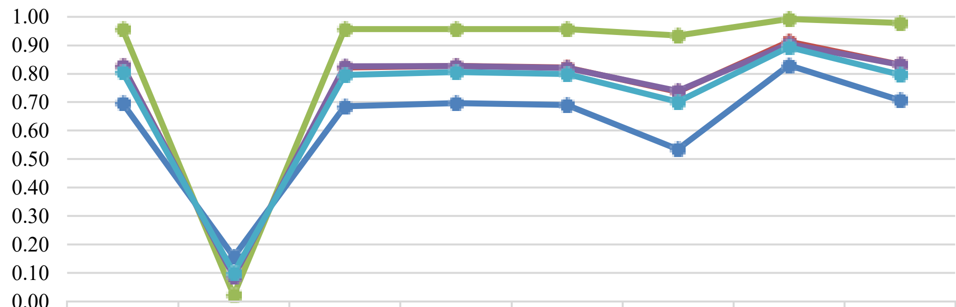
- Pengujian Skenario 1

Pada skenario pengujian ini dilakukan uji klasifikasi daging menggunakan metode k-Nearest Neighbor dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Pada pengujian skenario 1 dilakukan pemisahan data dari fungsi ekstraksi menjadi data latih dan data pengujian dengan rasio 30%, dan k = 3.

Tabel 1 Perbandingan variasi temperature dengan Skenario 1

	CODE	**TEMPERATURE**	**PREDICTION**		
			-22°C	**Room Temp.**	**55°C**
	B0P100	**-22°C**	14	0	0
		Room Temp.	0	10	6
		55°C	1	7	7
	B10P90	**-22°C**	14	0	0
		Room Temp.	0	12	4
		55°C	2	2	11
	B50P50	**-22°C**	14	0	0
		Room Temp.	0	15	1
		55°C	0	1	14
	B90P10	**-22°C**	14	0	0
		Room Temp.	0	12	4
		55°C	3	1	11
ACTUAL	**B100P0**	**-22°C**	14	0	0
		Room Temp.	0	12	4
		55°C	2	3	10

Detail Accuration using k-NN Method



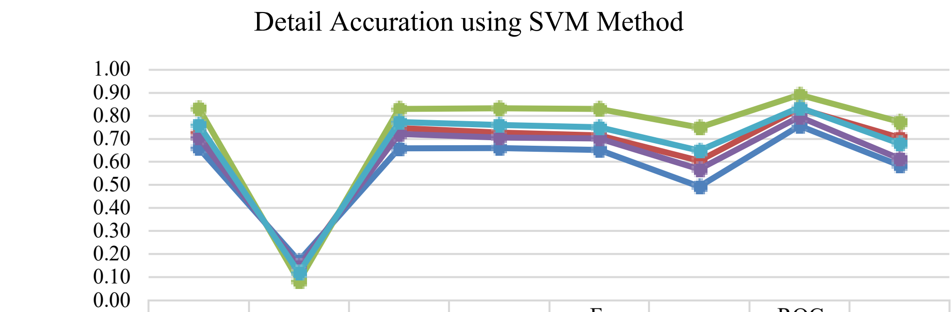
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.70	0.16	0.69	0.70	0.69	0.54	0.83	0.71
B10P90	0.83	0.09	0.82	0.83	0.82	0.74	0.91	0.83
B50P50	0.96	0.02	0.96	0.96	0.96	0.93	0.99	0.98
B90P10	0.83	0.09	0.83	0.83	0.82	0.74	0.91	0.83
B100P0	0.81	0.10	0.80	0.81	0.80	0.70	0.89	0.80

- Pengujian Skenario 2

Pada skenario pengujian ini dilakukan uji klasifikasi daging dengan menggunakan metode Support Vector Machine dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Dalam pengujian skenario 2, ini dilakukan dengan menggunakan k-fold cross-validation, dengan k = 10 untuk kernel RBF. Tujuan dari pengujian menggunakan k-fold cross-validation adalah untuk memilih parameter temperatur yang tepat sesuai dengan ketelitian tertinggi, sehingga ketepatan klasifikasi kemurnian SVM dapat ditingkatkan.

Tabel 2 Perbandingan variasi temperature dengan Skenario 2

	CODE	**TEMPERATURE**	**PREDICTION**		
			-22°C	**Room Temp.**	**55°C**
	B0P100	**-22°C**	43	2	5
		Room Temp.	8	32	10
		55°C	15	11	24
ACTUAL	**B10P90**	**-22°C**	47	1	2
		Room Temp.	6	39	5
		55°C	20	7	23
	B50P50	**-22°C**	50	0	0
		Room Temp.	2	39	9
		55°C	4	10	36
	B90P10	**-22°C**	40	8	2
		Room Temp.	6	39	5
		55°C	17	6	27
	B100P0	**-22°C**	48	2	0
		Room Temp.	5	39	6
		55°C	15	8	27



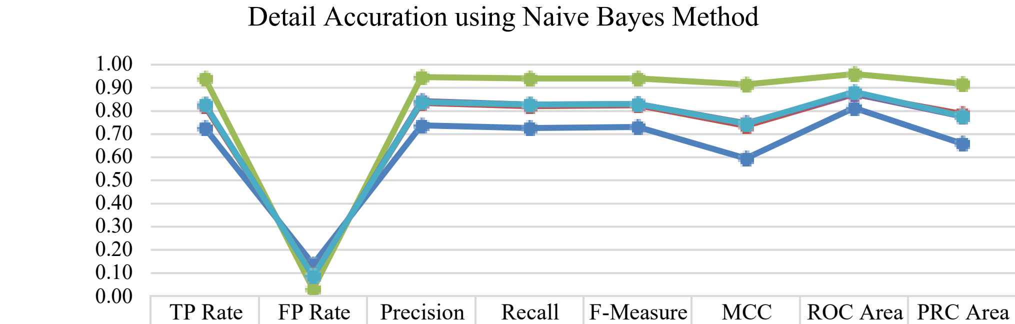
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.66	0.17	0.66	0.66	0.65	0.49	0.76	0.59
B10P90	0.73	0.14	0.75	0.73	0.71	0.60	0.83	0.70
B50P50	0.83	0.08	0.83	0.83	0.83	0.75	0.89	0.77
B90P10	0.71	0.15	0.72	0.71	0.70	0.57	0.80	0.61
B100P0	0.76	0.12	0.77	0.76	0.75	0.65	0.84	0.68

- Pengujian Skenario 3

Pada skenario pengujian ini, dilakukan uji klasifikasi daging dengan menggunakan metode Naïve Bayes dengan 5 variasi daging dengan 3 variasi temperatur yang berbeda. Pada pengujian skenario 3 digunakan k-fold cross validation, dengan k = 10.

Tabel 3 Perbandingan variasi temperature dengan Skenario 3

	CODE	TEMPERATURE	PREDICTION -22ºC	PREDICTION Room Temp.	PREDICTION 55ºC
ACTUAL	**B0P100**	**-22ºC**	46	2	2
		Room Temp.	0	29	21
		55ºC	0	16	34
	B10P90	**-22ºC**	43	3	4
		Room Temp.	0	38	12
		55ºC	0	8	42
	B50P50	**-22ºC**	48	1	1
		Room Temp.	0	43	7
		55ºC	0	0	50
	B90P10	**-22ºC**	42	4	4
		Room Temp.	0	38	12
		55ºC	0	6	44
	B100P0	**-22ºC**	44	3	3
		Room Temp.	0	38	12
		55ºC	0	8	42



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.73	0.14	0.74	0.73	0.73	0.60	0.81	0.66
B10P90	0.82	0.09	0.83	0.82	0.82	0.74	0.87	0.79
B50P50	0.94	0.03	0.95	0.94	0.94	0.91	0.96	0.92
B90P10	0.83	0.09	0.84	0.83	0.83	0.75	0.87	0.78
B100P0	0.83	0.09	0.84	0.83	0.83	0.74	0.88	0.78

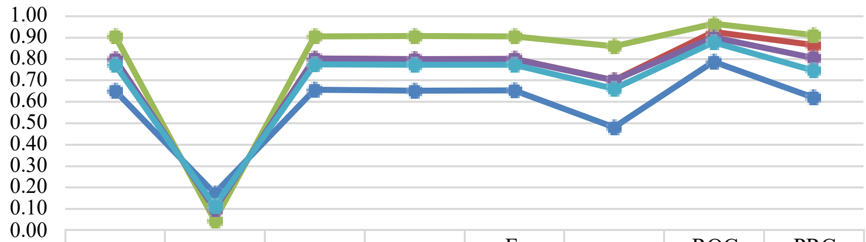
- Pengujian Skenario 4

Pada skenario pengujian ini dilakukan uji klasifikasi daging menggunakan metode random forest dengan 5 variasi daging dengan 3 variasi temperatur. Pada pengujian skenario ini digunakan k-fold cross validation, dengan k = 10.

Tabel 4 Perbandingan variasi temperature dengan Skenario 4

	CODE	**TEMPERATURE**	**PREDICTION**		
			-22°C	**Room Temp.**	**55°C**
ACTUAL	**B0P100**	**-22°C**	49	1	0
		Room Temp.	0	26	24
		55°C	0	27	23
	B10P90	**-22°C**	49	0	1
		Room Temp.	0	35	15
		55°C	0	14	36
	B50P50	**-22°C**	50	0	0
		Room Temp.	0	44	6
		55°C	0	6	42
	B90P10	**-22°C**	49	1	0
		Room Temp.	0	35	15
		55°C	0	14	36
	B100P0	**-22°C**	49	1	0
		Room Temp.	0	33	17
		55°C	0	16	34

Detail Accuration using Random Forest Method



	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
B0P100	0.65	0.17	0.66	0.65	0.65	0.48	0.79	0.62
B10P90	0.80	0.10	0.80	0.80	0.80	0.70	0.93	0.87
B50P50	0.91	0.05	0.91	0.91	0.91	0.86	0.96	0.91
B90P10	0.80	0.10	0.80	0.80	0.80	0.70	0.90	0.80
B100P0	0.77	0.11	0.78	0.77	0.77	0.66	0.88	0.75

Hasil Evaluasi menggunakan ROC

Untuk mengetahui suhu dan metode terbaik dalam percobaan ini, peneliti mengelompokkan nilai ROC terhadap metode dan suhu seperti pada tabel 6. Pada -22oC, metode yang memiliki akurasi tertinggi adalah metode random forest dengan nilai rata-rata ROC 1.000. Sedangkan metode yang memiliki akurasi tertinggi kedua adalah metode k-Nearest Neighbor dengan nilai rata-rata ROC 0.986. Metode naïve bayes menduduki peringkat ke-3 dengan nilai rata-rata ROC 0.971 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai rata-rata ROC 0.872. Pada suhu kamar, metode yang memiliki akurasi tertinggi adalah metode k-Nearest Neighbor dengan nilai rata-rata ROC 0.886. Sedangkan metode yang memiliki akurasi tinggi ke 2 adalah metode Naïve Bayes dengan nilai ROC rata-rata 0.856. Metode Random Forest menduduki peringkat ke-3 dengan nilai rata-rata ROC 0.839 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai ROC rata-rata 0.820. Pada suhu 55oC, metode yang memiliki akurasi tertinggi adalah metode Naïve Bayes dengan nilai ROC rata-rata 0.864. Sedangkan metode yang memiliki akurasi tertinggi kedua adalah metode K-Nearest Neighbor dengan nilai rata-rata ROC sebesar 0.848. Metode Random Forest menduduki peringkat ke-3 dengan nilai rata-rata ROC 0.836 dan metode SVM merupakan metode yang memiliki akurasi paling rendah dengan nilai rata-rata ROC 0.774

Berdasarkan hasil penelitian yang dilakukan oleh penulis maka diperoleh kesimpulan sebagai berikut:

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   a. k-Metode Tetangga Terdekat
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   c. Metode Bayer yang Naif
   d. Metode Hutan Acak
2. Ada pengaruh temperatur terhadap peningkatan akurasi, yaitu pada -22oC. Karena semakin rendah suhunya semakin stabil nilai yang didapat oleh electronic nose.
3. Berikut adalah metode yang memiliki akurasi tinggi berdasarkan suhu:
   a. Pada suhu -22oC urutan metode yang memiliki akurasi tertinggi sampai terendah adalah Random Forest dengan nilai rata-rata ROC 1,00; K-Nearest Neighbor dengan nilai rata-rata ROC 0.986; Naïve Bayes dengan nilai rata-rata ROC 0.971 dan Support Vector Machine dengan nilai rata-rata ROC 0.872.

b. Pada temperatur ruang urutan metode yang memiliki akurasi tertinggi sampai terendah yaitu K-Nearest Neighbor dengan nilai rata-rata ROC 0.886; Naïve Bayes dengan nilai rata-rata ROC 0.856; Random Forest dengan nilai rata-rata ROC 0.839 dan Support Vector Machine dengan nilai ROC rata-rata 0.821.
c. Pada suhu 55oC urutan metode yang memiliki akurasi tertinggi sampai terendah yaitu Naïve Bayes dengan nilai ROC rata-rata 0.864; K-Nearest Neighbor dengan nilai rata-rata ROC 0.848; Random Forest dengan nilai rata-rata ROC 0.836 dan Support Vector Machine dengan nilai rata-rata ROC 0.774.

Dokumen pendukung luaran Tambahan #1

Luaran dijanjikan: Prosiding dalam pertemuan ilmiah Internasional

Target: sudah terbit/sudah dilaksanakan
Dicapai: Published

Dokumen wajib diunggah:
1. Artikel yang terbit

Dokumen sudah diunggah:
1. Artikel yang terbit

Dokumen belum diunggah:
-

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Judul artikel: Recognition of Original Arabica Civet Coffee based on Odor using Electronic Nose and Machine Learning

Recognition of Original Arabica Civet Coffee based on Odor using Electronic Nose and Machine Learning

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***Abstract*—Many studies have used an electronic nose (E-nose) to detect several types of coffee. To the best of our knowledge, none of the studies have tried to detect odors from a mixture of several types of coffee. Therefore, this research proposes E-nose which can be used to recognize original Arabica civet coffee. The mixture of Arabica civet coffee and Robusta coffee (non-civet coffee) is used as the object of this research. Nine combinations of mixture are prepared in this study. Those combinations are referred to as classes. After collecting the data, a statistical calculation would be determined to obtain parameter statistics. Moreover, the classification method used in this study is to recognize original Arabica civet coffee and original Robusta coffee. Several classifications had been compared, namely Logistic Regression (LR), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN). The best result is the KNN method with an accuracy value of 97.7% for nine classes.**

Keywords—E-nose, Classification, Sensors, Arabica Coffee, Robusta Coffee, Civet Coffee.

I. INTRODUCTION

Traditionally, the aroma of coffee has been used to differentiate the originality of coffee. The aroma of coffee contains gas which is obtained by determining the gas content. During the roasting, temperature increases, and the biological process occurs. Then, coffee releases a robust aroma [1]. New compounds formed by physical and chemical reactions evaporate. E-nose has the ability to simulate the work of the human sense of smell. An electronic nose is made to catch the gas and recognize odors by using sensors [2]. The database of aroma produced by coffee is a pattern of odor, one of which functions to develop the system that can recognize a pattern, so it can be classified and be inspected [3].

In 2016, a study was conducted to classify coffee using a backpropagation neural network. The result showed that backpropagation neural network is capable of determining the differences [4] between Arabica and Robusta with a success rate of 40%.

Another E-nose study attained an accuracy of 71% for the Support Vector Machine (SVM) method and 57% for the Perceptron method. The study tried to classify the aroma of Arabica coffee and the aroma of Robusta coffee. The SVM method could recognize Arabica coffee and Robusta coffee with better results than the Perceptron method [5]. However, the research had a weakness in the classification method. The result of the classification has a lesser percentage of accuracy. Moreover, there was not any statistical calculation that could be used for preprocessing before classifying the data.

Therefore, this study aims to improve the weaknesses of the previous studies. E-nose used in this study has different characteristics to identify the odor and aroma of the gas because it consists of various types of sensors [6]. Then, the preprocessing stage using statistical calculations can obtain the characteristics from each signal response. This study has three values from a combination of statistical calculations; there are the values of average and standard deviation, the values between the minimum and maximum, and the values between average, standard deviation, and minimum and maximum values. After preprocessing stage, the calculation continues with the classification phase. Confusion matrix [7] is used in this study to evaluate the classification method.

Besides, we try to use other classification methods, so the results can be compared. Other classification methods that we use in this study are Logistic Regression (LR), Linear Discriminant Analysis (LDA) [8], and K-Nearest Neighbors (KNN). Comparing the result generated from three classification methods use the confusion matrix, and the best accuracy is chosen for the purpose of this study.

II. RELATED RESEARCH

A. *E-nose using Backpropagation Neural Network*

This study uses a system that puts several sets of gas sensors and receives input signals from TGS 2610, TGS 2611, TGS 2602, TGS 2620, and TGS 822 [4]. The resistance of the sensor results in a change of voltage when the sensor detects the presence of gaseous elements from the aroma of coffee. This signal is operated by a signal conditioning circuit to be delivered to the analog-digital converter (ADC) circuit and to change over into digital form. The process continues when the digital signal transmitted to the Personal Computer (PC) and to be processed using backpropagation NN (Neural Network). Backpropagation NN used is built with architecture 1 input layer 5 nodes (x_1-x_5), 1 hidden layer 6 nodes, and 1 output layer 2 nodes as shown in Fig. 1.

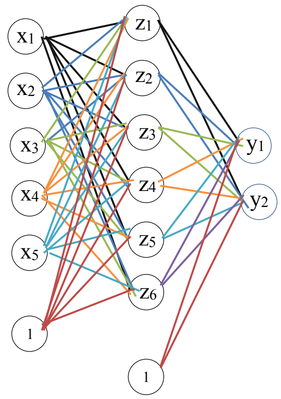

Figure 1. Backpropagation Design

The conclusion of this study is obtained after several tests and analyses. It can be concluded that the identification of Arabica coffee using Backpropagation NN is able to identify with a success rate of 40% and then for Robusta coffee of 100%. Besides, the system can also identify air or without coffee with an accuracy of 100%. Unfortunately, this study can only distinguish two classes of coffee, namely Arabica coffee and Robusta coffee.

B. *E-nose using SVM and Perceptron*

This study uses two methods for classifying the aroma of Arabica coffee and the aroma of Robusta coffee; they are the SVM and Perceptron methods. First, the study reduced data noise using discrete wavelet transforms. After finishing the process, the data would be passing through the feature extraction stage. The next step was using the SVM [5] and Perceptron methods for classification. The result of both methods showed the highest accuracy values and the lowest error for the classification of Arabica coffee and Robusta coffee. At the end of this study, the researcher would like to show that after classified using SVM and Perceptron methods [9], each result would be compared and the best result would be chosen. So, the conclusion is that the E-nose is able to identify between Arabica coffee and Robusta coffee. The best accuracy value is generated by the SVM method of which accuracy is 71%; however, this result still needs improvement.

C. *Classification using Radial Basis Function*

The gas sensors receive the aroma of coffee, change it into the transmitted signal, and analyze using pattern recognition. The E-nose used in this study is a sensor array polymer-coated for classification coffee variant, such as Arabica Bengkulu, Arabica Sidikalang, Arabica Papandayan, and Arabica Kerinci planted in different areas [10]. This study uses Artificial Neural Network Radial Basis Function to classify the coffees. The features comprise energy, contrast, correlation, and homogeneity. These features are trained using the Radial Basis Function neural network in order to classify coffee into four classes, namely Arabica Kerinci, Arabica Papandayan, Arabica Bengkulu, and Arabica Sidikalang.

D. *Statistical Data*

Statistics are a group of data in the system of numbers or not numbers relating to certain problems arranged in the form of tables, lists, diagrams, or others, so statistics are the result of data processing presented in tables, graphs, diagrams, etc. The purpose of statistics is to make it easier to interpret data used for a particular purpose. Statistics is scientific methods of how to collect, manage, analyze, interpret, and present data [11]. The purpose of statistics is to obtain a picture of a set of data that has been reviewed so that conclusions can be drawn from the data.

1) Random Data

Random or single data are data that have not yet been arranged or grouped into interval classes. A single data example in this study is when the MQ135 gas sensor receives gas in ppm units with the following results.

2) Group Data

Group data are data that have been arranged or grouped into interval classes. Group data are arranged in the form of frequency distributions or frequency tables using the formula:

$$K = 1 + 3{,}33 \log n$$
$$R = Biggest\ data - Smallest\ data$$
$$C = \frac{R}{K}$$

We can see the group of data in this study in Table 1. It consists of the values of the group data and the average of each range of values.

Table 1. Output data of five gas sensors

Data	Average
15-17	15.86
49-53	51.20
82-95	87.42
105-109	107.20
174-180	177.20

The data group in Table 1 is the output data from five gas sensors used in this study. The values obtained are different for each sensor. Therefore, we use the mean statistical calculation or so-called Average (Avg). The average value is very dependent on the magnitude of each data, including if there is an extreme value in the data, which is a very small or very large value and much different from the data group.

$$\bar{X} = \frac{\sum_{i=1}^{n} xi}{n} = \frac{x1+x2+x3+\cdots+xi}{n} \quad (1)$$

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(xi-\mu)^2}{n-1}} \quad (2)$$

Eq. (1) means the standard deviation (SD) is the root of the middle of the square of the deviation of the mean or the square root of the mean squared. Eq. (2) is the standard deviation/sample deviation symbolized with s.

To determine the standard deviation, the method is to draw the root of the variance. For a set of data x_1, x_2, x_3, ..., x_n (single data), the standard deviation can be determined i.e. the formula.

The smallest (minimum) and the largest (maximum) value is often used in calculating statistical data, including to find out how large the range or the difference is between the smallest data and the largest data. Minimum and maximum (Minmax) normalization is a normalization method by performing a linear transformation of the original data to produce a balance of comparative [12] values of data before and after the process.

III. METHODOLOGY

The implementation of this study began when E-nose received the signal [13] from the aroma of coffee. Then the signal was processed by Arduino into data and sent to the computer. The initial stage of data analysis [14] in this study was statistical calculation. The combined values of the statistical calculation with the classification value determined the best value of each method. The best method was evaluated by comparing the accuracy [15] values of the three methods in this study.

A. *Data Collection*

E-nose is a combination of several gas sensors to form an instrument that has the same function as the human sense of smell to detect odors. The gas sensor used is a gas sensor from the MQ family. It is composed of electrochemical sensors. Each of the sensors has a different level of selectivity combined to form a sensor array. The individual sensor patterns may not be selective, but the collective response of the whole array can be predicted. The sensor array characteristic pattern in the presence of a particular gas is tantamount to a signature which can be effectively learned with sufficient training data [16]. The list of sensors in this study aiming to recognize the aroma of coffee can be seen in Table 2.

Table 2. Gas Sensors in This Study

Sensor	Target
MQ 2	LPG, I-Butane, Propane, Methane, Alcohol, H2, Smoke
MQ 3	Alcohol, Methane, Benzene, Hexane, LPG, CO
MQ 4	Methane, Natural gas
MQ 7	CO
MQ 135	Carbon Dioxide

There are sensing elements, sensor base, and sensor cap that build the sensor. The detector of elements is divided into two common parts; they are sensing material and heater that function to heat the sensing element. Depending on the target of the gas, the detector reprocesses different gases, such as Alcohol, NH4, and CO_2. The gas contained in the aroma of coffee will be recognized and captured by each sensor used in this study. The sensors will send the data through Arduino to the computer. The E-nose design capturing the aroma of coffee can be seen in Figure 2.

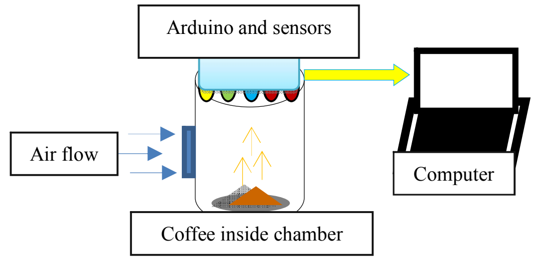

Figure 2. E-Nose Design for Recognition

The dataset used is the data in the form of a gas of coffee aroma. The aroma released by the coffee is the result of roasting process. The process begins with a process called the first crack; in which coffee explode due to gas pressure from the coffee until the flavour is formed from a coffee due to changes in chemical reactions within, this is called the second crack [17]. This study uses a comparison of mixed coffee. This study uses a comparison of mixed coffee (mixture) between Arabica Civet coffee and Non-civet coffee [18]. Nine mixes are used as data which are referred to as classes. The comparison of Arabica Coffee in Table 3 was carried out 50 times to nine classes.

Table 3. Arabica Civet Coffee and Non-Civet Coffee Classes

Proportion Arabica Civet Coffee and Non-Civet Coffee	Class
Civet 0% and Non-Civet 100%	L0-NL100
Civet 10% and Non-Civet 90%	L10-NL90
Civet 20% and Non-Civet 80%	L20-NL80
Civet 25% and Non-Civet 75%	L25-NL75
Civet 50% and Non-Civet 50%	L50-NL50
Civet 75% and Non-Civet 25%	L75-NL25
Civet 80% and Non-Civet 20%	L80-NL20
Civet 90% and Non-Civet 10%	L90-NL10
Civet 100% and Non-Civet 0%	L100-NL0

Each data was collected for 15 minutes at room temperature. During 15 minutes, 300 data were collected. Each class had 50 tests. Coffee used as the experiment material is ground coffee with an ideal grinder level, from coarse to medium size, with coffee weight of each class being 15 grams. The output of the detection of coffee aroma produced a digital value derived from each sensor.

B. *Preprocessing Data*

The next step is to process the data detected by E-nose on the coffee as seen in Figure 3. This process used machine learning to estimate the accuracy of the best model in the invisible data by evaluating the actual data that is not visible [19]. So, the accuracy was estimated using statistical methods for data validation purposes. The first process study is to calculate the Avg and SD value. The second is to calculate the Minmax value. The last is to calculate using the Avg, SD, and Minmax statistical methods.

The first calculation started by collecting data on Avg values and SD values of nine classes of the mixture Arabica civet coffee and Non-civet Arabica coffee into tables and stored in a Microsoft Excel file. Afterward, a new file was created in Microsoft Excel which contained the recapitulation result of the nine classes. The amount of data collected from the recapitulation was 450 data with a detail of 50 data from each class. The second data processing is to calculate the Minmax value of the nine classes of the mixture of Arabica civet coffee and Non-civet Arabica coffee [18].

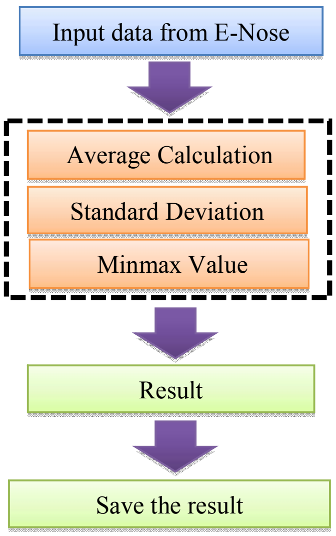

Figure 3. Preprocessing Data Flowchart

The result of data processing of this study was saved in a .csv (Comma Separated Values) format. The process of changing the file extension from (Microsoft Office Excel) .xls to .csv was done online by uploading the file, selecting the convert option, and downloading the result. The next stage is to run the .csv file using the Visual Studio Code. Eventually, the accuracy was obtained using formulation in a python programming language.

C. *Data Analysis*

The data used in this study were divided into two parts with the cross-validation method. The process was followed by the classification phase. Finding an effective data partition or sampling method is a method used to minimize errors in estimating accuracy, comparing methods, and finding the best method [20].

Calculations carried out at the data processing stage were classified using the Logistic Regression (LR), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN) methods. The aim is to estimate the accuracy of the statistical calculation when processing data. On the classification stage, the dataset that had been stored was divided into two types of data, namely training data and testing data. The data stored were of nine classes of the mixture of Arabica civet coffee and Non-civet Arabica coffee. The data, amounting to 50 data from each class, were divided into 80% for training data and 20% for testing data from the total input data.

D. *Data Evaluation*

The evaluation of the data classified in this study used the CF (Confusion Matrix) method [21]. CF is one of the tools commonly used in evaluating machine learning [22] which contains two or more categories. This method divides data into 2 classes, namely data generated from the classifier (Predictive Class) and originally known data (Actual Class). The classification process using CF had four terms of results used to calculate the performance of classification, namely TP, TN, FP, and FN. TP is positive data that were discovered correctly. If the category generated by the classifier [23] is similar to the existing data class, the data are recorded in the TP. TN is the number of negative data that were discovered correctly, while FP is negative data but detected as positive. On the other hand, FN is the reverse of TP; it means that the data are positive, but detected as negative [24].

TP is the data from class 1 classified as class 1. Data from class 0 that is correctly classified as class 0 in TN. Then, the opposite of TN is FN meaning the amount of the data from class 1 incorrectly classified as class 0 [25]. Based on the value of TN, FP, FN, and TP [26], the value of precision, memory, and accuracy can be obtained. The precision value describes the amount of data that is categorized positively, then classified correctly divided by the total data results in positive classification. Precision can be seen in Eq. (3).

$$Prc = \frac{TP}{(TP+FP)} \times 100\% \tag{3}$$

Meanwhile, recall establishes the percentage of positive data correctly classified by the system. In binary classification, recall is also known as sensitivity. The calculation can be seen in Eq. (5).

$$Recall = \frac{TP}{(TP+FN)} \times 100\% \tag{4}$$

$$f1 - score = \frac{2TP}{(2TP+FP+FN)} \times 100\% \tag{5}$$

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100\% \tag{6}$$

The accuracy value describes how precise the system can classify data correctly [27]. In other words, the value of accuracy is the comparison between correctly classified data and all data. The accuracy value can be obtained by Eq. (6).

Table 4. Confusion Matrix Result in Python

Classes	Precision	Recall	F-1 Score	Support
L75-NL25	0,90	0,90	0,90	10
L0-NL100	1,00	1,00	1,00	9
L10-NL90	1,00	1,00	1,00	8
L100-NL0	1,00	1,00	1,00	15
L20-NL80	1,00	1,00	1,00	12
L25-NL75	1,00	1,00	1,00	5
L50-NL50	1,00	1,00	1,00	14
L80-NL20	1,00	1,00	1,00	7
L90-NL10	0,86	0,86	0,86	10

The result of calculating the Confusion Matrix using the LR classification method to form a classifier model is presented in Table 4 [28]. This model is a representation used to predict new data classes that have never existed. The logic is to let the machine learn from the training set and be tested using the testing set.

IV. RESULTS AND DISCUSSION

This study was conducted aiming at utilizing E-nose to detect the aroma of coffee followed by calculating the statistics included in the initial process (pre-processing). The data were divided into nine classifications based on the value of percentages of coffee mixture as presented in Table 3. First, we attempted to obtain the accuracy of the average calculation and standard deviation. The accuracy of the LR method calculated statistically in terms of average and standard deviation is 91.38%, and of the LDA method is 91.38%. The highest result of accuracy is the KNN method of 96.11%. Upon the completion of calculating the accuracy from average and standard deviation, the next step is to determine the other accuracy value from other statistical calculations. The highest accuracy is obtained by the KNN method of 95.27%. The process is followed by the statistical calculation of average-standard deviation-min-max. So, three statistical calculations are essential to make to classify the comparison between one method to the others. From the result, the highest result is the KNN method of which accuracy is 96.38%. The result of the classification in this study was compared and selected by statistical methods in terms of the highest accuracy value.

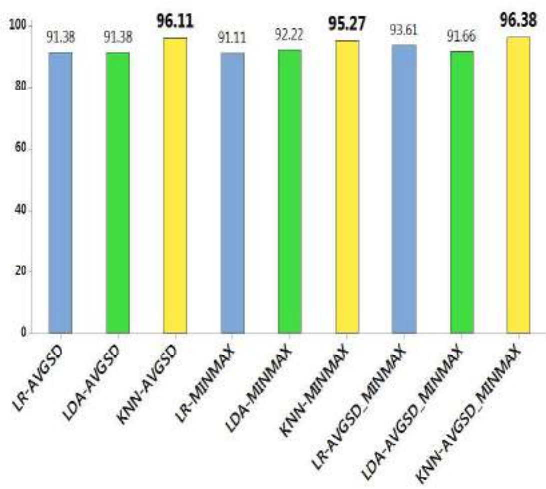

Figure 4. Classification Using Statistical Methods

Figure 4 shows that the KNN classification method obtains the highest accuracy result. The KNN classification method had passed three statistical calculations for data validation, namely the calculation of the minmax value of 95.27%, the calculation of the average and standard deviation value of 96.11%, and the calculation of the min, max, average and standard deviation value of 96.38% [29]. The process is followed by evaluating the accuracy of the classification using the confusion matrix in machine learning.

Classification of the three methods was combined using machine learning calculation and the result showed that the KNN method obtained the highest value among the other methods. The classification value with the initial process using the overall statistical calculation obtained the highest value of 96.38. The next step is to calculate classification accuracy using CF (Confusion Matrix). The calculation was also done using ML.

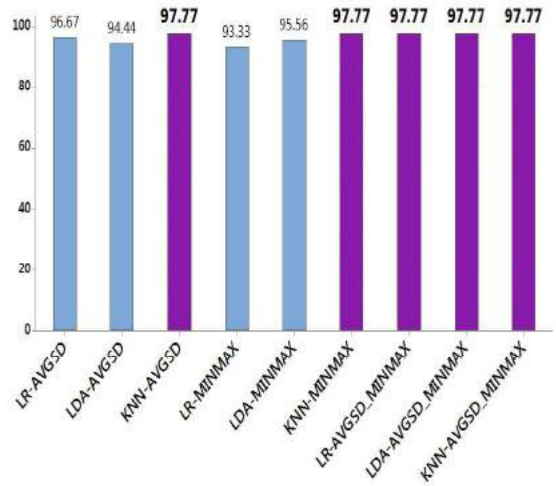

Figure 5. Accuracy of Classification Using Confusion Matrix

Once the best classification method was determined, the KNN method was applied to the existing data using a confusion matrix to prove its accuracy. The result of CF in finding the best classification method and finding the best validation method using the statistical method is KNN of which value is 97.77%. For the data validation method, the best result is obtained when using more statistical calculations. In Figure 5, for instance, the best result is obtained when all statistical calculations were applied (Avg, SD, minimum and maximum value).

Table 5. Confusion Matrix of KNN for Avg-SD Value

		TARGET								
		L75-NL25	L0-NL100	L10-NL90	L100-NL0	L20-NL80	L25-NL75	L50-NL50	L80-NL20	L90-NL10
PREDICTION	L75-NL25	**10**	0	0	0	0	0	0	0	0
	L0-NL100	0	**9**	0	0	0	0	0	0	0
	L10-NL90	0	0	**8**	0	0	0	0	0	0
	L100-NL0	0	0	0	**15**	0	0	0	0	0
	L20-NL80	0	0	0	0	**12**	0	0	0	0
	L25-NL75	0	0	0	0	0	**5**	0	0	0
	L50-NL50	0	0	0	0	0	0	**14**	0	0
	L80-NL20	0	0	0	0	0	0	0	**7**	0
	L90-NL10	0	0	0	0	0	0	0	0	**8**

The result of the classification accuracy, using the confusion matrix of the mixture of Arabica civet coffee and non-civet Arabica coffee obtained an accuracy of 97.77% from the KNN algorithm and Avg-SD statistical calculation. From Table 5, the coffee mixture data of the L75-NL25 prediction class is classified into 10 data in the target class. The L0NL100 prediction class classifies 9 data in its target class. The L10NL90 prediction class classifies 8 data in its target class. The L100NL0 prediction class classifies 15 data in its target class. The L20NL80 prediction class classifies 12 data in its target class. The L25NL75 prediction class classifies 5 data in its target class. The L50NL50 prediction class classifies

14 data in its target class. The L80NL20 prediction class classifies 7 data in its target class. And, the L90NL10 prediction class classifies 8 data in its target class.

Table 6. Confusion Matrix of KNN for Minmax Value

		TARGET								
		L75-NL25	L0-NL100	L10-NL90	L100-NL0	L20-NL80	L25-NL75	L50-NL50	L80-NL20	L90-NL10
PREDICTION	L75-NL25	**10**	0	0	0	0	0	0	0	0
	L0-NL100	0	**9**	0	0	0	0	0	0	0
	L10-NL90	0	0	**8**	0	0	0	0	0	0
	L100-NL0	0	0	0	**15**	0	0	0	0	0
	L20-NL80	0	0	0	0	**12**	0	0	0	0
	L25-NL75	0	0	0	0	0	**5**	0	0	0
	L50-NL50	0	0	0	0	0	0	**14**	0	0
	L80-NL20	0	0	0	0	0	0	0	**7**	0
	L90-NL10	0	0	0	0	0	0	0	2	**8**

The accuracy result using confusion matrix in Table 6 of the L90NL10 classification shows that there are 2 data included in the L80NL20 class target, meaning that the detection between the aroma of coffee from the 2 types of mixture indicates similarity when detecting the aroma of coffee. The similarity in the aroma detection data leads to the predicted [30] data to a class different from the target class. So, the result of the classification of the mixture of Arabica civet coffee and non-civet Arabica coffee obtains an accuracy of 97.77% from the KNN algorithm and Minmax statistical calculation.

Table 7. Confusion Matrix of KNN for Avg-SD-Minmax

		TARGET								
		L75-NL25	L0-NL100	L10-NL90	L100-NL0	L20-NL80	L25-NL75	L50-NL50	L80-NL20	L90-NL10
PREDICTION	L75-NL25	**10**	0	0	0	0	0	0	0	0
	L0-NL100	0	**9**	0	0	0	0	0	0	0
	L10-NL90	0	0	**8**	0	0	0	0	0	0
	L100-NL0	0	0	0	**15**	0	0	0	0	0
	L20-NL80	0	0	0	0	**12**	0	0	0	0
	L25-NL75	0	0	0	0	0	**5**	0	0	0
	L50-NL50	0	0	0	0	0	0	**14**	0	0
	L80-NL20	0	0	0	0	0	0	0	**7**	0
	L90-NL10	0	0	0	0	0	0	0	2	**8**

Similarly, the result of the classification accuracy using the confusion matrix in Table 7 of a coffee mixture between Arabica civet coffee and non-civet Arabica coffee using the KNN algorithm and Avg-SD-Minmax statistical calculation obtains an accuracy percentage of 97.77%. If seen from the average of all accuracy generated, the classification of Arabica civet coffee and non-civet Arabica coffee can be done using data from the aroma detection result using E-nose. Data classification highly affects the value of accuracy produced, the more the attributes used in the classification process, the higher the accuracy value.

Table 8. Algorithm Performance of Confusion Matrix

	Precision	Recall	F1-Score
Mix 75-NL25	1.00	1.00	1.00
Mix L0-NL100	1.00	1.00	1.00
Mix L10-NL90	1.00	1.00	1.00
Mix L100-NL0	1.00	1.00	1.00
Mix L20-NL80	1.00	1.00	1.00
Mix L25-NL75	1.00	1.00	1.00
Mix L50-NL50	0.78	1.00	0.88
Mix L80-NL20	1.00	1.00	1.00
Mix L90-NL10	1.00	1.00	1.00
Accuracy		**0.98**	

Table 8 shows that the accuracy result of the dataset classification is significant, as the amount of false negative data and false positive data produced is highly similar or of symmetric value.

V. CONCLUSION

This study aims to recognize original Arabica civet coffee using the Electronic Nose (E-nose) system with the MQ family of gas sensors, namely MQ2, MQ3, MQ4, MQ7, and MQ135. Statistical calculation in the preprocessing stage was used to obtain the characteristics of each signal which, in turn, indicated a good enhancement. The highest result of the classification accuracy using the confusion matrix of the mixture of Arabica civet coffee and non-civet Arabica coffee was from the KNN algorithm of which accuracy is 97.77%. The result of the confusion matrix also showed that the best method to validate data is to use all of the statistical calculations. Thus, it is imperative for future studies to achieve higher accuracy values by adding other combination statistical calculation methods in the preprocessing data stage.

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Detecting Pork Adulteration in Beef for Halal Authentication using an Optimized Electronic Nose System

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ABSTRACT Recently, the issue of food authentication has gained attention, especially halal authentication, because of cases of pork adulteration in beef. Many studies have developed rapid detection for adulterated meat. However, these studies are not yet practical and economical methods and instruments and a faster analysis process. In this context, this paper proposes the Optimized Electronic Nose System (OENS) for more accurately detecting pork adulteration in beef. OENS has advantages such as proper noise filtering, an optimized sensor array, and optimized support vector machine (SVM) parameters. Noise filtering is carried out by cross-validation with different mother wavelets, i.e., Haar, dmey, coiflet, symlet, and Daubechies. The sensor array was optimized by dimension reduction using principal component analysis (PCA). An algorithm is proposed for the optimization of the SVM parameters. An experiment was conducted by analyzing seven classes of meat, comprising seven different mixtures of beef and pork. The first and seventh classes were 100% beef and 100% pork, respectively, while the second, third, fourth, fifth, and sixth classes contained 10%, 25%, 50%, 75%, and 90% of beef in a sample of 100 grams, respectively. Sample testing was carried out for 15 minutes for each sample. The classification test results to detect beef and pork had an accuracy of 98.10% using the optimized support vector machine. Thus, OENS has a favorable performance to detect pork adulteration in beef for halal authentication.

INDEX TERMS Electronic nose, beef, pork, adulteration, halal authentication, optimized SVM.

I. INTRODUCTION

The issue of food authentication has recently attracted the attention of consumers because of religious or lifestyle reasons [1]–[4]. Especially for Muslims, food authentication regarding halal food is essential [5]. Pork is food that Muslims cannot eat (The Holy Quran, 1:173; 5:3; 6:145; 16:115). However, pork adulteration in beef has been discovered in the market [3], [6]. The practice of mixing beef with pork is sometimes done for economic reasons [7], [8]; the seller adulterates pork in beef because pork is cheaper than beef [9].

Recent research has discussed meat authentication using visual detection. The procedure includes DNA isolation from fresh meat samples, amplification of specific DNA sequences, and detection using lateral flow assays. This research can authenticate horse meat and pork meat with high selectivity and reproducibility values. However, this process still takes quite a long time, namely, 25-30 minutes [10]. Another recent study used lateral flow sensing (LFS) and polymerase chain reaction (PCR) for the rapid visual detection of adulterated meat [11]. The samples used in this study were the adulterated beef samples prepared by mixing with duck meat in a series of proportions of 0%, 0.01%, 0.05%, 0.1%, 0.5%, 1%, 5%, 10%, 50%, and 100%. This research took less than 2 hours to process. Various scientific methods have been developed to identify mixed meats, including gas chromatography (GC) and mass spectrometry (MS) [12], high-performance liquid chromatography (HPLC), nuclear magnetic resonance (NMR) spectroscopy [13], and Fourier transform infrared (FTIR) spectroscopy [14]. However, several things have to be considered when using these tools, such as cost, time, and experience [15], [16]. The price of GC-MS instrument is around USD 120,000 in 2017 [17], while the cost of testing a sample is about USD 50. In addition, the testing process of one sample can take about 1 to 2 days, depending on the complexity of the gases. Another consideration is the assistance of a person who has experience with operating the GC-MS instruments.

A solution is needed to meet these considerations using more practical and economical methods and instruments, and a faster analysis process with reliable results. This paper proposes the Optimized Electronic Nose System (OENS). An electronic nose (e-nose) is the main instrument in OENS. E-noses are devices with several advantages over other techniques for analyzing food smell, for example, the small amount of sample required, fast performance, simple usage, high sensitivity, and good correlation between the data from sensor analysis. The e-nose features offer five main categories of food analysis that can be used: monitoring, expiry checking, freshness evaluation, purity testing, and other food quality control investigations. Hence, the motivation for this study can be formulated as follows:

1. Several types of research have used an e-nose to identify pork adulteration in beef for food quality control. However, most of them were focused on the differentiation and classification of species of meat. Only a few researchers have tried to determine different gas contents, which can be used for halal authentication in food.
2. In the existing studies, e-nose systems have been developed for halal authentication. They show the potential of e-nose for halal authentication, even though their experiments were quietly limited without performing classification or regression tasks. For example, e-nose with PCA was used to differentiate pure lard, pure chicken fats, beef fats, mutton fats, and adulterated samples [18]. Moreover, e-nose with PCA was employed to discriminate four meat samples and three types of sausage [12]. Furthermore, another study attempted to perform binary classification to differentiate beef and pork using Naïve Bayes classifier [19].

According to these motivations, the main contribution of this study is to propose OENS for performing multiclass classification to differentiate seven mixtures of beef and pork. Therefore, this study makes the e-nose implementation for the practical application of halal authentication closer. In addition, e-nose produces signals that are sent to a computer for processing and analyzing. The proposed OENS can prevent the distortion of e-nose signal analysis by: (i) proper noise filtering, (ii) optimizing the sensor array, and (iii) optimizing the support vector machine (SVM) parameters.

The rest of this paper is organized as follows. Section 2 discusses previous works related to the topic of this study. Section 3 explains the details of OENS, including a specification of the materials and methods used in the experiment, such as the classification method and the discrete wavelet transform for signal processing. Section 4 describes the results of the experiment. Section 5 is the conclusion.

TABLE 1. Application of electronic noses for food assessment in the last five years

Sample	Application	Data Processing	Ref
Pork	Adulteration pork in minced mutton	MLW, PLS, BPNN	[20]
Tomato juice	Adulteration levels in tomato juices	Spectral clustering	[21]
Coffee and bell pepper	Adulteration coffee with bell pepper powder	Unfolded CA	[22]
Wine	Authenticity assessment of wine	PCA, SLDA, CA	[23]
Mutton	Adulteration pork in minced mutton	PCA, SLDA, CDA	[24]

Acronyms used: Metal oxide semiconductor, MOS; Principal component analysis, PCA; Stepwise linear discriminant analysis, SLDA; Cluster analysis, CA; Critical discourse analysis, CDA.

II. RELATED WORKS

E-nose can be used for food authentication and adulteration assessment, as summarized in TABLE 1. Research to detect meat adulteration using an electronic nose has developed and is being studied. The latest research can detect a mixture of minced mutton in pork [20]. The study made six mixed combinations, namely mixing minced pork at 0%, 20%, 40%, 60%, 80%, and 100% by weight with minced mutton. To build the predictive model, these studies using multiple linear regression (MLR), partial least square analysis (PLS), and backpropagation neural network (BPNN). The predictive R2 result for the six classes is 0.97.

An electronic nose to detect adulteration levels in tomato juices is discussed [21]. This research compared six previous methods with the most recent popular one, spectral clustering using three methods of evaluating the clustering performance, i.e., mutual information criteria (MI), precision, and rand index (RI) which give statistical significance result (alpha = 0.05), thus outperformed the other methods. Rodriguez [22] studied two food adulteration cases (a pure variety of green coffee beans and pure cayenne adulteration with bell pepper powder). This work aimed to report improvements achieved in the differentiation of aroma samples with minimal differences in odor pattern.

Moreover, wine traceability and authenticity can be used to prevent outlawed adulteration practices, such as (i) addition ethanol, coloring and flavoring compounds; (ii) diluting wine with water; and (iii) replacing with cheaper wine. Therefore, the combination between e-nose and multivariate statistical methods improved the traceability and the classification of grapes and wine (especially the varieties and the geographical origin of grape) [23]. E-nose was also succeeded in detecting adulteration of mutton, which led into developing a model capable of detecting and estimating the adulteration of minced mutton with pork [24]. The volatile compounds occurring in the samples were collected by utilizing MOS-based e-nose. Later, an optimal data matrix is obtained using feature extraction methods, PCA, loading analysis, and SLDA.

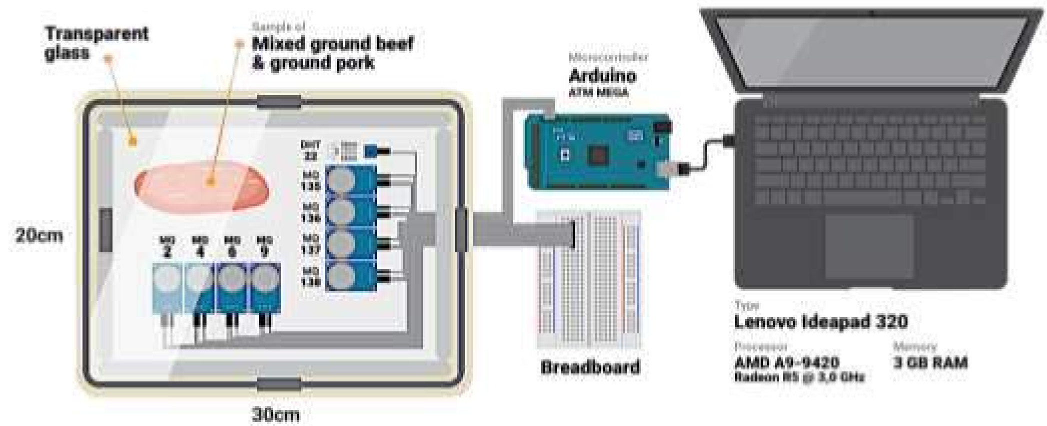


FIGURE 1. Schematic of the e-nose experiment for OENS.

TABLE 2. Gas sensors in the sensor array.

No	Sensor	Initial	Selectivity
1	MQ2	S1	LPG, i-butane, propane, methane, alcohol, Hydrogen, smoke
2	MQ4	S2	Methane (CH_4), Natural gas
3	MQ6	S3	LPG, iso-butane, propane
4	MQ9	S4	Methane, Propane, and CO
5	MQ135	S5	NH_3 (Ammonia), NO_x, alcohol, Benzene, smoke, CO_2
6	MQ136	S6	Hydrogen Sulfide (H_2S)
7	MQ 137	S7	Ammonia
8	MQ 138	S8	Toluene, acetone, ethanol
9	DHT22	S9	Temperature & Humidity

Most of the studies on using e-noses only distinguished between 2 products or more and did not consider possible noise contamination of the gas sensor signals from the e-nose. However, in certain conditions, noise can affect the raw signal by 20% [25]. The noise influences the classification performance. While being sent to the computer, the signals can be interrupted and mixed with unwanted signals, which creates noise [26]–[28]. These noises may interfere with the authenticity of the information, for example, caused by air that is contaminated by certain substances or smells. This noise should be removed to prevent the distortion of the analysis and the classification process. Several researchers have used the discrete wavelet transformation (DWT) to reduce noise in data signals [29]–[35]. However, these studies only focused on the use of the DWT method without involving the use of suitable parameters, such as mother wavelet and level decomposition, although these parameters could improve the performance based on the noise-filtered signal [36]–[38]. Apart from that, the number of sensors has also not been considered, even though using more sensors than necessary incurs extra costs. Based on the analytics, some of the sensors provide no significant information on the samples, hence the costs can be decreased by eliminating unnecessary sensors. Several works also perform sensor array optimization to reduce data dimensions, electrical consumption, production cost, computational and traffic overhead, etc. [39]–[41]. For interested readers, recent development and challenges for e-nose signal processing are summarized here [42].

III. MATERIALS AND METHOD

A. MATERIALS

In this study, an e-nose was built using nine MQ series gas sensors from Zhengzhou Winsen Electronics Technology Co., Ltd. The gas sensors were also used to detect different types of gases, as in our previous study [19]. The list of gas sensors is given in TABLE 2. These gas sensors were assembled to an Arduino microcontroller. For data communication, a universal serial bus (USB) interface was used to transfer the signals from the microcontroller to the computer. The gas sensors were placed in a sample chamber made of transparent glass. FIGURE 1 depicts the component of the e-nose system.

The samples used were ground beef and ground pork bought in fresh condition from the same store on the same date. In the experiment, samples of seven combinations of beef and pork were used. Both ground beef and pork were used in samples with a weight of 100 gr each with various compositions, which were divided into seven classes: the first and seventh classes were 100% beef and 100% pork, respectively. The second, third, fourth, fifth, and sixth classes contained 10%, 25%, 50%, 75%, and 90% of beef from a total sample of 100 grams, respectively. A scale was used to ensure that the weight of the mixture was appropriate. The compositions of the respective samples can be seen in TABLE 3. The following steps were used to collect the data samples:

1) the e-nose was turned on, and the sensors were warmed up for 15 minutes;
2) the sample was placed in the sample chamber with the gas sensors;

3) the processes of data retrieval and transfer to the computer using the USB interface took 15 to 20 minutes for each sample;
4) the sample chamber was cleaned using a flashing fan for 5 minutes after every sampling, so the next sampling was not affected by gas residue from the previous sampling.

TABLE 3. Composition of samples

Labels	Initial	Beef (grams)	Pork (grams)	The amount of data
Class 1	S000	100	0	60
Class 2	S010	90	10	60
Class 3	S025	75	25	60
Class 4	S050	50	50	60
Class 5	S075	25	75	60
Class 6	S090	10	90	60
Class 7	S100	0	100	60

As mentioned previously, the data were divided into seven classes, with 60 data for each class. Therefore, the total number of recorded data was 420. Each data had 10 digital outputs, i.e., S1, S2, S3, S4, S5, S6, S7, S8, S9 for temperature, and another S9 for humidity. In this paper, the digital output is called the raw signal. The data of all 7 classes are shown in TABLE 3. For interested readers, our dataset has also been uploaded here [43], [44].

B. PROPOSED METHODS

After the dataset had been generated, the raw signals were analyzed through several steps, as shown in FIGURE 2. The first step is signal pre-processing, which cleans up the noise and produces output in the form of a reconstructed data signal. The next step is statistical parameter extraction, which utilizes the reconstructed data signal and extracts it to obtain the characteristics of the signal. The third step is the dimensional reduction, where the signal obtained is analyzed to select only the sensors that have the largest impact on pork adulteration detection. The final step is constructing the classification model from the 7 classes. The data obtained from the previous processes are divided into testing data (30%) and training data (70%) to be evaluated by the classification model. The data acquired from the e-nose are processed using a computer with scikit-learn by Python-based machine-learning software [45].

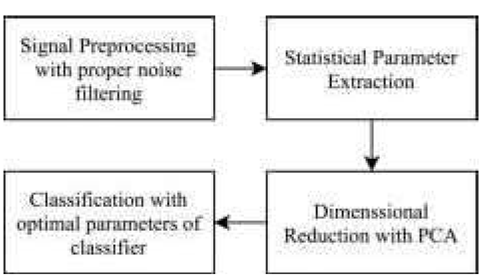


FIGURE 2. Signal analysis steps for OENS.

1) SIGNAL PRE-PROCESSING

Signal pre-processing is carried out to eliminate noise in the signals [46]. In this research, the noise was caused by the internal sensors, changes in ambient conditions such as humidity and temperature, and changes in electrical conditions such as voltage and current. The signals produced by an e-nose are usually non-stationary, where the statistical properties of the signal change with time [46], making the noise reduction process more complicated. This study used the discrete wavelet transform (DWT) and then compared several mother wavelets to determine the best-suited mother wavelet for noise filtering. This technique identifies the data from various aspects of signal analysis, trends, breakdown points, discontinuities, and similarities. The data produced by the e-nose are then divided into 7 classes. The first step is to look at the shape of the signals. In the second step, the type of wavelet, the so-called mother wavelet, is determined; this is indispensable because it is varied and is grouped based on the respective basic wavelet functions. The most popular types of mother wavelets in signal processing are Haar, dmey, coiflet, symlet, and Daubechies, all of which were compared in our experiment, with several decomposition levels. The discrete wavelet transform process for a given signal $x(t)$ is expressed in Equation 1.

$$dwt(m,n)=\left\langle x(t),w_{m,n}(t)\right\rangle=\frac{1}{\sqrt{2^m}}\int_{-\infty}^{\infty}x(t)\omega\times\left(\frac{t-n2^m}{2^m}\right)dt \tag{1}$$

where m, n, ω represents scaling parameter, translation parameter, and mother wavelet, respectively. The explanation for the wavelet transform process is as follows: the first step is transforming the data with Equation 2,

$$T(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty}x(t)\omega\times\left(\frac{t-b}{a}\right)dt \tag{2}$$

where $\omega\square(t)$ is the conjugation of wavelet complex function analysis, a is the wavelet dilation parameters, and b is the location or position of the parameters. The wavelet function in discrete form is as follows:

$$\omega_{m,n}(t)=\frac{1}{\sqrt{a_0^m}}\omega\left(\frac{t-nb_0a_0^m}{a_0^m}\right) \tag{3}$$

where m, n represent dilatation and wavelet translation control, respectively. a_0 is a constant dilatation parameter with a value of more than one and b_0 is the location parameter, which should be more than 0. If $a_0=2$ and

$b_0 = 2$ are substituted into Equation 2, the dyadic grid of the wavelet transform is written as follows:

$$\omega_{m,n}(t) = 2^{\frac{-m}{2}} \omega(2^{-m}t - n) \quad (4)$$

By using this discrete wavelet function, the discrete transformation is obtained:

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\omega_{m,n}(t)dt \quad (5)$$

$T_{m,n}$ is known as the detail wavelet coefficient with index scale m and location n. The discrete wavelet is related to the scaling function and its dilatation equation. The use of the scaling function is meant to smoothen the signal. The result of the scaling function is convoluted with the signal, which provides the approximation coefficient. In this experiment, PyWavelets was used [47].

2) STATISTICAL PARAMETER EXTRACTION

In this step, parameter extraction is performed to extract the most relevant and informative values to represent the characteristics of the overall sensor response. The pre-processing values of sensor responses are averaged to get a single value [48]. In this research, several statistical parameter extraction methods were carried out (e.g., standard deviation (ST), mean (M), kurtosis (K), and skewness (SK). This study also made several combinations of the main parameter extraction methods such as mean combined with standard deviation (M + ST), mean with skewness (M + SK), mean with kurtosis (M + K), mean with standard deviation and skewness (M + ST. + SK), mean with standard deviation and kurtosis (M + ST + K), and mean with all major parameter extractions (M + ST + SK + K). Statistic parameter extraction using M parameter, the average of the signals to be reconstructed is represented by $y(t)$. To reconstruct the signals using the mean parameter, Equation 6 is used.

$$\overline{y(t)} = \frac{\sum y(t)}{N} \quad (6)$$

where $\sum y(t)$ is the sum of the results of one sensor, and N is the total number of data. Meanwhile, if using standard deviation (ST) as a statistical parameter, Equation 7 is used.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{y(t)})^2} \quad (7)$$

where x_i is each value from the population. The formula for reconstructing the signals using skewness (α) is represented by Equation 8.

$$\alpha^3 = \frac{1}{N\sigma^3}\sum_{i=1}^{N}(x_i - \overline{y(t)})^3 \quad (8)$$

where σ is a variance. While using one statistical parameter method, the resulting features are 10 features. Furthermore, 20 features are generated while using two statistical parameter methods, and so on.

3) DIMENSIONAL REDUCTION

The features generated can be spread across multiple dimensions; for this reason, dimension reduction is used to eliminate variables that do not have a significant role in detecting pork adulteration. Principal component analysis (PCA) is the dimensional reduction method that was used in this research. The eigenvector is used to consider the relationship between the variables. From the experimental results, the digital outputs are considered as PCA variables. The steps to perform principal component analysis are as follows:

a) calculate the covariance (Cov) using Equation 9, where x is the signal and y is the class target from the signal.

$$Cov(x,y) = \frac{\sum xy}{n} - (\bar{x})(\bar{y}) \quad (9)$$

b) calculate the eigenvalue using Equation 10.

$$(A - \lambda I) = (0) \quad (10)$$

where A, λ, I are square matrices of size n x n, scalar numbers, and identities, respectively.

c) calculate the eigenvector using Equation 11.

$$[A - \lambda I][X] = [0] \quad (11)$$

d) determine the new variable (component) by multiplying the natural variable with the eigenvector.

$$\rho I = \frac{\lambda_i}{\sum_{j=1}^{D}\lambda_i} \times 100\% \quad (12)$$

If the resulting value from one component combined with another component is 0, then the correlation is considered low and can be interpreted as no relationship [49]. The variables that have 0 value are removed. After the number of dimensions has been reduced, the results are standardized so that the values are not too large or too small. The method used for the standardization process is Standard Scaler. This method gives a threshold according to the existing data

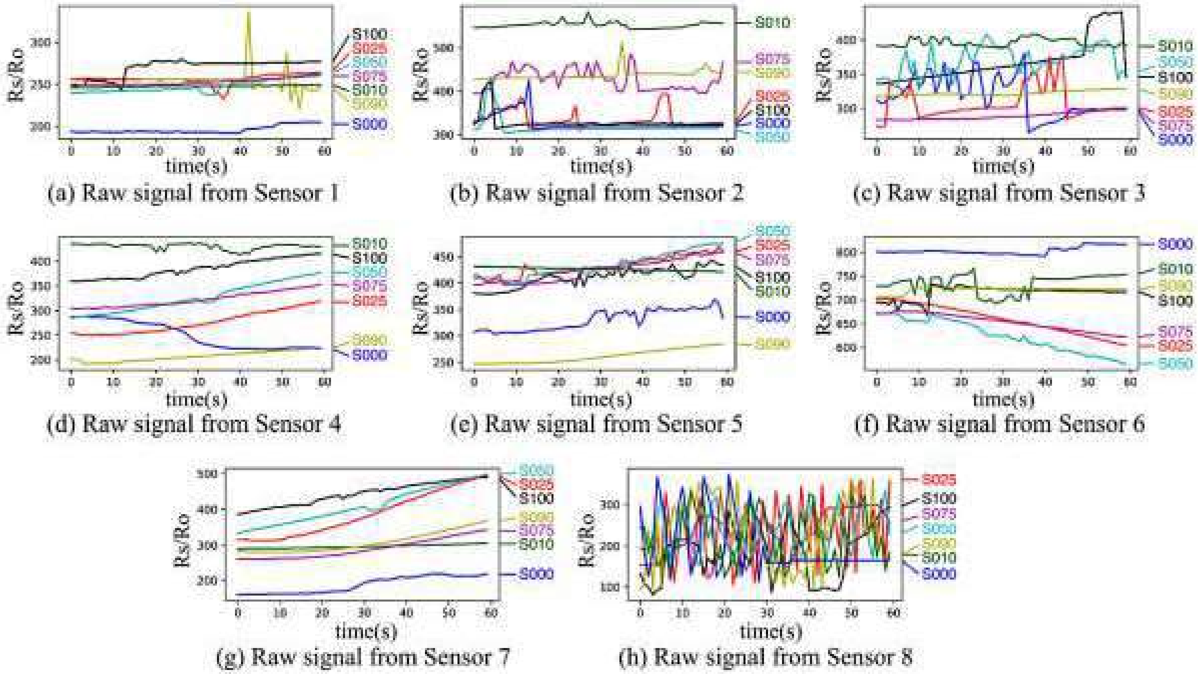


FIGURE 3. **Graphic of the raw signal before preprocessing**

Algorithm 1 Optimized Parameters of SVM

```
c_param = [0.001, 0.01, 0.1, 1, 10, 100,200,1000]
gamma_param = [0.001, 0.01, 0.1, 1, 10, 100]

for c in c_param:
    for g in gamma_param:
        for training, testing dataset:
            model = svm_train(training, c, g)
            score = svm_predict(test, model)
            cv_list.insert(score)
        scores_list.insert(mean(cv_list),c,g)
print max(scores_list)
```

4) OPTIMIZING THE CLASSIFICATION PARAMETERS

Classification is a process of dividing the variables into classes. The division of the classes should match the real condition, i.e., if the meat sample is beef, then the sample should be classified into the beef class by OENS. In this research, OENS used the optimized support vector machine (SVM) as the classification method since this method is capable of learning the data and generating the classification classes by itself [50]. SVM is based on the use of a hyperplane that separates objects based on different classes. SVM has two main parameters, which are C and gamma (γ) [50]. Adjustment of these parameters can produce satisfactory performance [51]. C is regularization parameter in the SVM algorithm. It trades off maximization of decision margin against correct classification of training data to prevent overfitting. In addition, gamma parameter is a part of kernelized SVM using radial basis function (RBF). It refers to the influence of a single training data. These parameters can increase the accuracy as well as the performance of the algorithm.

Unfortunately, there are no exact parameter values for use in the classification process. Several researchers have tried several different value combinations for the parameters, but it takes a long time to execute this process [52]. Hence, this research developed an algorithm to find the best parameters, which can be seen in Algorithm 1. The values were determined based on an experiment with the value of C, ranging from 0.01 to 1000 and γ ranging from 0.001 to 100.

IV. RESULTS AND DISCUSSION

A sensor test was done to find out the response of the e-nose when executing sample testing [21]. The response generated by the e-nose sensors can be seen in FIGURE 3. Each class is indicated in different colors. Classes 1, 2, 3, 4, 5, 6, and 7 are shown in blue, green, red, cyan, magenta, yellow and black, respectively. The sensor response can be seen for each sensor. The different combination of beef and pork leads to different response of gas sensor. It is influenced by the gas emitted from a meat sample. The different compositions of protein and lipid can produce different gas. The different drawing order of different classes indicates the different response values of each gas sensor. It can be good sign of capability to detect beef adulteration. For example, FIGURE 3(a) is a graph of the signals generated by Sensor 1 for the 7 classes. In total 420 signals were recorded, which were stacked against each class. These stacks would be difficult to identify through the images. For example, the grouping will be incorrect when the data from Class 1 are close to those of Class 2. There was also some interference in each signal caused by noise, as can be seen in FIGURE 3(b), 3(c), and 3(h). The severe noise can be found in sensor 8.

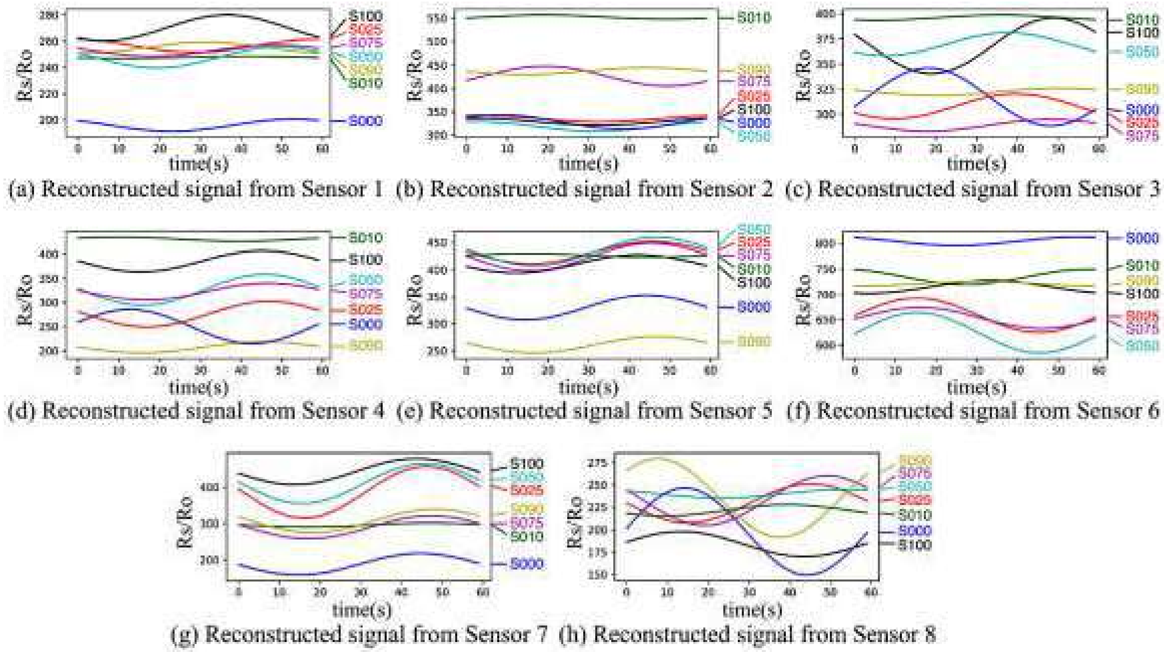


FIGURE 4. Graphic of the raw signal after processing

TABLE 4. Wavelet decomposition level of eleven gas sensors

Mother Wavelet	Decomposition Level	Accuracy (%)
Haar	1	87.00
Dmey	1	87.20
Coiflet	3	73.34
Svmlet	2	65.19
Daubechies (db1)	1	88.00
Daubechies (db6)	1	88.76

This sensor has selectivity to detect toluene, acetone, and ethanol. The volatility of the three compounds can cause the unstable responses. Furthermore, the raw signal has to be optimized by OENS to ensure that the result is appropriate.

A. RESULTS OF PROPER NOISE FILTERING

This research used the discrete wavelet transform for noise reduction, using cross-validation to find the best parameter through mother wavelet and level decomposition. TABLE 4 shows that the db6 wavelet was compatible with the aims of this research based on a comparison with the mother wavelet. The result from 20 experimental runs was level 1 of decomposition; db6 gave a satisfactory result. Furthermore, this research also calculated the accuracy of the raw data signal. The result was 87.61%, which means that the accuracy was increased by 1% by employing proper noise filtering using DWT with wavelet db6. The preprocessing result is shown in FIGURE 4. The signal looks smoother and the noise is lowered or smoothed. As depicted in FIGURE 3(h), the original signal shows significant noise; it has been reduced after finishing signal reconstruction by DWT with db6, as can be seen in FIGURE 4(h). After the signal was reconstructed, the signal results were extracted by statistical parameter extraction. This research has made 10 combinations of statistical parameter extraction. These statistical parameters will be used as features, as has been done in previous research [53]. Dimensional reduction is used in this study to see which features or variables affect the detection of the mixture of pigs in beef.

B. OPTIMIZED SENSOR ARRAY

The dimensional reduction is used in this study for dimensional reduction; other than that, it is used as an optimization sensor array. From these experiments, the gas sensor produces ten digital outputs considered as variables in PCA. However, before entering PCA, 10 digital outputs were extracted using several parameter statistical methods. In this manuscript, an example is presented using the Mean (M) as the statistical parameter extraction. Because the extraction parameter is only one, the resulting feature is only 10 features. These ten features will be used as input into the PCA formula.

TABLE 5. Result of eigenvalue calculation

Component	Eigenvalue	Proportion of variance (%)	Cumulative
PC 1	14155.24	0.57	0.57
PC 2	4679.99	0.19	0.76
PC 3	4679.99	0.12	0.88
PC 4	14155.24	0.05	0.93
PC 5	14155.24	0.03	0.96
PC 6	14155.24	0.02	0.98
PC 7	349.59	0.01	0.99
PC 8	246.03	0.01	1.00

PC 9	119.20	0.00	1.00
PC 10	119.20	0.00	1.00

TABLE 6. **Result of eigenvector calculation**

Feature / Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
S1	-0.030	0.160	0.107	-0.029	-0.323	-0.303	-0.285	0.825
S2	-0.270	0.757	-0.281	0.443	0.131	0.061	-0.217	-0.113
S3	0.020	0.332	0.207	-0.258	-0.319	0.759	0.285	0.149
S4	-0.320	0.225	0.610	-0.386	0.552	-0.115	-0.102	-0.011
S5	-0.700	-0.352	-0.212	-0.176	-0.172	0.273	-0.441	-0.047
S6	0.550	0.006	0.133	-0.052	0.044	0.261	-0.755	-0.148
S7	-0.160	-0.183	0.647	0.657	-0.268	0.051	-0.023	-0.122
S8	-0.030	-0.282	0.112	-0.349	-0.607	-0.407	-0.062	-0.495

TABLE 7. **Result of feature selection with PCA**

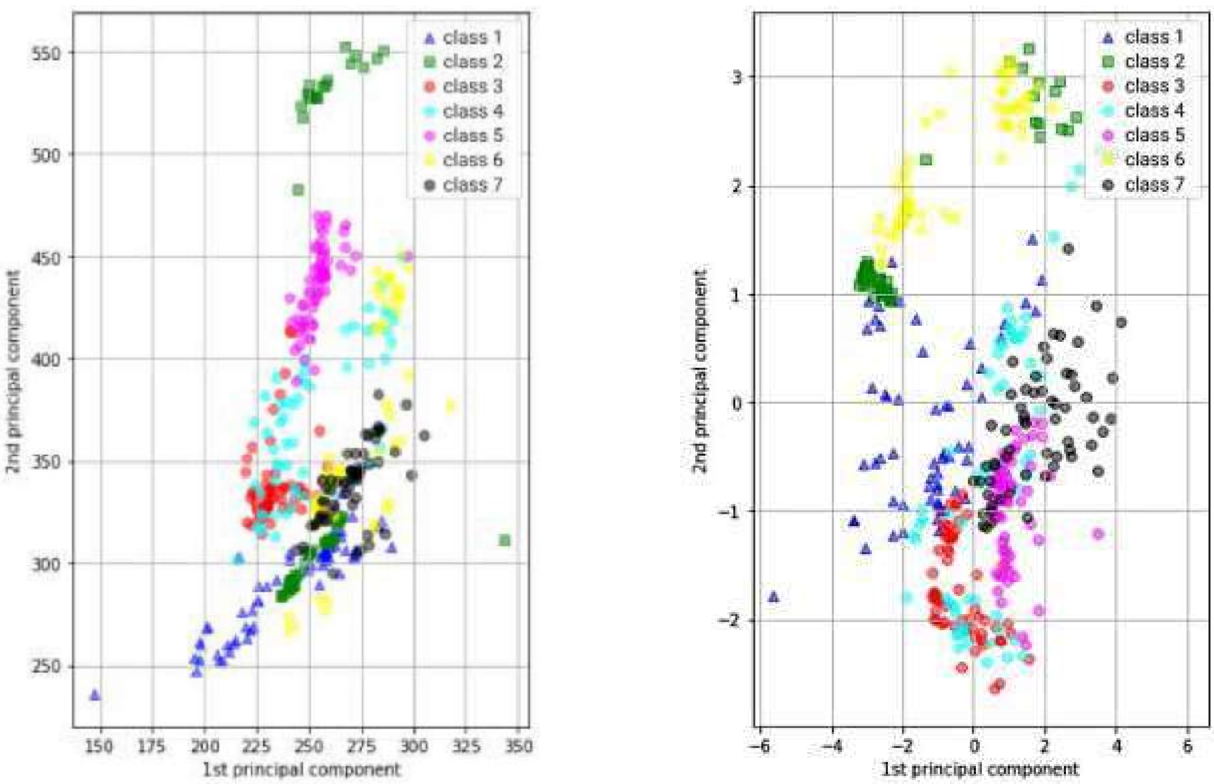
n_Component	Initial	Factor	Eigenvalue > 0.600 (+/-)
PC 1	S5	MQ 135	0.700
PC 2	S2	MQ 4	0.757
PC 3	S4	MQ 9	0.610
	S7	MQ 137	0.647
PC 4	S7	MQ 137	0.657
PC 5	S8	MQ 138	0.607
PC 6	S3	MQ 6	0.759
PC 7	S6	MQ 136	0.755
PC 8	S1	MQ 2	0.825

This research tried to reduce the number of variables. The first step is to calculate the covariance to reduce the number of dimensions or components. TABLE 5 shows the calculation of the eigenvalue, proportion of variance, and cumulative variance that contributes to each component. The next step is choosing the principal component (PC) that will be used. If a cumulative variance of 50% does not give significant accumulation, then a cumulative variance of more than 50% is the best option to get a significant result. From the result, this research used PC 1, which showed 57% of recent variation. For PC 2, it was 75%, for PC 3 it was 87%, for PC 4 it was 92%, for PC 5 it was 96%, for PC 6 it was 98%, for PC 7 it was 99%, and PC 8 it was 100%. PC 9 and PC 10 were not selected because they did not show a significant contribution. The proportion of variance is the percentage after the eigenvalue was generated, 8 components had a substantial contribution (PC1, PC2, PC3, PC4, PC5, PC6, PC7, and PC8). The next step was calculating the eigenvector, as shown in
TABLE 6. The eigenvector was calculated for each gas sensor based on the PC that was obtained previously and sorted from the largest to the smallest. Based on the results of PCA calculations, the data from e-nose to detect the adulteration of pork in beef was using 8 most dominant components based on 8 variables provided. These eight components had a fairly big correlation with a proportion of variance of 100%, namely the highest and most dominant factor, MQ 135 factor, with a proportion of variance of 57%, the MQ 4 factor, with a proportion of variance of 19%, and the MQ 9 factor, with a proportion of variance of 12%. The total variance obtained from the 8 variables was 100%.

TABLE 8. **Comparison of the accuracy of the reduced features and parameter optimization**

Classifier	Results	Statistical Parameter Method									
		ST	SK	K	M	M+ST	M+SK	M+K	M+ST+SK	M+ST+K	M+ST+SK+K
ANN	n component	10	10	10	10	17	20	20	25	27	40
	Accuracy without PCA (%)	70.48	50.00	42.86	94.52	95.48	93.10	92.14	94.76	93.57	93.57
	Accuracy optimization (%)	70.71	50.95	46.90	96.90	96.42	94.52	96.19	96.42	95.71	95.95
LDA	n component	10	10	10	9	17	20	20	23	30	17
	Accuracy without PCA (%)	66.90	36.19	38.57	89.29	92.86	89.29	90.00	93.10	90.71	93.10
	Accuracy optimization (%)	70.24	47.62	47.62	96.67	93.81	87.38	90.24	88.10	90.00	86.67
SVM	n component	10	10	10	8	17	20	20	27	30	35
	Accuracy without PCA (%)	66.90	47.86	40.71	95.24	96.19	90.24	89.52	93.10	87.86	91.90
	Accuracy optimization (%)	76.19	49.29	48.10	98.10	97.14	93.10	94.05	96.43	96.43	96.67
KNN	n component	10	10	10	9	15	20	20	30	29	40
	Accuracy without PCA (%)	65.48	44.29	38.10	94.52	91.90	84.76	86.90	87.38	89.05	84.29

Accuracy optimization (%)	66.90	36.19	36.19	89.29	92.86	89.29	90.00	92.38	93.10	93.10



(a) (b)

FIGURE 5. Plot diagram of the dimensional reduction result using PCA: (a) the data before normalization; (b) the data after normalization using Standard Scaler.

Besides that, from the eight components that have been selected, this study determines which n_component sensor has the most dominant factor. TABLE 7 shows that in the first component, the dominant factor is S5 or MQ 135. The most significant factor in all components is S1 or MQ 2, which is in component 8. TABLE 8 shows the dimensional reduction results of the ten statistical parameter extraction combinations. Some components from the results of several feature extraction methods can be reduced, such as using the M parameter statistical method. It can reduce the dimensions from 10 to 8 components using the SVM classifier. The M + ST parameter statistical method can reduce the dimensions to 15 from 20. While the M parameter statistical method + SK using four classifiers does not reduce dimensions, 20 components are still being used. The statistical parameter method that produces the most features is M + ST + SK + K with 40 features, which can be reduced using the ANN classifier. FIGURE 5 shows the data after dimensional reduction using PCA. FIGURE 5 a and b denote the data before and after feature scaling using Standard Scaler (Z-score) normalization, respectively. The standardization was used for collecting the distributed data. It can be inferred from FIGURE 5 that the data from the first class became more clustered compared to the other classes.

C. OPTIMIZED SUPPORT VECTOR MACHINE (SVM) PARAMETERS

The algorithm to find optimal SVM parameters from the 420 data required 16 seconds of execution time. The data is divided into two, namely, training data and testing data using cross-validation. This study compared three cross-validation types to get fair results, namely 3-fold, 5-fold, and 10-fold. The optimal values found for parameters C and γ were 100 and 0.1, respectively, using 10-fold cross-validation, as shown in TABLE 9. The tests were run 20 times to optimize the parameters. The final step was the classification using SVM. In FIGURE 6, all of the data from Classes 1, 6, and 7 were correctly predicted.

Meanwhile, for Class 2, 59 data were predicted correctly, and 1 data was predicted incorrectly; for Class 3, 58 data were predicted correctly, and 2 data were predicted incorrectly; 4 data were predicted incorrectly for Class 4, and 1 data was predicted incorrectly for Class 7, and 3 data were predicted incorrectly for Class 3. Lastly, for Class 5, 59 data were predicted correctly and 1 data was predicted incorrectly. In addition, TABLE 10 denotes the results of evaluation SVM with optimal parameters.

TABLE 9. Comparison of evaluation results using cross-validation of the classification method

Classifier	3 -fold cross-validation		5 -fold cross-validation		10-fold cross-validation	
	Train 280 data	Test 140 data	Train 336 data	Test 84 data	Train 378 data	Test 42 data
SVM		80.48%		93.31%		98.10%
LDA		75.95%		82.85%		96.67%
KNN		77.14%		88.57%		93.10%
ANN		73.33%		86.42%		95.48%

TABLE 10. Results of evaluation SVM with optimal parameters

Class	Precision	Recall	F1-Score	Kappa Score	Avg Accuracy
1	1.00	1.00	1.00	97.78	98.10%
2	1.00	1.00	1.00		
3	0.98	0.98	0.98		
4	0.92	0.97	0.94		
5	1.00	0.98	0.99		
6	1.00	1.00	1.00		
7	0.97	0.93	0,95		

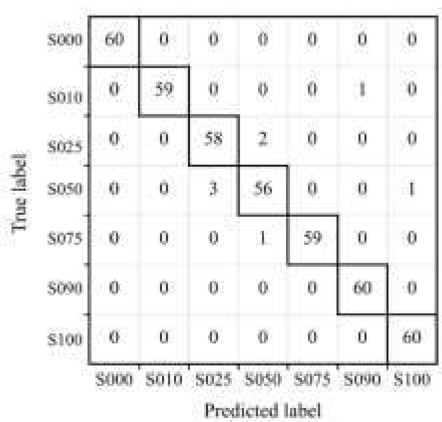


FIGURE 6. Confusion matrix from SVM classification with optimal parameters.

Furthermore, this research also compared several classification methods, i.e., artificial neural network (ANN) [54], linear discriminant analysis (LDA), K-nearest neighbors (KNN), and SVM, without using the parameter optimization algorithm 89%, 54%, 87%, and 91%, respectively. SVM with parameters optimization algorithms, which are C and γ, were 100 and 0.1, respectively, and yielded the best result (98.10%). In comparison, ANN with parameter optimization algorithm relu as activation generated 95.48%, KNN with parameter optimization algorithm neighbors = 1 and distance as the weight generated 93.10%, and LDA with parameter optimization algorithm generated 92.86%. These results show that the optimized SVM has superior performance than others. The optimization of hyperparameter settings makes the best decision boundary to classify seven classes of beef and pork mixtures.

V. CONCLUSION

In this study, an OENS was developed, employing 9 gas sensors and producing 10 digital outputs. The noise of the signals was reduced by reconstructing the signals using DWT with mother wavelet db6, which could increase classification accuracy by 1%. By using mean as the statistical parameter method, generates 10 features and is spread into 10 dimensions. PCA successfully reduced the number of components/dimensions from 10 to 8 components. These 8 components had a fairly big correlation with a proportion of variance of 100%, namely the highest and most dominant factor, MQ 135 factor, with a proportion of variance of 57%, the MQ 4 factor, with a proportion of variance of 19%, and the MQ 9 factor, with a proportion of variance of 12%. The total variance obtained from the 8 variables was 100%. Thus, the optimization algorithm supported the efficiency of the SVM classification process in obtaining the best solution, which was 98.10% on average. This result indicates that OENS is potentially developed for halal authentication and brings closer to practical applications.

For future work, the fingerprint of pork adulteration in smaller portions of beef will be developed.

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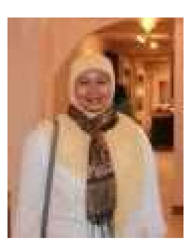

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