

Detection of Chicken Meat Adulteration in Cattle Meat Using BME688 Gas Sensor and Convolutional Neural Networks

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ABSTRACT

Meat adulteration through the substitution of high-value meat with cheaper animal species remains a significant concern for food authenticity, consumer trust, and regulatory control. This study investigated the potential of a low-cost electronic nose system based on the BME688 gas sensor, combined with one-dimensional convolutional neural networks (1D-CNN), for detecting chicken meat adulteration in cattle meat. Binary mixtures of chicken and cattle meat at different proportions were prepared and analysed using a dual-sensor matrix configuration with four distinct heater profiles. Raw gas resistance signals were subjected to labelling, low-pass filtering, spline interpolation, logarithmic transformation, and background subtraction prior to model development. Two complementary prediction tasks were performed: multi-class classification of mixture categories and regression-based estimation of chicken meat proportion. All classification models achieved 100% accuracy on the independent test set, demonstrating clear discrimination among mixture classes regardless of heater profile. For regression, the best-performing model, trained using heater profile HP-412, achieved a mean squared error of 0.005440 and a mean absolute error of 0.015029, corresponding to an average prediction error of approximately 1.5 percentage points. These findings indicate that the proposed BME688–CNN framework can provide rapid, non-destructive, and accurate detection of meat adulteration. The results further highlight the potential of compact sensor systems integrated with artificial intelligence for portable, real-time food authenticity applications.

Keywords: electronic nose, food authenticity, convolutional neural network, meat adulteration, artificial intelligence, food safety

1. INTRODUCTION

Food adulteration remains a persistent global challenge affecting the integrity, safety, and transparency of the food supply chain [1], [2]. Among various forms of fraud, the substitution or partial replacement of high-value meat with cheaper animal species is one of the most frequently reported practices, primarily motivated by economic gain [3]. Such fraudulent activities mislead consumers, create unfair competition in the market, and undermine confidence in food labelling systems. Beyond economic concerns, undeclared meat substitution may also pose public health risks due to potential allergenic reactions, species-specific contaminants, or residues from unauthorised sources [4], [5]. In addition, meat adulteration carries important religious and ethical implications, particularly for consumers who avoid specific animal species based on halal, kosher, vegetarian, or cultural dietary preferences [6], [7]. Therefore, the reliable identification of meat species in commercial products has become increasingly important for regulatory authorities, industry stakeholders, and consumers alike.

Reliable identification of meat species in food products has therefore attracted considerable scientific and regulatory attention, leading to the development of a wide range of analytical techniques for species authentication.

Molecular approaches such as conventional polymerase chain reaction (PCR), real-time PCR, multiplex PCR, and DNA barcoding are among the most widely used methods due to their high specificity and sensitivity [8], [9], [10]. Immunological techniques, including enzyme-linked immunosorbent assay (ELISA), have also been employed for species differentiation based on protein markers [11]. In addition, physicochemical and spectroscopic approaches such as near-infrared spectroscopy (NIR) [12], Fourier-transform infrared spectroscopy (FTIR) [13], [14], Raman spectroscopy [15], [16], chromatography-based analyses [17], and mass spectrometry [18] have been investigated for rapid and accurate meat identification. Collectively, these methods have significantly improved the detection of fraudulent meat substitution and have played an important role in strengthening traceability and food control systems.

Although these conventional analytical methods often provide highly accurate and reliable results, their practical implementation in routine monitoring and field applications remains constrained by several limitations. Many of these techniques require labour-intensive sample preparation, specialised laboratory infrastructure, expensive instrumentation, and trained personnel to operate the equipment and interpret the data. In addition, analytical workflows can be time-consuming, making them less suitable for rapid decision-making in supply chains that require immediate screening [19], [20]. Most laboratory-based methods are also poorly suited for on-site deployment and continuous real-time monitoring [21]. Furthermore, integrating such systems into digital inspection platforms, embedded devices, or automated quality-control environments can be technically challenging. Consequently, there is growing interest in alternative technologies that can deliver fast, low-cost, portable meat authentication without compromising analytical performance [22].

In response to these limitations, increasing attention has been directed toward next-generation sensing systems that can support rapid, portable, and digitally connected food authentication. In particular, there is a growing need for analytical tools that can be deployed directly at points of sale, processing facilities, storage units, or border inspection checkpoints without reliance on centralised laboratories. Such systems should ideally provide non-destructive measurements, minimal sample preparation, short analysis times, and compatibility with automated decision-support frameworks. Moreover, the expansion of smart agriculture, Industry 4.0, and Internet of Things (IoT)-based food monitoring has further emphasised the importance of sensors that can be integrated into mobile devices, embedded platforms, and cloud-based traceability systems. Despite this demand, studies focusing on practical, low-cost, and field-deployable technologies for reliable identification of meat species remain relatively limited.

Among emerging alternatives, electronic nose systems have gained considerable attention as rapid tools for assessing food authenticity. These systems operate by capturing the collective response of gas sensors to volatile organic compounds (VOCs) released from food matrices, thereby generating characteristic chemical fingerprints associated with product composition and quality. Because different animal species exhibit distinct biochemical compositions, lipid oxidation pathways, moisture contents, and protein degradation patterns, their headspace volatile profiles may also differ measurably. Electronic noses have therefore been explored for a variety of meat-related applications, including freshness evaluation, spoilage detection, storage monitoring, geographical origin discrimination, and species identification. When combined with modern data analytics, such sensor platforms offer a

promising route to rapid, non-destructive screening of meat products without the need for complex laboratory procedures.

Recent studies have increasingly demonstrated the applicability of electronic nose systems and intelligent sensing platforms for meat authentication and adulteration detection. Han et al. developed a low-cost colourimetric electronic nose to identify pork adulteration in beef and demonstrated that the system could perform both qualitative classification and quantitative estimation of adulteration levels [23]. Pulluri and Kumar introduced a smart electronic nose framework capable of rapidly detecting pork adulteration in beef by extracting early-stage signals and applying machine learning algorithms, substantially reducing analysis time while maintaining high classification performance [24]. Similarly, Huang and Gu proposed a metal-oxide-semiconductor-based electronic nose combined with a one-dimensional convolutional neural network and random forest regressor for the quantitative detection of pork adulteration in beef, achieving a coefficient of determination of 99.7% [25].

Another study by Weng et al. proposed a multimodal framework integrating an electronic nose, computer vision, and artificial tactile technologies for comprehensive meat freshness assessment, showing that the fusion of complementary sensor systems can enhance predictive reliability and provide a more holistic evaluation of meat quality [26]. Putri et al. developed a compact, portable electronic nose integrated with supervised machine learning to identify the origin of meat floss products and successfully discriminated among beef, chicken, and pork samples, achieving test accuracies exceeding 99% [27]. Jia et al. developed a data-fusion approach that combines near-infrared spectroscopy and an electronic nose for rapid detection of adulterated lamb meat, demonstrating that integrating complementary sensing modalities can significantly improve classification and quantification performance in meat authenticity assessment [28]. Boray et al. introduced a biologically inspired electronic nose system for meat analysis, demonstrating that olfaction-based sensor design strategies can effectively characterise meat samples and enable rapid classification via pattern recognition of volatile compounds [29].

More recently, Zuhri et al. developed a redundant gas-sensor system combined with an optimised convolutional neural network to detect beef adulterated with pork, reporting classification accuracies up to 99.72% and highlighting the effectiveness of multi-sensor architectures for meat authentication [30]. Lu et al. investigated chicken-derived adulteration in pork patties using electronic nose responses together with physicochemical and amino acid-related quality indicators, and reported that a BP-ANN model achieved 98% accuracy on an independent test set [31]. Collectively, these studies confirm that volatile-profile-based sensing, when combined with machine learning, can be an effective strategy for detecting species substitution in meat products.

Despite these advances, several limitations remain in the current literature. Many reported studies have focused primarily on pork adulteration in beef, while investigations involving chicken substitution in cattle meat remain comparatively limited. In addition, some previously proposed systems rely on multiple analytical instruments, complex sensor-fusion architectures, or laboratory-oriented platforms, which may limit portability and large-scale routine implementation. Furthermore, a considerable proportion of earlier studies focused solely on classification tasks, whereas accurate estimation of the adulteration level is equally important for regulatory and commercial decision-making.

To address these gaps, the present study proposes a compact, low-cost authentication framework based on the BME688 gas sensor and one-dimensional convolutional neural networks to detect chicken meat adulteration in cattle meat. Unlike many previous approaches, the developed system was evaluated under four distinct heater profiles and designed to perform both multi-class classification of mixture categories and continuous regression-based prediction of chicken meat proportion. Importantly, the proposed framework is not limited to standalone detection; it can also generate sensor-derived digital data and provide model-based decision outputs that may be integrated into automated inspection, quality control, and food traceability systems. Therefore, this study contributes not only to rapid and non-destructive meat authentication but also to the development of portable, digitally integrable, and automation-compatible decision-support technologies for future real-world applications.

2. MATERIALS AND METHODS

In this study, headspace measurements of volatile organic compounds (VOCs) in containers storing meat mixtures prepared from two species at varying ratios were conducted to characterise the mixtures. VOC analyses were performed using the Bosch BME688 metal-oxide semiconductor (MOS) gas sensor [32]. The BME688 is an integrated multi-parameter environmental sensor capable of simultaneously measuring gas response, temperature, relative humidity, and barometric pressure. Rather than selectively detecting a single gas compound, the sensor responds to changes in resistance to complex environmental gas mixtures, thereby producing a sample-specific chemical fingerprint.

Through this approach, differences in VOC profiles originating from meat samples can be distinguished via sensor response patterns, and variations associated with mixture ratios can be evaluated. In addition, the sensor's compact size, low power consumption, and ability to generate high-frequency time-series signals under programmable heater profiles provide practical advantages for rapid screening and portable sensing applications. For these reasons, the BME688 sensor has recently emerged as a promising electronic nose platform, successfully employed by researchers, particularly in volatile-compound-based classification studies.

The BME688 sensor has demonstrated remarkable versatility across a wide spectrum of application domains in recent literature. In the realm of environmental monitoring, it has been extensively employed for both indoor and outdoor air quality assessment [33], [34]. The food industry has also benefited significantly from its capabilities, with applications spanning food and drink classification [35], [36], freshness evaluation [37], and adulteration detection [38], [39]. From a safety and security perspective, the sensor has been used in early fire detection within building, forestry and agricultural settings [40], [41], anomaly detection in critical infrastructure and laboratory environments [42], and the early identification of environmental hazards in military facilities and field operations [43], as well as bad-smell and leak-detection monitoring [44]. Beyond these domains, BME688 has found relevance in healthcare and biological research, particularly for disease diagnosis, patient monitoring, and detection of microbial activity [45]. Its sensitivity to Volatile Organic Compounds (VOCs), volatile sulphur compounds (VSCs), and gases such as carbon monoxide and hydrogen further broadens its potential for future applications.

Beyond these areas, the BME688 sensor offers promising opportunities for real-time monitoring across many similar use cases. In particular, its integration with embedded platforms and machine learning algorithms can provide rapid, on-site monitoring tools that do not require complex laboratory infrastructure. Moreover, its sensitivity to subtle shifts in VOC signatures opens avenues for proactive anomaly detection and continuous quality control in industrial and environmental settings, where early intervention is critical.

2.1. System Architecture and Workflow

The proposed system integrates a low-cost gas sensor array with a deep learning pipeline to enable rapid, non-destructive detection of chicken meat adulteration in cattle meat. The overall architecture consists of five sequential stages: (1) sample preparation, (2) VOC acquisition via the BME688 dual-sensor matrix, (3) multi-step signal preprocessing, (4) one-dimensional convolutional neural network (1D-CNN) inference, and (5) dual prediction output. Figure 1 illustrates this end-to-end workflow, highlighting the key components and data transformations at each stage.

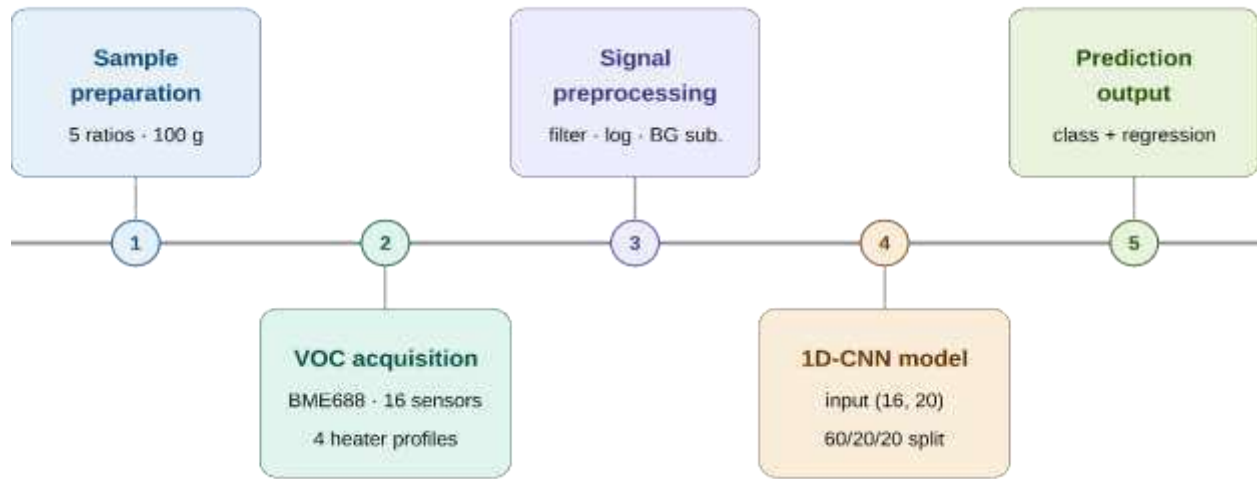


Figure 1. End-to-end workflow for cattle–chicken meat adulteration detection using a BME688 gas sensor array and 1D-CNN.

As depicted in Figure 1, the workflow is designed to be modular and sequentially dependent. In the first stage, binary meat mixtures are homogenised at five defined composition levels and sealed in glass measurement cups to allow headspace equilibration. The second stage employs two independent BME688 sensor matrices operating simultaneously: Matrix 0 acquires the combined volatile response of the meat sample and the ambient environment, while Matrix 1 serves as a control unit, capturing only the environmental background signal. This dual-matrix configuration is central to isolating the net chemical contribution of the meat mixtures. In the preprocessing stage, the raw time-series resistance data are labelled by mixture class, denoised using a low-pass filter, temporally aligned via spline interpolation, compressed using a logarithmic transformation, and finally background-corrected by subtracting the Matrix 1 signal from the Matrix 0 signal. The resulting net signal vectors are then presented to the 1D-CNN, which

processes them through alternating convolutional and fully connected layers with batch normalisation and ReLU activations. In the final output stage, two specialised prediction heads operate on shared feature representations: a classification head that produces discrete mixture-class labels, and a regression head that estimates the continuous chicken meat proportion. The entire pipeline from raw sensor acquisition to model prediction is thus designed to be computationally lightweight, making it well-suited for future deployment on embedded or edge-computing platforms.

2.2. BME688 Development Kit and Sensor Configurations

Because many uncontrollable factors influence environmental measurements, reproducing the same conditions at different times is impractical. Therefore, deploying multiple sensors simultaneously is important to assess different profile settings within the same experimental environment. Instead of relying on a single sensor to identify the chemical fingerprints of various meat mixture ratios within the study, an 8-sensor matrix capable of independent measurements was employed [46]. This approach validated the sensor environment measurements against each other and generated a more comprehensive dataset.

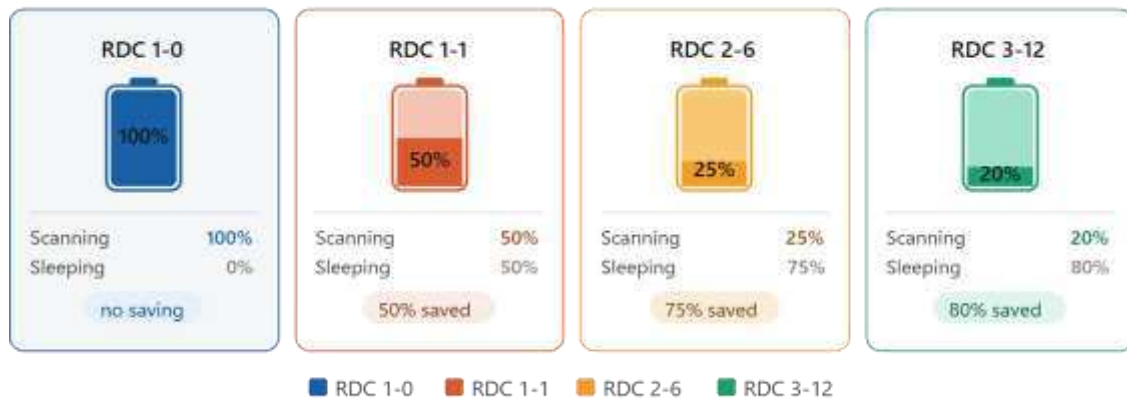


Figure 2. RDC profile configurations available for the BME688 sensor. Each profile defines the ratio of active scanning time to sleep time within a single measurement cycle.

Two key configurations influence the sensor's measurement abilities and the dataset's characteristics. The first, the Real Duty Cycle (RDC) profile, controls the sensor's scanning and sleep routines. Properly configured, the RDC profile can reduce power consumption by up to 80%, especially for sensor nodes that are externally powered and located far from the city grid, thereby prolonging their operational life. Figure 2 illustrates various RDC profiles that can be customised for BME 688 sensors across different applications.

In this study, the RDC 1-0 profile was adopted for all measurements, as the sensor matrix was powered directly from the city's electrical grid rather than relying on battery-operated nodes. Since energy consumption was not a limiting factor in the experimental setup, continuous scanning mode was preferred over duty-cycled alternatives. Operating at 100% scanning with no sleep interval maximises the number of data samples collected per unit time, which is a critical consideration when training machine learning models. A higher sampling density exposes the model to richer temporal variation in the gas sensor signals, enabling more robust feature extraction and improving the ability

to distinguish between different chemical environments. Consequently, the RDC 1-0 profile was selected not as a power management strategy, but as a deliberate choice to enhance dataset quality and support the generalisation capability of the learning algorithms employed in this work.



Figure 3. Temperature modulation profiles applied to the BME688 sensor array in this study (HP-332, HP-354, HP-412, and HP-504).

The second key parameter governing sensor behaviour is the Heater Profile (HP). In MOS sensors, gas detection relies on surface interactions, in which VOC molecules adsorb onto or desorb from the active sensing layer. These two competing processes are highly sensitive to operating temperature, and modulating this temperature alters their relative rates and equilibrium. As a result, temperature modulation fundamentally shapes the dynamic response characteristics of MOX sensors by influencing VOC adsorption-desorption kinetics and the associated surface reactions. To determine the optimal temperature modulation for detecting chicken meat adulteration in cattle meat, four different temperature modulation profiles were applied simultaneously across the sensor array. Figure 3 shows the four HP profiles used (HP-332, HP-354, HP-412, and HP-504), each representing a different thermal operating regime.

In this study, four distinct HPs were applied simultaneously to the BME688 sensor array to investigate the effect of temperature modulation on detecting chicken meat adulteration in beef. Each profile defines a sequence of 10 discrete temperature steps, each applying a distinct thermal excitation pattern to the MOX sensing surfaces. The operating temperatures vary considerably across profiles: HP-332 cycles between 50°C and 350°C with sharp transitions, HP-354 operates between 100°C and 320°C with a structured low-high pattern, HP-412 ranges from 100°C to 320°C with more gradual intermediate steps, and HP-504 follows a descending thermal trajectory from 350°C down to 70°C before recovering. By exposing the sensor array to these varied temperature-modulation regimes

simultaneously, the study aimed to identify which HP configuration most effectively captures the VOC signatures associated with beef adulteration with chicken meat.

2.3. Experimental Setup

Lean ground beef and chicken, both of the same freshness level, were sourced from a local butcher (Bolu Birlik A.Ş.). Ground chicken was added to the ground beef to create mixtures containing 100%, 90%, 80%, 70%, and 50% beef, totalling 100 g. Each mixture was homogenised for 2 minutes at a standard speed using a high-speed laboratory blender (Waring Commercial 8010ES, USA) to ensure complete homogenization within the matrix and minimise deviations that might result from weighing errors. The meat mixtures prepared for sensor measurements and the laboratory environment are shown in Figure 4.

After each process, the blender was cleaned and sterilised before proceeding to the next mixture, thereby preventing cross-contamination between samples. The homogenised mixtures were shaped into patties approximately 1.5 cm high, matching the measuring cup's diameter, and then left at room temperature for 30 minutes. At the end of the resting period, each sample was placed in sealed glass measuring cups. Sensors were fixed approximately 3 cm above the sample surface inside the sealed glass cups. All measurements were taken under room conditions.



Figure 4. Meat mixtures prepared at different cattle-to-chicken ratios used for sensor measurements, and the laboratory environment in which the experiments were conducted.

2.3. Data Preprocessing

Two distinct datasets were constructed from measurements obtained by two separate sensor matrices. The first dataset, acquired from sensor matrix 0 (the sample matrix), comprises gas resistance readings collected from chicken–cattle meat mixtures of varying composition. The second dataset, acquired from sensor matrix 1 (the control matrix), captures the ambient gas resistance of the experimental environment. Figure 5 presents representative raw gas resistance data recorded by sensor 7 of sensor matrix 0.

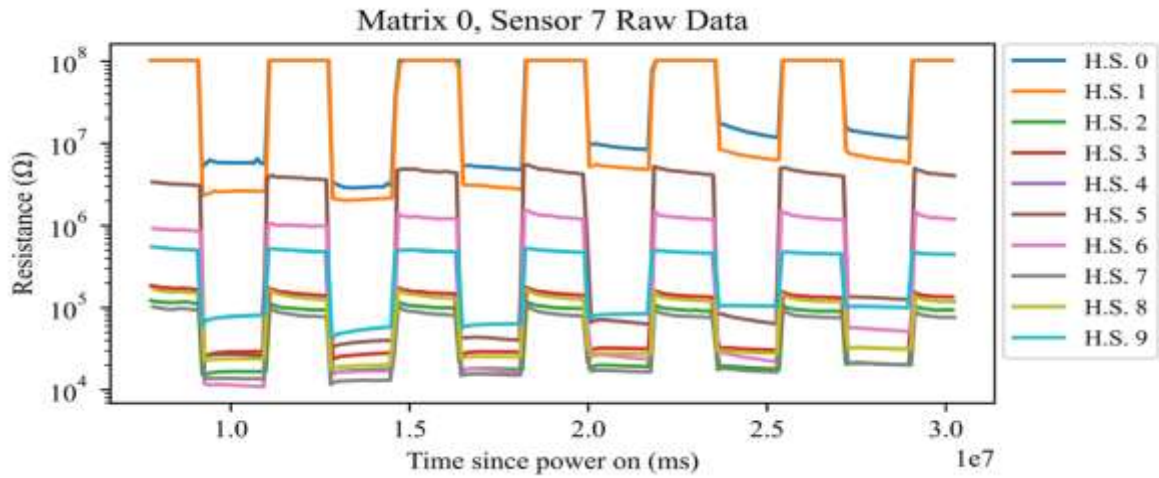


Figure 5. Raw data obtained from the seventh sensor of the meat mixture matrix. H.S. i corresponds to the heater step index of assigned heater profile. Signal drop regions represent the data obtained from meat mixtures.

The first step in data preprocessing was the labelling of relevant data regions. As illustrated in Figure 6, segments corresponding to measurements taken from meat mixtures were identified and annotated. Each labelled region—designated as Ctl 100, Ctl 90, and so forth—indicates the percentage of cattle meat present in the respective mixture.

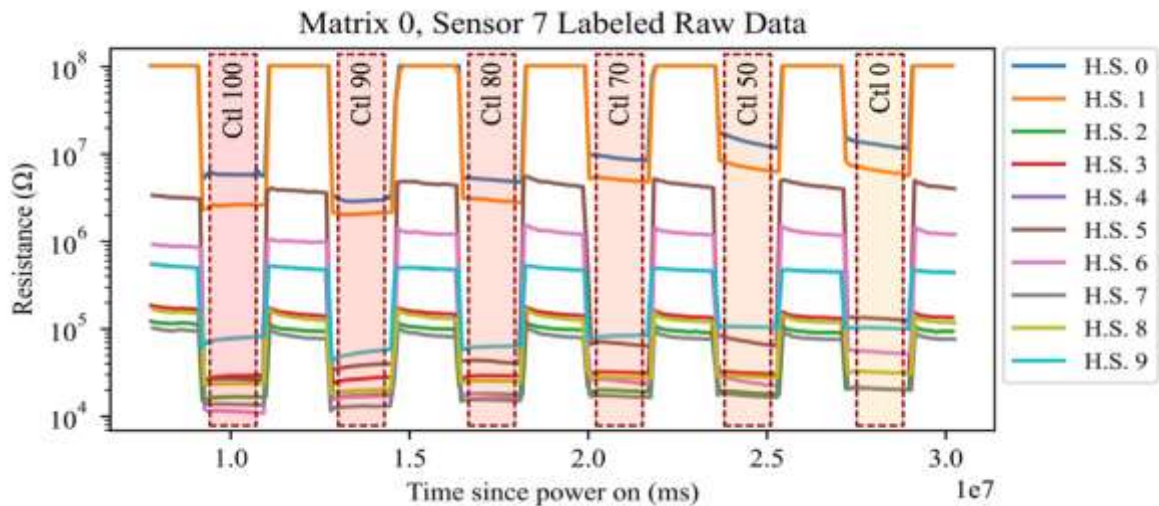


Figure 6. Illustration of labelled regions from sensor 7 of matrix 0. *Ctl* 100 corresponds to 100% cattle and 0% chicken, *Ctl* 90 corresponds to 90% cattle and 10% chicken, and so forth.

Subsequently, low-pass filters were applied to all signals to suppress measurement noise. Given that the sensor array comprises 16 sensors distributed across two sensor matrices, with each sensor operating under 10 distinct heater steps, this stage yielded 160 noise-attenuated time series of gas resistance readings.

Each sensor acquires ten resistance values at distinct time points and temperatures throughout its assigned heater profile cycle. Consequently, these measurements are inherently non-synchronous. Furthermore, different heater profiles complete their cycles over different time durations. To normalise the quantity of data across heater profiles and to achieve temporal alignment of samples, spline interpolation was applied. By fitting spline polynomials to the discrete measurements, the data were transformed into a continuous representation, enabling values to be sampled at any arbitrary time point. Figure 7 presents a zoomed-in section of the matrix 0 data: the left panel displays the original sample points prior to low-pass filtering, while the right panel shows the resulting increase in sample density alongside the noise-attenuated signal.

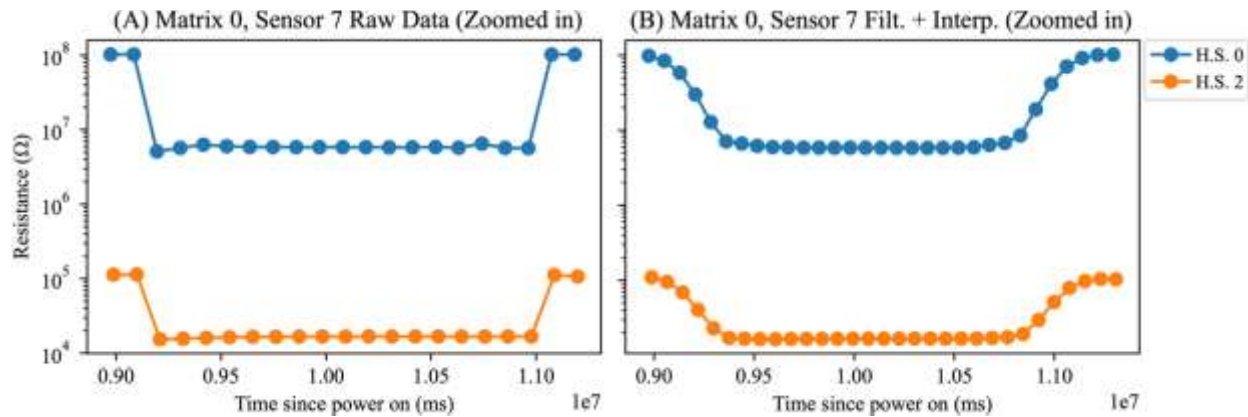


Figure 7. (A) Zoomed section of the raw sensor data. (B) Data from the same region after applying a low-pass filter and interpolation. Only heater step 0 and step 2 data are shown to reduce visual clutter.

Following interpolation, the net contribution of the gases released by the meat mixtures to the sensor readings was computed. The signals recorded by matrix 0 represent the combined resistance response to both the gases emitted by the meat mixtures and the background gases present in the ambient experimental environment. Matrix 1, by contrast, captures exclusively the resistance response to environmental background gases. The net effect attributable to the meat mixture emissions was therefore obtained by subtracting the matrix 1 readings from the corresponding matrix 0 readings. Prior to subtraction, all sensor data were transformed to a logarithmic scale to reduce the dynamic range and facilitate comparison across sensors. Figure 8 presents the resulting net data derived from sensor 7 of matrices 0 and 1.

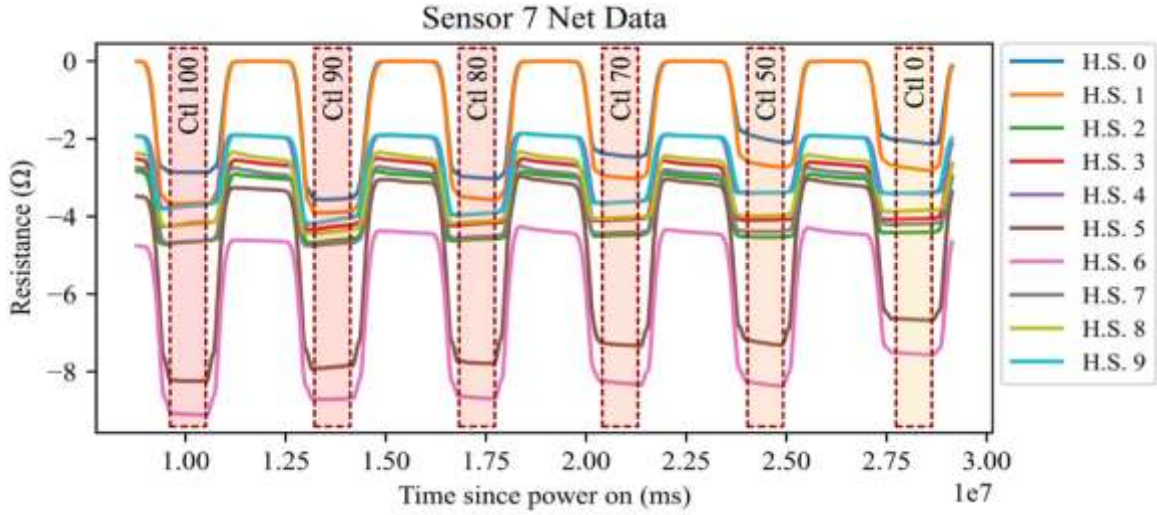


Figure 8. Processed data obtained from Sensor 7 after applying a logarithmic transformation to both control and sample data, followed by subtraction of the control data from the sample data. Mixture samples are labeled as Ctl x , where x denotes the percentage of cattle meat in the mixture. The percentage of chicken meat is therefore given by $100 - x$.

2.4. Model Architecture

Two neural networks were designed: one for classification and one for regression. Both models share the same architecture, differing only in their final output layers.

As shown in Figure 9, the networks consist of two sequential stages that process batched input tensors of shape (16, 20), where the batch size is 16 and each sample contains 20 features corresponding to 20 heater-step resistance values obtained from a sensor pair. First, the input is processed in a convolutional stage. The input tensor is expanded using an *unsqueeze* operation from (16, 20) to (16, 1, 20) and then passed through a one-dimensional convolutional layer (Conv1d) [47] that increases the channel dimension, producing a (16, 8, 20) feature map. This is followed by batch normalization (BatchNorm1d) and a rectified linear unit (ReLU) activation function, both preserving the (16, 8, 20) shape.

Next, the resulting tensors are passed to the fully connected stage. The feature map is flattened using a view operation from (16, 8, 20) to (16, 160), then projected through a linear layer to (16, 64), followed again by BatchNorm1d and ReLU activation, both maintaining the (16, 64) shape. A second linear layer further reduces the representation to (16, 32), followed by BatchNorm1d and ReLU activation [48].

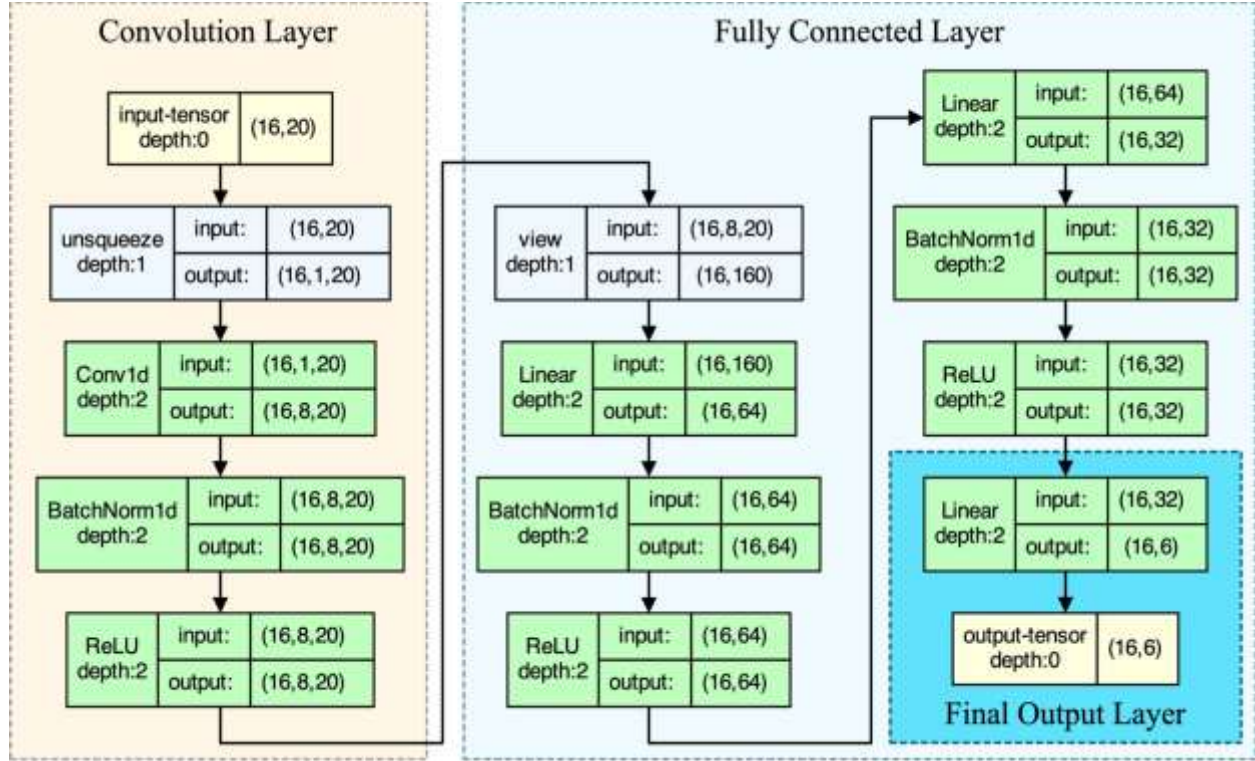


Figure 9. Architecture of the proposed one-dimensional convolutional neural network (CNN) classification model. The proposed regression model shares an identical architecture with the classification model, differing only in the final output layer. The regression model uses a single-output linear layer to predict the proportion of chicken meat in the mixture as a continuous real-valued number.

For the classification model, the final linear layer maps the features to an output tensor of shape (16, 6), corresponding to six target classes. For the regression model, the final output layer maps the features to an output tensor of shape (16, 1), representing the ratio of chicken meat in the cattle–chicken meat mixture within the interval 0.0–1.0.

2.5. Model Training and Evaluation

A total of eight training experiments were conducted: four for the classification task and four for the regression task. In each experiment, the net sensor data collected from a sensor pair configured with a single heater profile were used exclusively, such that each experiment corresponded to one of the four available heater profiles. For every training session, the dataset was partitioned into training, validation, and test subsets using stratified splitting, with proportions of 60%, 20%, and 20%, respectively. Stratified splitting was employed to ensure that the class distribution was preserved across all subsets.

Feature standardisation was applied to each subset: the training set was standardised using *fit-transform*, in which the mean and standard deviation were estimated from the training data. The validation and test sets were

subsequently standardised using the mean and standard deviation values derived from the training set (transform only), thereby preventing data leakage.

Early stopping was applied during training, with each model's training loop terminated once no further improvement was observed on the validation set [49]. Following training, each model's performance was evaluated on the held-out test set. For the classification models, predictive performance was assessed using classification accuracy, defined as the proportion of samples for which the predicted class label matched the true class label. For the regression models, performance was quantified using mean squared error (MSE) [50] and mean absolute error (MAE) [51].

3. Results

All four classification models, each trained on data from a sensor pair operating under a distinct heater profile, achieved 100% accuracy on the held-out test set. Every sample in the test set was assigned to its correct mixture class across all six categories, indicating that the gas resistance signatures produced by the different mixture ratios are sufficiently discriminative to be perfectly separated by the proposed CNN architecture, regardless of which heater profile was used.

The MSE and MAE values of the regression models trained using data obtained from different heater profiles are presented in Table 1. All four models achieved low error scores, demonstrating that the regression task is well-suited to the proposed architecture across all tested configurations. The model trained on data from the sensor pair configured with HP-412 achieved the best overall performance, with MSE and MAE values of 0.005440 and 0.015029, respectively, followed closely by HP-332 (MSE: 0.005451, MAE: 0.016622). HP-504 yielded intermediate performance (MSE: 0.006629, MAE: 0.017146), while HP-354 produced the highest error scores (MSE: 0.011432, MAE: 0.023455), suggesting that this heater profile generates less discriminative gas resistance patterns for the regression task. An MAE of 0.015029 on a target scale of 0.0 to 1.0 corresponds to an average estimation error of 1.5 percentage points in predicted chicken meat proportion, demonstrating that the model localises adulteration levels with high precision across all six mixture classes.

Table 1. Mean squared error (MSE) and mean absolute error (MAE) scores for regression models trained using data from different heater profiles. The model trained using HP-412 achieved the lowest MSE and MAE values.

Heater Profile	MSE	MAE
HP-412	0.005440	0.015029
HP-354	0.011432	0.023455
HP-504	0.006629	0.017146
HP-332	0.005451	0.016622

Figure 10 presents the regression model predictions plotted against the line of perfect prediction for the HP-412 model. The predicted values lie in close proximity to the line across the full concentration range, confirming that the model generalises well to unseen samples at all mixture ratios rather than performing selectively at particular

adulteration levels. The absence of systematic deviation from the line of perfect prediction further indicates that the model does not exhibit a directional bias towards over- or under-estimating the chicken meat proportion.

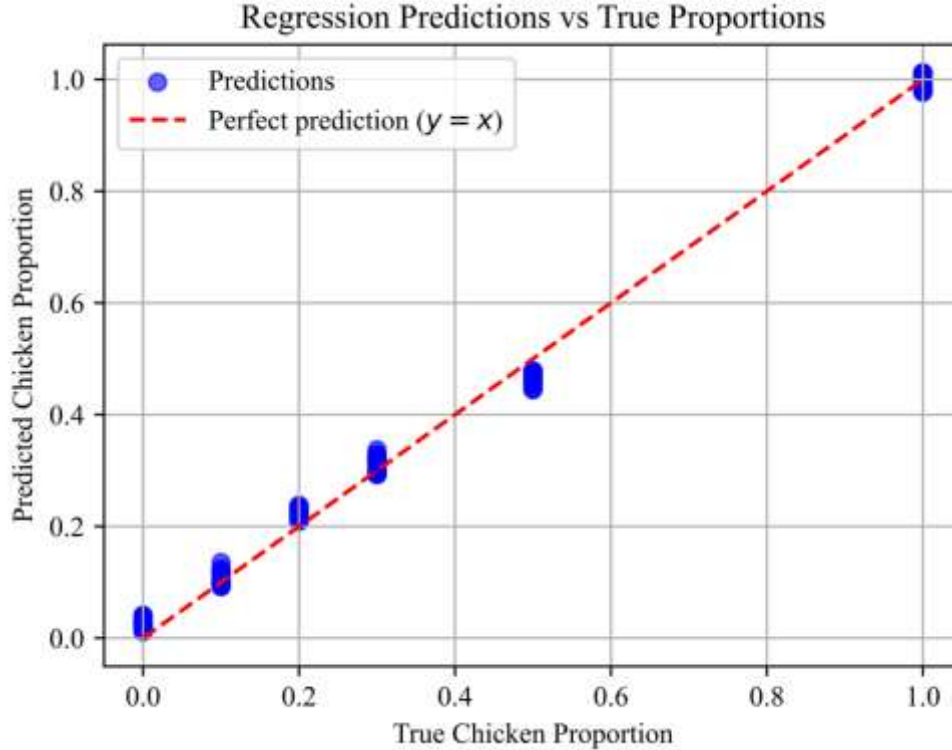


Figure 10. Scatter plot of predicted versus true chicken proportions on the test set. Each point represents a sample, and the red dashed line indicates perfect agreement between predicted and true values. The predictions lie close to this line, demonstrating that the regression model accurately estimates chicken content with minimal error.

4. Conclusions

This study demonstrated that the BME688 gas sensor array, in combination with a one-dimensional convolutional neural network, constitutes an effective system for detecting chicken meat adulteration in cattle meat. Two complementary tasks were addressed: multi-class classification of mixture composition, and continuous regression estimation of the chicken meat proportion.

All four classification models, each trained on data acquired from a sensor pair operating under a distinct heater profile, achieved 100% accuracy on the held-out test set. This result indicates that the proposed pipeline can reliably distinguish between the defined mixture classes regardless of the heater profile employed, demonstrating the robustness of the approach to sensor configuration. The regression models likewise achieved strong predictive performance: the best-performing model, trained on data from the sensor pair configured with HP-412, yielded an MSE of 0.005440 and an MAE of 0.015029, corresponding to an average estimation error of approximately 1.5 percentage points. These results confirm that the system is capable of quantifying adulteration levels with high precision, not merely detecting their presence.

These findings highlight the potential of low-cost electronic nose systems as practical tools for food authenticity verification [52]. Unlike conventional laboratory-based analytical methods, the BME688-based approach is compact, relatively inexpensive, and well-suited to deployment in settings where rapid, non-destructive screening is required. The success of the CNN architecture across all four heater profiles further suggests that the methodology may be adaptable to other meat adulteration scenarios involving different species combinations or varying degrees of processing.

Nevertheless, several limitations of the present study should be acknowledged. The experiments were conducted under controlled laboratory conditions using freshly prepared meat mixtures, which may not fully reflect the variability encountered in real-world settings, such as differences in animal breed, diet, post-mortem ageing, or sample storage conditions. Additionally, the dataset was collected from a single experimental run with a limited number of mixture ratios, and the models were evaluated exclusively on data drawn from the same experimental session. The generalization of the trained models to independently collected samples therefore remains to be established.

Future work should address these limitations by acquiring data from a larger number of independent samples spanning a wider range of mixture concentrations, storage durations, and preparation conditions. Cross-validation across multiple experimental sessions would provide a more rigorous assessment of model robustness. Furthermore, investigating the transferability of the approach to other species pairs, as well as exploring more interpretable model architectures, would strengthen both the practical applicability and scientific transparency of the system. Integration with embedded hardware platforms could also be explored with a view to developing a portable, field-deployable adulteration detection device [52].

Data Availability

The data and source code described and used in this article are available and can be accessed at https://github.com/ihpar/cattle_chicken.

Conflicts of Interest

The authors declare that there are no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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