IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 13 October 2024, accepted 10 December 2024, date of publication 18 December 2024,
date of current version 31 December 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3520029

RESEARCH ARTICLE

IoT Based Meat Freshness Classification Using Deep Learning

ZARIF WASIF BHUIYAN, SYED ALI REDWANUL HAIDER, ADIBA HAQUE, MOHAMMAD REJWAN UDDIN, (Member, IEEE), AND MAHADY HASAN
Department of Computer Science and Engineering, Independent University, Bangladesh (IUB), Dhaka 1229, Bangladesh

Corresponding author: Zarif Wasif Bhuiyan (zarifwasif20@gmail.com)

This work was supported by the Department of Computer Science and Engineering; Independent University, Bangladesh (IUB).

ABSTRACT Meat quality and safety are critical concerns in the food industry, especially for products like beef and mutton, which are susceptible to spoilage and fraud. Traditional methods of assessing meat freshness and species classification, such as manual inspection, are often inefficient and prone to error. This paper introduces a novel Internet of Things (IoT) system that integrates gas sensors and advanced machine learning models, particularly deep learning, to address these issues effectively. The system combines image-based classification using a custom Convolutional Neural Network (CNN) with gas sensor data to provide a comprehensive, real-time solution for the classification of both beef and mutton in terms of species and freshness. The custom Convolutional Neural Network (CNN) was trained on a dataset comprising 9,928 images, 6,672 of which were utilized for meat freshness classification and 3,256 for meat species classification. The model achieved a classification accuracy of 99%, surpassing the performance of other models, including ResNet-50, Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN). It is important to note that identical training and validation datasets were employed across all four models, ensuring a consistent and equitable comparison of their performance. The custom CNN showed a clear advantage in handling the complex image data, particularly in distinguishing between beef and mutton species as well as their freshness levels. The system incorporates three gas sensors—MQ135, MQ4, and MQ136—to detect gases such as ammonia (NH3), methane (CH4), and hydrogen sulfide (H2S), which are released during the spoilage of meat. These gas sensor readings are utilized specifically for the classification of meat freshness. The system provides real-time feedback via LED indicators: green for fresh meat, yellow for meat that is neither fresh nor fully rotten, and red for spoiled meat. The results of the classification, based on both image data and gas readings, are displayed on an LED screen. This offers an efficient, scalable, and practical solution for real-time quality monitoring of beef and mutton. This integrated approach significantly improves the accuracy, reliability, and efficiency of meat safety management within the food supply chain.

INDEX TERMS Classification, meat quality, MQ135 gas sensor, MQ136 gas sensor, MQ4 methane natural gas sensor, meat freshness, IoT.

I. INTRODUCTION

Ensuring food safety and quality control has become an increasingly critical issue, particularly in the food industry, where meat products are prone to spoilage and fraud. The accurate identification of meat freshness and species is essential to prevent foodborne illnesses, maintain consumer trust, and reduce economic losses caused by fraudulent practices. Traditional methods of determining meat quality, such as visual inspection and manual labeling, are often time-consuming, error-prone, and insufficient to meet the demands of large-scale food processing and distribution. As a result, there is an urgent need for innovative, real-time, and automated solutions that can accurately assess the quality and freshness of meat, ensuring both safety and transparency in the supply chain. In response to these challenges, our research

The associate editor coordinating the review of this manuscript and approving it for publication was Ye Liu.

focuses on developing a novel Internet of Things (IoT) device that integrates gas sensor technology with advanced machine learning and deep learning models for meat freshness and species classification. We employed a custom Convolutional Neural Network (CNN) model, where additional features were incorporated to improve its performance [2], [3]. This custom CNN was compared with one deep learning model, ResNet-50, and two traditional machine learning models, k-Nearest Neighbors (k-NN) and Support Vector Machines (SVM). After the comparative analysis, it was clear that our custom CNN performed exceptionally well, surpassing the other models in accuracy [4], [5], [6]. While previous studies on meat freshness classification have typically focused on visual analysis using camera sensors or gas sensor readings, they often address these aspects in isolation. For example, some studies rely solely on image analysis to detect freshness, while others use gas sensors to monitor volatile compounds associated with spoilage. However, none of these approaches combines both techniques within a single IoT device for real-time meat freshness and species classification. This study uniquely integrates camera-based image analysis and gas sensor readings, utilizing a dataset of approximately 9,928 images and multiple classification models to assess freshness and species. In addition, a comparative analysis was conducted between traditional machine learning models such as k-NN and SVM and deep learning models, including a custom CNN and ResNet-50. By combining these two techniques and evaluating the performance of various models, our approach offers a more comprehensive and robust solution than existing methods [2], [3], [4], [5], [6], [7], [8], [9], [10], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33]. The IoT device is equipped with an ESP32-CAM module that captures high-resolution images of the meat. These images are sent to a Raspberry Pi 3, where they are classified using our custom CNN model, and the results are displayed on the IoT device's screen. Additionally, the IoT device integrates three gas sensors–MQ135, MQ136, and MQ4—that detect gas emissions such as ammonia (NH3), methane (CH4), and hydrogen sulfide (H2S), which are released during the spoilage of meat [6], [7], [8]. These sensors are also connected to the Raspberry Pi 3 and provide real-time freshness classification via three LED indicators: green for fresh meat, yellow for meat that is neither fresh nor rotten, and red for rotten meat. By leveraging the strengths of both deep learning and IoT technologies, our device offers a comprehensive, reliable, and scalable solution for ensuring the safety and authenticity of meat products, contributing to improved public health and greater transparency in the food supply chain [9], [10].

To enhance the accuracy and robustness of the IoT device, our research employs a comprehensive machine learning and deep learning approach, comparing the performance of several models. Our custom CNN model is the core of the IoT device, optimized to process both image and sensor data for highly accurate meat classification [11], [12].

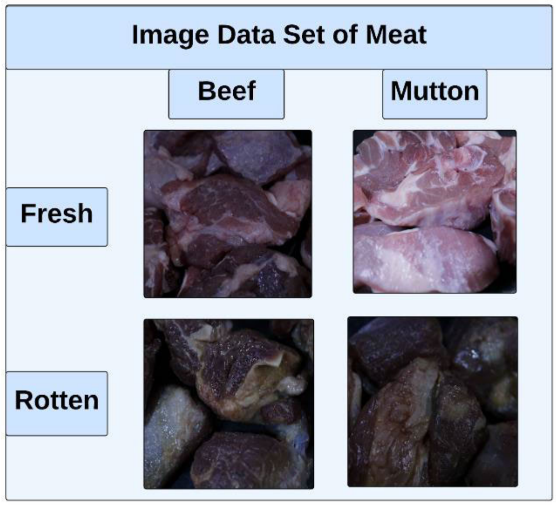

FIGURE 1. Fresh and rotten meat sample.

As illustrated in Fig. 1, which displays the clear visual differences between fresh and rotten meat samples for both beef and mutton—where fresh samples exhibit vibrant colors and firmness, and rotten samples show discoloration and decay—these features were critical for training our models [1]. To validate the effectiveness of the custom CNN, we compared its performance against ResNet-50, k-NN, and SVM. Each model was trained and tested on an expanded dataset of 6,672 samples for meat freshness classification and 3,256 samples for species classification, allowing for a thorough comparison of accuracy, precision, recall, and other performance metrics [1]. The visual cues shown in Fig. 1 were crucial in helping these models accurately classify meat freshness and species. Our experimental results demonstrated that the custom CNN achieved outstanding performance, with 99% accuracy in both meat freshness and species classification. ResNet-50 also performed well, achieving 98% accuracy in both tasks, while k-NN and SVM achieved lower accuracies of 86% and 97%, respectively, in species classification, and 83% and 96%, respectively, in freshness classification. These results confirm the superiority of deep learning approaches, particularly our custom CNN, in handling complex tasks that involve both image and sensor data. The development of this IoT device represents a significant advancement in the field of food safety and quality control [13], [14], [15]. By integrating real-time gas sensor data with deep learning models, the system provides a more accurate, efficient, and scalable solution for meat classification compared to traditional methods. The comparative analysis of different models underscores the robustness of the custom CNN model, which demonstrates exceptional performance and can be effectively deployed in real-world settings for monitoring meat freshness and species in real time [16], [17]. This research lays the groundwork for future innovations in food safety, with the potential to extend the technology to other perishable food products, further enhancing consumer protection and transparency in the food supply chain [18], [19], [20].

The primary contributions of this paper are as follows:

1. Development of a custom CNN for multiple meat classification, achieving 99% accuracy for beef and mutton freshness and species classification.
2. Integration of IoT technology for real-time monitoring of meat quality using both image data and gas sensor readings.
3. Utilization of gas sensors (MQ135, MQ4, MQ136) for freshness detection through the measurement of emitted gases (NH3, CH4, H2S).
4. Real-time feedback provided by LED indicators for freshness classification (green for fresh, yellow for not fresh but not yet rotten, red for rotten).
5. Comprehensive performance comparison between deep learning models (custom CNN, ResNet-50) and traditional machine learning models (SVM, k-NN).
6. Scalable and practical solution for real-time meat quality monitoring in the food supply chain, enhancing food safety and transparency.

II. LITERATURE SURVEY

There have been significant changes in artificial intelligence and deep learning technologies over the past few years. They have had a significant impact on various industries, including the food industry. It has vastly improved the classification and quality assessment of meat products. Johnson et al. outline that fully understanding meat's essential parameters such as freshness and quality is crucial to ensuring consumer satisfaction and health. This paper presents a literature review on a number of studies that focus on using deep learning neural networks for meat freshness classification and quality assessment. Various researchers found that traditional methods of classifying meat, which commonly involve manual inspections, were time-consuming and error-prone [2]. However, artificial intelligence has brought about changes to the meat industry, subsequently innovating the process of meat classification through image analysis and deep-learning technologies. Many approaches for classifying meat freshness have been developed, relying on several perspectives of image, spectroscopy, and electronic sensing [2], [3]. Therefore, the main topic of this literature review will be looking at the various methods and approaches by which several studies implemented deep learning for meat classification and freshness ratings, and accompanying issues.

Fig. 2 shows the deep learning workflow, starting with data normalization and splitting into training, testing, and validation sets. The data is then fed into the AI model, where the Artificial Neural Network (ANN) is configured and optimized. Once the model meets the terminating conditions, it proceeds with training, followed by result prediction. The data is then denormalized, and the final output is generated. This process ensures the model is fully optimized before deployment. Gc and Zhang [2] present a novel method in which TensorFlow and a pre-trained convolutional neural network model – such as Visual Geometry Group or Inception ResNet Vb are used to predict and classify beef cuts quickly. The study shows superior accuracy in the classification of specific beef cuts in 100% of the cases, showing the great possibilities of AI technology for identifying exact beef cuts, thus supplying customers and meat companies with critical information. Kolosov et al. [3] expand upon this idea and suggest a novel technique in which multispectral imaging and deep CNN models are used to estimate microbial populations in meat samples. In their study, these deep learning models are effectively moved to the embedded hardware systems, allowing the process to be completed in real-time without the need for additional servers. The scholars underline the merits of the AI-on-the-edge approach on the embedded platforms, such as XavierNX, Nano, and RP4, which will be a beneficial and cost-effective way to assess meat quality and safety. In a similar manner, Bajpai et al. [4] contributes an efficient CNN-based technique, which applies to the classification of fresh red meat. The authors successfully created a HarNet model for this purpose, which delivers an 80% accuracy rate instead of using some of the pre-trained CNN models suggested in the research. The authors' classification of fresh meat into three categories fresh, half-fresh, and spoiled will be very useful for the food industry, which in the case of meat sold in India is beneficial. With the help of the ResNet152V2 algorithm, Hidayat et al. [5] found a solution to the problem of differentiating between three types of red meat: pork, mutton, and beef. Thanks to the extensive use of a CNN approach and high costs of preprocessing stages, the authors managed to prove the efficiency of their model in classifying different types of meat using images. In this way, it became possible to increase the public's awareness regarding the products that they consume and avoid the occurrence of fraud in the sphere. Ayaz et al. [9] realized that the existing methods to determine the freshness of the meat are traditionally associated with hyperspectral imaging and that the goal is to surpass the shortcomings of other approaches. As a result, the developers developed a new model with a 100% accuracy level and the ability to analyze image data and make predictions as to the degree of meat freshness. They also realized the potential of utilizing deep learning and hybrid neural networks and explored the characteristics of five machine models towards

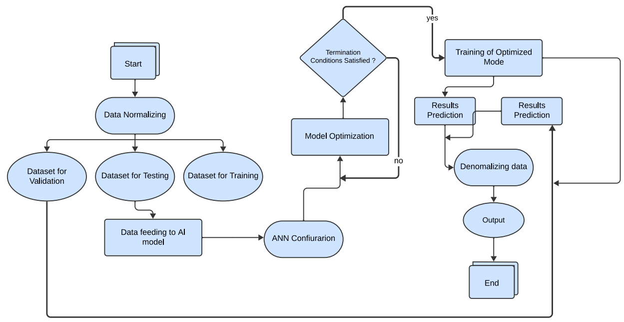

FIGURE 2. Deep learning flowchart.

making the models effective in classifying meat. Abuzaid and Atia [10] also considered the problem of recognizing beef retail cuts as the challenge in the meat science sphere and paid specific attention to different deep learning pre-trained systems. In another work, Kointarangkul and Limpiyakorn [11] proposed an AI-based food identification approach that conveyed the rightful sources of the Wagyu beeves through image identifications. The primary purpose of their study was to equip the buyers with a perception variable for separately determining the trustworthy sources of the Wagyu beeves, thus promoting equality movements in the market. The deep-learning strategy that they applied conveyed a high-grade reliability of the Wagyu beef source. These results demonstrated that AI technologies can be employed in felt improvement to food quality and security. According to Zhou et al. [12] deep learning has been well-reviewed in all applications with the food domain, explaining that it is effective in identifying food quality, recognition, and safety inspection. Yuan and Chen [13] in their research work, introduced a fresh identification approach of different vegetables and fruits instead of using deep learning pre-trained models to extract deep attributes. They employed these deep features with the application of principal component analysis and realized an excellence grade accurate freshness control. These studies have shown great motivation in different identifications in the food industry. By automating the accuracy of food determinations using image technologies in the meat and products, the applications remain suitable as they drive high accurate production and high precision. The identified challenges need a critical approach to achieve the real greatness of DL technologies. In addition, deep learning has enjoyed better application in various food science and engineering fields. In addition, Jmour et al. [14] described the development of deep learning-based convolutional neural networks in traffic sign categorization. These studies are examples to prove the versatility nature of deep learning in various fields, including food quality identification. Shin et al. [15] developed a novel rapid non-destructive spectroscopic tool for beef freshness categorization using deep spectral networks coupled with myoglobin information fusion. Apart from collecting reflectance spectra of beef samples, the research team used the convolutional neural network - based deep spectral network selection to achieve higher efficiency in the categorization of beef quality. Based on the experiment results, the deep spectral network yielded the potential for high beef quality categorization. Liao et al. [16] further described food quality categorization innovation with the introduction of a meat freshness identification model based on ResNet34 deconvolution neural network with a squeeze-and-excitation module. This model uses transfer learning and attention mechanisms and results in higher meat quality identification than other machine learning models. There are information systems attempting to identify food quality from images. For example, Agustin and Dijaya [17] created a beef quality classification system based on image processing and the k-NN. Through analyzing hue and texture highlights separated from meat photos and utilizing the k-NN calculation for order, the specialists demonstrated the viability of their procedure in separating between new and deteriorated beef in view of visual prompts. In another examination, Ren et al. [18] created a propelled convolutional neural system dependent on dynamic highlights removed from a profoundly touchy miniature electro-mechanical frameworks sensor gathering for characterizing sustenance newness. By consolidating dynamic highlight extraction into the CNN-based request unit, they accomplished high exactness in order sustenance newness, giving a quick and non-obtrusive strategy for quality control in the food business. Furthermore, Guo et al. [19] planned a convenient sustenance freshness figure stage dependent on counteractive action shading dimension labels and profound convolutional neural systems. By building unique scent fingerprints utilizing shading dimension labels and preparing a DCNN for example acknowledgment, they accomplished high exactness in anticipating meat newness, giving a momentary and precise technique for observing sustenance quality in actual time. Together these investigations cast appreciable insight into how significant progress has advanced and how adaptable deep getting to know is within the domain of meat scientific discipline. Whether distinguishing among diverse beef cuts, gauging microbial quality, or evaluating meat freshness, deep getting to know is turning in a noteworthy effect. And it's not simply about streamlining things, it's moreover about enhancing them. By utilizing AI, we are not just getting increasingly efficient and precise, yet in addition tackling a portion of the enormous difficulties in the meat business, which at last advantages us all who appreciate meat and those who work in the business. Looking ahead, there is such a great guarantee for even more invention and improvement in how we assess meat quality [20]. These examinations truly drive home how innovative deep getting to know innovation can be in arranging sustenance and ensuring it meets our principles. By tapping into progressed AI calculations, scientists and sustenance specialists can make frameworks that not just keep our nourishment protected yet in addition make it tastier and progressively fulfilling [21].

Freshness classification of meat is critical in ensuring quality and safe meat products which meet consumer demands and regulatory standards. Recent years have seen remarkable contributions to the accurate and reliable assessment of meat freshness through the integration of machine learning and artificial intelligence with different sensing technologies [22]. Besides, researchers have been coming up with innovative ways of evaluating the freshness of meat and meat products, as a measure of enhancing food safety and quality in both poultry and meat industries. It is shown on an LED monitor, and it has real-time meat freshness feedback from fresh meat to transition meat to rotten meat using the LED light indicators. This approach is an effective and scalable method for state-of-the-art meat quality control in food industry applications.

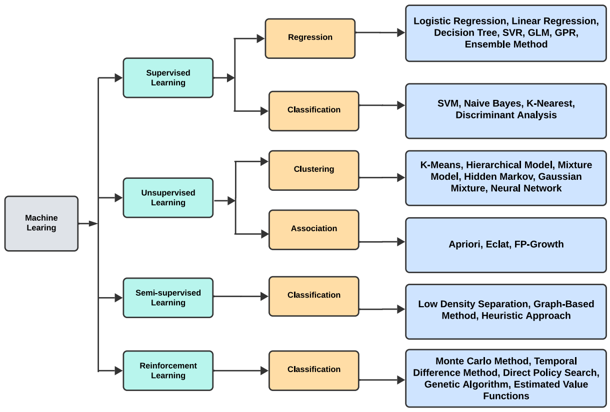

FIGURE 3. Machine learning algorithm overview.

The machine learning algorithms are categorized into four main types: supervised, unsupervised, semi-supervised, and reinforcement learning, as summarized in Fig 3. Supervised learning involves approaches such as regression and classification, whereas unsupervised learning is centered around techniques like clustering and association. Semi-supervised and reinforcement learning focus on classification, utilizing various advanced methods. This diagram offers a concise view of different machine learning approaches and their uses [6]. Bhuiyan et al. [6] has a new approach to symbolize freshness of meat using various AI and ML methodologies. This system detects and senses objects by using gas sensors, esp32-cam camera mounted on the car which collects data and passes it to an Arduino UNO microcontroller. Using supervised learning algorithms and a labeled beef dataset, researchers were able to correctly classify these videos 91 percent of the time. Therefore, this method improves the freshness existing practical methods for meat assessment when systems are generally not compatible with many systems so that these two assessments will be possible to use in a single portable device. A similar study by Li et al. [24] provides an alternative approach. In researchers classified beef cuts using spectral imaging which result from training ML classifiers on the measurements and attained over 90% prediction accuracy by implementing optimized classifiers. This process helps in an orderly identification of cuts and is a very rapid technique for non-destructive measurements. This is a major benefit as the application of AI imaging techniques is likely to become essential in the food industry in terms of quality assessment and identification. Shi et al. [25] presents a review of various non-destructive methods to assess meat. The methods discussed in this review include, among others, ultrasonic, machine vision, near-infrared spectroscopy, hyperspectral imaging, Raman spectroscopy, and the concept of the electronic nose/tongue. The authors analyze the characteristics of each method, as well as provide an overview of the relevant studies and reviews that use these technologies. At the same time, the review shows the growing importance of AI techniques and algorithms that can increase the efficiency of the rate of such assessment methods, as well as validate and ensure accurate and automatic evaluation of meat considering increasing demands of consumers and regulators. Kaya et al. [26] also suggest an ML-based approach for food quality assessment that is tolerant to sensor failure; however, the focus was on the evaluation of beef cut quality. The authors proposed the Single Plurality Voting System as a classification approach that enables the mitigation of sensor failures in electronic noses and, thus, allows for higher prediction accuracy. This method is innovative in terms of being capable of addressing the challenges associated with sensor drift and instability. As a result, the use of ML in electronic nose systems can become more reliable for food quality monitoring. While for meat, portable NIR spectrometry used in combination with ML applied to the freshness of other types of products is another viable option. As for the study by Brasil et al. [27] it was focused on the application of the approach to the quality of quail eggs to demonstrate how prediction and classification models could be used to quantify the parameters of freshness and classify samples properly. Such a non-destructive measurement would be particularly beneficial in real-time operation for the food industry that aims to enable interventions to preserve food quality and safety in time. Moreover, regarding eggs, Sehirli and Arslan [28] introduce a machine learning approach to classify the quality of eggs without using the traditional HU. They analyzed 20 features of egg traits obtained from 438 chickens to develop ML models, with logistic regression being the most appropriate one. Huh et al. [29] present a system of non-invasive meat freshness assessment, for which the EIS was combined with image classification techniques. The use of machine learning techniques significantly improved the prediction of freshness by comparing EIS with the traditional measures. Vargas-Sansalvador et al. [30] introduced a smartphone-based sensor integrated with pork meat packages for meat freshness classification. The sensor based on CO_2 level changes due to bacterial growth and meat spoilage offered a great solution to detect pork's freshness. It was completely convenient for the consumers to check the meat quality by scanning the smartphone without most of the required equipment and intended training. Park et al. [31] also proposed a solution using hyperspectral imaging data and ML methodologies to solve the problem of identifying fresh and frozen-thawed beef. Although little is known from their study paper, it seems to be feasible that constructing a predicting model with ML methods offers a rapid and non-invasive solution. Arsalane et al. [32] preferred to design a Digital Signal Processor or DSP platform-based embedded system for fast beef meat freshness prediction and identification by employing PCA and SVM algorithms. The study shows successful results in real-time classification and prediction of beef meat with freshness. It can be seen that portable and miniaturized detection systems can be used in the meat processing industry. Farinda et al. [33] introduced an automated beef quality classification system by using color and texture features to avoid the problems of the variations leading to the subjectivity of manual inspection methodologies. The study prepared 480 images and created a dataset that could be used to train and test an SVM classifier. In addition, statistical approaches and GLCM methods were implemented to extract color features in the HSI color space and classify cold beef and others. According to the results, the system provided great performance when normal beef is stored at room temperature and cold beef is stored in a fridge as accuracy was 97% to classify these two. Avianto and Wibowo [34] propose an automated system using Support Vector Machine (SVM) and RGB color moment features to classify chicken meat freshness. By extracting nine features from the red, green, and blue color layers, they evaluate the system with linear and RBF kernels, achieving 71.6% and 60.5% accuracy, respectively. The study highlights the potential of SVM in meat freshness detection and suggests further optimization to improve accuracy. Arsalane et al. [35] propose a non-destructive method for assessing beef meat freshness using artificial vision and machine learning. They extract color and texture features from meat images and apply three algorithms: *k*-NN, SVM, and NB. Their findings show that *k*-NN performs best with an accuracy of 92.59%, followed by SVM at 90.12% and NB at 87.65%. As stated above, all the studies except that of Park et al. provide solutions to the fresh meat identification as solutions are constructed to be rapid and portable in contrast to the manual inspection procedures except for the one consisting of hyperspectral imaging methodology. These studies collectively demonstrate the tremendous progress made in ML and AI-powered approaches for the classification of meat freshness. By combining cutting-edge sensing technologies with sophisticated ML algorithms, these solutions provide a fast, non-destructive, and reliable means to evaluate meat quality, meeting the rigorous standards imposed by contemporary consumers and guaranteeing food safety and security [36]. Altogether, these studies contribute to the advancement of food quality evaluation by presenting new methods and technologies to scientifically measure meat quality and sensorially evaluate meat freshness [37]. The integration of machine learning, sensor technology, and non-destructive testing offers a substantial prospect for improving food safety and quality in the poultry and meat industries [38].

Meat freshness classification is a vital element of securing food safety and quality levels in the industry. Historically, the evaluation of product quality has been more reliant on human judgment, manifested subjectively, depending on such indicators as smell, color, and touch [7]. Nevertheless, the introduction of innovative technological solutions has enabled operators to enhance their evaluations, making them more accurate. There have been several interesting points in recent research that address the challenge of identifying freshness. Using the electronic nose and machine learning approach, e-nose technology researchers offer a new solution to food safety and quality evaluations [8]. Juannata et al. [7] proposed an original method for multiclass classification of meat quality based on scent or odor, introducing an Electronic Nose technology grounded on an exceptional algorithm termed Neural Network. Owing to a dataset of 2220 data points acquired through machine learning, the e-nose technology was validated as accurate at an impressive 0.92 in classifying meat quality based on microbial population. The demonstrated abilities of e-nose technology, especially when aided by machine learning algorithms such as NN, can help consumers accurately pick safer meat products. In a similar effort, Mohamed and Hashim [8] developed an e-Nose tool providing a sound verification of the quality of chicken meat based on the gases from the spoilage process via the backpropagation algorithm: the latter obtained a significant accuracy of 96.6667%. This demonstrates a promising capacity for fresh determination in various industries which may not afford subjective or human-based assessments. Kartika et al. [39] suggested a novel approach to automatically offer the human-like classification of meat spoilage levels via semiconductor gas sensors, image processing, and a success rate of 82%. The novel integrated approach ensures objectivity and a reduced proportion of health risks in the industry. A more comprehensive approach was suggested by Weng et al. [40], it is the quality assessment of meat freshness with an electronic nose, computer vision and tactile artificial equipment. That is –it gets you the best reliability and the most detections. By concluding the quality of meat through this mechanism, a detailed inspection with video enhanced images recognizes its texture as well color and smell to much lesser extent making new possibilities in identifying its quality. Denih et al. [41] proposed the design of an electronic cart that detects beef freshness based on color and gas sensor data using K-Nearest Neighbor algorithm. This one supply information to the clients who purchase goods from the market. The device was able to differentiate between three different states of freshness in meat products (fresh, semi fresh and not fresh) with an accuracy rate of 93%. Somewhat similar, Feyzioglu and Taspinar [42] applied the e-nose data for various beef body parts to develop a decision support system that predicted meat quality. Approach: The researchers used a dataset that was rich in animal carcass features to develop a system allowing accurate prediction of beef quality through machine learning and post hoc test-based efficient feature selection. Pereira et al. [43] also investigated the use of electric gas sensors such as e-noses to monitor meat freshness. Such a sensor of meat-emitted volatile organic compounds can help monitor food safety for humans as shown in the researchers' results. Grassi et al. [46] defined the technology for fresh pork, beef, and mutton samples as an electronic nose (e-nose) applied to distinguish different species of meat and freshness status. They also developed a portable and simplified e-nose model named Master sense to help estimate the freshness of raw meat or fish. The high sensitivity and specificity of the tool is demonstrated by its ability to score 2 unrelated food groups as two different foods.

Advances in data fusion, machine learning algorithms and sensor technology have revolutionized the way we classify meat freshness. These techniques have been used for rapid, accurate and objective evaluation of meat quality, which has added to food safety and consumer confidence from packing aesthetic point of view [44], [47]. Moreover, additional research during this injury creates the potential to continue to enhance quality assessment in meat and contribute to the development of the food industry. Furthermore, the studies mentioned above serve as a testament to the successful use of e-nose technology in meat freshness classification [48]. The application of machine learning algorithms, the solvent selection of the relevant features and the inventive methods used to construct the sensing systems introduced in the studies above set premises for the increased standards for food safety.

To address the challenge of ensuring food safety and maintaining the quality of meat products, we conducted research to develop an innovative IoT-based system for real-time meat species and freshness classification [49], [50]. The system integrates a custom CNN for image classification and a set of gas sensors (MQ135, MQ4, and MQ136) to detect gases emitted during the spoilage of meat. Using an ESP32-CAM to capture high-resolution images and a Raspberry Pi 3 to process both the image and sensor data, the system performs accurate classification tasks. The results are displayed on an LED screen, and real-time feedback on the meat's freshness is provided through LED indicators, signaling fresh, transitional, or rotten meat. This solution offers an efficient, scalable, and reliable method for ensuring meat quality and safety in the food industry.

III. METHODOLOGY

This research integrates deep learning models, gas sensor data, and IoT technology to classify meat species and assess meat freshness in real-time, creating a comprehensive solution for ensuring meat quality and safety. High-resolution images of fresh and rotten meat were captured at two key time points, with fresh meat photographed at 0 hours and rotten meat after 48 hours of spoilage. The dataset includes 6,672 images for meat freshness classification and 3,256 images for species classification [1]. In order to improve performance and generalization, data augmentation methods such as rotation, scaling, flipping or color adjustments are used in order to increase the size and diversity of the dataset. It increased the accuracy of models in general and saved them from overfit. The IoT device need to monitor the gases released from the meat as well (MQ135 for ammonia, MQ4 for methane and MQ136 for hydrogen sulfide) using three gas sensors in addition to image data as the proteins and fats in the meat break down, they release gases such as ammonia, methane, and hydrogen sulfide, which serve as key indicators of the meat's freshness. These gas emissions, detected by the integrated sensors, provide valuable insights into the degree of spoilage, enabling real-time freshness classification. The gas sensor measurements were recorded at 0, 12, 24, 36 and 48 hours, giving the system insights to monitor variations in the meat chemistry as the meat decayed and time stamped spoiling process. We study the combined gas and visual sensor data generated by an Internet of Things (IoT) system for meat species and quality evaluation. A sample meat is examined simultaneously using a camera sensor and three dedicated gas sensors (MQ135, MQ4, MQ136). They are crucial for detecting gases that may spoil like ammonia, methane, or hydrogen sulfide. A Deep Learning Model is used to analyze the work done by the raspberry pi 3 to identify the species and meat quality. The outcome of this analysis takes place in real-time: an LED display visually informs you about the type and quality of meat, while LED indicators impressions of gas sensors are providing a more thorough and timely state evaluation for the meat. k-NN and SVM. These models were train and test through different model's metrics including, accuracy, precision, recall, F_1-score. ResNet-50 was fine-tuned on the meat classification task, and baselines from k-NN and SVM were put in place to compare how well the models learned versus more traditional methods. Additionally, the IoT gadget incorporates information from the gas sensor to separate its freshness level of the meat as well. Using the gas sensors, the meat was categorized as fresh, half-fresh or rotten with predefined thresholds of what amount of ammonia, methane and hydrogen sulfide were detected from the pork. The user is presented with this classification through LED indicators, where fresh meat is represented by green, half-fresh meat by yellow, and rotten meat by red. This real-time feedback guarantees that the apparatus offers a trustworthy and accurate evaluation of meat freshness. It is based on data from both image and gas sensors.

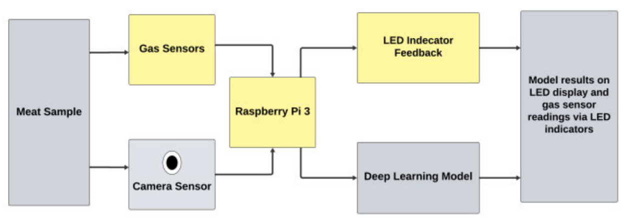

FIGURE 4. Conceptual framework of the proposed method in this research.

In Fig. 4, we see an IoT-based system engineered to evaluate meat quality and species through integrated visual and gas sensor data. A meat sample is simultaneously examined by a camera sensor and three specific gas sensors–MQ135, MQ4, and MQ136, which are critical for detecting gases like ammonia, methane, and hydrogen sulfide that signify spoilage. The data captured is processed by a Raspberry Pi 3, and a deep learning model analyzes it to classify the meat's species and quality. The outcomes of this analysis are displayed in real-time: visual data regarding the meat species and quality are shown on an LED display, while readings from the gas sensors are presented via LED indicators, offering a detailed and immediate assessment of the meat's condition.

A. DATA COLLECTION

We gathered beef and mutton for this study from nearby markets to guarantee a varied sample for species and freshness categorization. To preserve a thorough record of the origin and quality of each piece of meat, meticulous documentation was kept [1]. We took high-resolution photos at two critical times using an advanced IoT device with an ESP32-CAM module: first, at 0 hours to set a baseline for fresh meat, and then, at 48 hours, to record the condition after it had gone bad. In addition to the visual evaluations, our Internet of Things device was equipped with gas sensors (MQ135, MQ4, and MQ136) that tracked gas emissions suggestive of meat deterioration. These sensors gave off continuous readings every 0–12, 12–24, 24–36, and 36–48-hour periods. As a result, they produced a thorough chemical profile that matched the stages of visual decay that the camera was able to capture. In order to guarantee accurate calibration and validation of our classification models, we first collected a predetermined number of images, which we then further enlarged through the application of image augmentation techniques. The dataset was initially composed of 6,672 images for the classification of meat freshness and 3,256 images for the classification of species. Following the application of augmentation techniques to improve both volume and diversity, we were able to produce a refined dataset that included multiple categories: For the freshness classification, there were 1,608 images of fresh beef, 1,648 images of fresh mutton, 1,712 images of rotten beef, and 1,704 images of rotten mutton; for the species classification, there were 1,608 images of beef and 1,648 images of mutton. Table 1 presents a detailed summary of the image dataset used for meat freshness and species classification, outlining the total number of images collected, as well as the distribution of images allocated for training and validation across different categories of fresh and rotten beef and mutton. This enriched dataset is crucial in bolstering the robustness and reliability of our findings, providing a comprehensive basis for the advanced IoT-enabled methodology aimed at revolutionizing meat processing. By delivering real-time, reliable data, our study supports the highest standards of safety and quality, builds consumer trust, and ensures regulatory compliance in the meat industry. The vision and nose data were temporally synchronized using the timestamps in all the sensors as well as the timestamps of each frame from the camera. This synchronization allows a robust multi-modal study for significantly classifying the meat according to its kind and freshness as shown in Fig. 5. The images that we periodically capture by camera sensors is perfectly in sync with the gas readings from MQ135, MQ4, MQ136 and other types of pollution sensing sensor units to enable us a multi-modal analysis. It would be making classifying meat by species and freshness accurate. By claiming that we use continuous gas measurements of the released gases and that our system allows for high-resolution images, it makes it possible to identify subtle variations in the state of the meat which may not be visible from picture alone. This dual approach provides a time course of changes during the decay process of meat, essential for establishment of predictive models to predict spoilage before it is obvious. This high-tech IoT-based proposition is designed to drive the transformation of the meat processing industry by delivering immediate accurate data, assuring the pinnacle levels of safety and quality, enhancing consumer confidence as well as meeting regulatory needs. While the experimental setup was designed to ensure accurate and reliable data acquisition, certain biases and limitations may influence the performance of the gas sensors. A notable limitation pertains to the impact of environmental factors on the sensor readings. Variations in temperature, humidity, and air pressure could affect the sensitivity and accuracy of the gas sensors, as they are known to be responsive to such environmental changes. To mitigate these influences, the sensors were calibrated under controlled conditions before each experiment, and testing was conducted in environments with minimal fluctuations in temperature and humidity. Nonetheless, it is essential to acknowledge that these environmental factors may still introduce some degree of variability into the data. Future work could further refine the system by incorporating additional calibration procedures in diverse environmental conditions or by integrating environmental sensors to account for these variables.

B. DATA PROCESSING AND MODEL TRAINING WORKFLOW

In our project, we utilize a combination of custom CNN and standard architectures such as ResNet-50 for deep learning tasks, along with traditional machine learning models like k-NN and SVM for comparative analysis. The main goal is to evaluate with established models, our custom CNN in fresh meat species classification. The custom CNN is developed to make the most of the dataset with specific challenge as above: features extraction and accurate classification between images of fresh meat at marginal freshness level of different species. On the positive side, we use ResNet-50, a well-known deep learning model that is famous for its depth and residual learning capability, and it achieved high accuracy on large-scale image recognition tasks. We also implement k-NN and SVM, for a higher-level model evaluation. k-NN is chosen for its simplicity and good performance when compared to those methods which require training of a model. We chose the SVM because it is a relatively robust algorithm that can handle high-dimensional data and that delivers strong baseline by maximizing the margin between one class of training samples split and their neighbors from other classes of examples. We use accuracy, precision, recall, F_1-score and Matthew's correlation coefficient (MCC) to evaluate the performance of our custom CNN with ResNet-50 and k-NN and SVM. These metrics have been computed using a ten-fold cross validation technique, demonstrating the robustness and effectiveness of our custom CNN on different data partitions, and demonstrating the potential of our trained models in real world scenarios against other state-of-the-art models for meat classification tasks. This comparative study

TABLE 1. Dataset creation time-table.

Feature Name	Meat Freshness Classification				Meat Species Classification	
	Fresh Beef	Fresh Mutton	Rotten Beef	Rotten Mutton	Beef	Mutton
Number of Total Images	1608	1648	1712	1704	1608	1648
Number of Images Use for Training	1286	1318	1369	1363	1286	1318
Number of Images Use for Validation	322	330	343	341	322	330

provides a valuable reference for this purpose, demonstrating the advantages and limitations of these models, which offer guidance for redesigning our workflow in relation to meat freshness and species classification. Fig. 5 illustrates the framework for detecting meat freshness and quality using a machine learning approach. It starts with the collection of an image dataset, which contains both fresh and rotten samples of beef and mutton. The images are acquired and processed to create a structured dataset. After pre-processing, the dataset is divided into a training set and a test set. The training set undergoes cross-validation to fine-tune the performance of machine learning models, including custom CNN, ResNet-50, k-NN, and SVM algorithms. Once trained, these models are tested, and their performance is assessed for accurately classifying meat samples as fresh or rotten, contributing to the evaluation of meat freshness and overall quality.

1) CUSTOM CONVOLUTIONAL NEURAL NETWORK (CNN)

The architecture of our custom CNN model, which is specifically optimized to be organized in such a way that it performs the best, for classification of meat species and freshness. The first layer is a series of Conv LSTM layers with 32 filters, which grow to a maximum of 512. This configuration thus allows the network to capture both simple and deeply complex features in a widespread sense, making it suitable for classification of fine-grained differences in meat texture and conditions. Each convolutional layer uses a kernel size of (3, 3) typically for capturing the spatial hierarchy in images. Same padding ensures that after convolution the spatial dimensions will remain, which is essential when learning boundaries in meat images. Following each convolutional block, a Max Pooling layer with a pool size of 2×2 and a stride of 2 reduces the spatial dimensions of the feature maps. The down sampling step, which pools together the information on the presence of features in all 4 quadrants of the feature map and reduce both computational resources while decreasing also overfitting risks. In our model, the Dropout layer set at a rate of 0.25 after the pooling layers serves as a form of regularization to prevent overfitting.

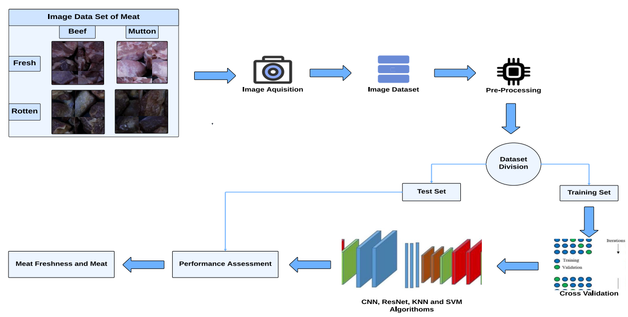

FIGURE 5. Meat freshness and species classification system framework.

This is particularly important given the complexity of the network and the detailed nature of the meat image data. The architecture converges into densely connected layers, which synthesize the learned features into predictions. The first dense layer contains 1500 neurons, providing substantial capacity to learn from the high-level features extracted by the convolutional layers. A second dropout at a rate of 0.4 follows, further aiding in regularization before the final classification layer. In our custom CNN model, the inclusion of additional layers enhances feature extraction, contributing to improved robustness. The convolutional layers process input images by applying filters and generating feature maps, as defined by Equations (1) – (4). In Equation:

$$W_2 = \frac{W_1 - F + 2 * P}{S} + 1 \tag{1}$$

$$H_2 = \frac{H_1 - F + 2 * P}{S} + 1 \tag{2}$$

where $W_1 * H_1 * D_1$ are input dimensions, F is filter size, P is padding, and S is stride, with:

$$D_2 = \mathrm{K} \tag{3}$$

representing the number of filters. Max-pooling layers down sample spatial dimensions using,

$$W_2 = \frac{W_1 - F}{S} + 1 \tag{4}$$

where F is the pooling size and S is stride, preserving the depth D_1. Your model includes additional convolutional layers with higher filter depths (up to 512 filters) to capture more complex patterns. After the final convolutional block, the output is flattened and passed through multiple dense layers, with an additional dense layer to further improve learning. Dropout is applied for regularization, and the model concludes with a SoftMax layer for class prediction. This extra layer configuration improves accuracy and ensures better generalization [14].

2) ResNet50

Convolutional Neural Network (CNN) model utilizing the ResNet50 architecture is applied for the classification of meat freshness and species. The ResNet50 model, pre-trained on the ImageNet dataset, serves as the feature extraction backbone. The top fully connected layers of ResNet50 are omitted, allowing extracted features to be passed through custom fully connected layers to perform classification tasks. Convolutional layers process input data, producing feature maps, with the spatial dimensions of these maps determined by the following equations (5) and (6):

$$W_2 = \frac{W_1 - F + 2 * P}{S} + 1 \tag{5}$$

$$H_2 = \frac{H_1 - F + 2 * P}{S} + 1 \tag{6}$$

Here, W_1 and H_1 are the input width and height, F denotes the filter size, P represents the padding, and S refers to the stride applied. These dimensions are further reduced through max-pooling layers, which assist in down sampling the spatial representation while preserving the important features for classification. The final classification is achieved through a series of fully connected layers, concluding with a SoftMax activation function, represented by the following equation (7):

$$softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{zj}} \tag{7}$$

where zi indicates the score for class i, and K is the number of output classes. The model is optimized using the Adam optimizer with a learning rate of 0.0001, and categorical cross-entropy is used as the loss function. The model's performance is evaluated using metrics such as accuracy, precision, recall, F_1-scores, and a confusion matrix. The trained model and associated metrics are saved for deployment and further analysis [14], [16].

3) *k*-NEAREST NEIGHBORS (*k*-NN)

The *k*-NN algorithm is a non-parametric, supervised machine learning model that classifies data points based on the distance between them. In this study, K=3 is used, with the Euclidean distance defined by the following equation (8):

$$\mathrm{d}\left(D_1, D_2\right) = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \tag{8}$$

Loading Training and Validation Image Datasets Then I: — Extract the features of image using PCA to reduce dimensionality – Normalize data by using StandardScaler Perform a grid search to find the optimal K and train the best *k*-NN model on scaled features. During validation predictions are generated and performance is evaluated using a confusion matrix, precision, recall and F_1-scores. A Heatmap from Seaborn is used to plot the confusion matrix. Consequently, the trained *k*-NN model is saved in conjunction with PCA and scaler for use in future real-time plant disease classification [28].

4) SUPPORT VECTOR MACHINE (SVM)

This In this project, SVM model for classifying meat's freshness and type using image data. First, the images from the training and validation datasets are loaded and resized to a standard size. Then it is feature extracted on the image data, then dimensionality reduced using PCA reducing the feature set to 20 principal components. It improves computational efficiency while preserving the key data points. The extracted features are then standardized using the 'StandardAero' to normalize the data for consistent input into the SVM. Hyperparameter tuning is performed using 'GridSearchCV', which optimizes key SVM parameters, such as C (the regularization parameter that controls the trade-off between maximizing the margin and minimizing classification error), the kernel type (evaluating both linear and Radial Basis Function (RBF) kernels), and (which defines the influence of each training example for the RBF kernel). The SVM's decision boundary is determined by the following function, as shown in equation (9):

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b) \tag{9}$$

where $K(x_i, x)$ represents the kernel function, α_i are the Lagrange multipliers, y_i are the class labels, and b is the bias term. This function defines how the SVM separates the data points into their respective classes. The performance of the model is evaluated using a confusion matrix and standard classification metrics, including precision, recall, and F_1-scores, to assess its accuracy. Finally, the trained SVM model is saved along with the PCA transformation and scaling parameters using joblib to be reused in future classification tasks [32], [33].

C. PERFORMANCE EVALUATION

We evaluated the performance of our meat classification and analysis method in terms of accuracy, precision, recall, Matthew's correlation coefficient (MCC) and F_1-score, as described above. These metrics give you a much broader picture of how well your model is functioning for different aspects of meat classification and analysis.

1) ACCURACY

Overall Accuracy: Rate which class of features the model has predicted correctly It is determined by the number of correctly classified samples (true positives and true negatives) divided by the total samples

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

2) PRECISION

Precision is the number of true positive predictions made by models over the total number of positive predictions predicted by the model. Precision is calculated as true positive predictions divided by the total number of positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{11}$$

3) RECALL

Recall (or Sensitivity) considers the number of positive instances that have correctly been detected by proportionately dividing all the true positive cases. Sensitivity is computed as true positive predictions divided by the total number of actual positive instances.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{12}$$

4) MATTHEWS CORRELATION COEFFICIENT (MCC)

The Matthews correlation coefficient provides a balanced measure of the quality of binary classifications, considering both true positive and true negative predictions, while also accounting for false positives and false negatives. It is defined as

$$\text{MCC} = \frac{TP*TNFP*FN}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \tag{13}$$

5) F_1-SCORE

The F_1-score is harmonic means of precision and recall; it represents the balance between precision and recall. It is defined as the harmonic means of precision and recall.

$$F_1 = \frac{2 * Pre * Rec}{Pre + Rec} \tag{14}$$

We calculated these performance metrics using the results from ten-fold cross-validation on our proposed approach. They provide insights on how the model has been good at identifying different types of meat and its conditions which speaks to the models' performance [13].

IV. HARDWARE DEVELOPMENT AND TESTING

In our last project on Meat Freshness Classifier with Machine and AI we performed the construction of an IoT device using MQ135 gas sensor, MQ4 methane gas sensor and Arduino Uno for processing [6]. We also make a minor enhancement to the system by adding MQ136 gas sensor for hydrogen sulfide detection and replaced processing hardware with Raspberry Pi 3 in order to accommodate the custom CNN model since it is not CPU-friendly compared to mm Labs Frozen Inference Graph. The previous system used simpler machine learning algorithms, for which the Arduino Uno was sufficient, but the higher computational demands of the custom CNN model necessitated the transition to the more powerful Raspberry Pi 3. Both projects incorporated the ESP32-CAM module to capture high-resolution images of meat samples for analysis. In this updated version of the IoT device, the ESP32-CAM captures images, while the three gas sensors–MQ135, MQ4, and MQ136–monitor the emissions of gases such as ammonia (NH3), methane (CH4), and hydrogen sulfide (H2S), which are indicative of meat spoilage [49]. The Raspberry Pi 3 processes both the visual data from the camera and the gas sensor data to classify the meat's species and freshness. The results are displayed on an LED display, and the system uses three LED indicators (red, yellow, and green) to provide real-time feedback: the green LED signals fresh meat, the red LED indicates rotten meat, and the yellow LED represents meat that is neither fully fresh nor fully rotten, indicating an intermediate state. The hardware setup, illustrated in Fig. 6 (Circuit Diagram of our IoT device), was carefully designed for seamless integration and optimal performance.

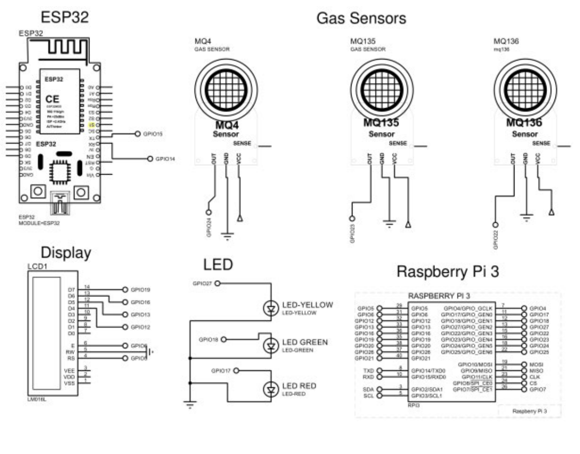

FIGURE 6. Circuit diagram of our IoT device (proteus).

The gas sensors and ESP32-CAM are connected to the Raspberry Pi 3 using jumper wires. The Raspberry Pi 3 acts as the main processing unit, regulating power, controlling the sampling rate of the sensors, and processing the captured images using the custom CNN model. A gas calibration kit was used to ensure accurate readings from the MQ135, MQ4, and MQ136 sensors, while the exposure and settings of the ESP32-CAM were adjusted to ensure the capture of

TABLE 2. Primary system components'.

S/N	*Component Required*	*Quantity*
1	MQ136 Sensor	1
2	MQ135 Sensor	1
3	MQ4 Sensor	1
4	ESP32-CAM module	1
5	Raspberry Pi 3	1
6	Bread Board	1
7	LED (Red, Green, Yellow)	3

clear, high-resolution images. Preprocessing techniques, such as image normalization, resizing, and noise reduction, were applied to ensure high-quality input for the custom CNN model. The gas data was similarly formatted. The gas data triggered the indications in led lights only. Once the data is processed, the classification results from the images are displayed on the LED screen, and the LED lights provide an immediate indication of the meat's freshness based on the gas sensor readings [50].

Additionally, the final assembled device, with all components integrated for real-time meat monitoring, is depicted in Fig. 7. The system components used in this enhanced IoT device are outlined in Table 2, which summarizes the primary hardware elements. This enhanced IoT system offers a more robust, accurate, and scalable solution for real-time meat classification and freshness classification, improving upon the previous design through the incorporation of more advanced hardware and algorithms.

FIGURE 7. Picture of final device.

V. RESULTS AND DISCUSSION

Meat Quality and Species Classification: The dataset consists of 9,928 images at 512 by 512-pixel resolution. In general, 6,672 images were separated for meat quality classification to classify whether beef or mutton is rotten or fresh. The dataset was organized into fresh beef, rotten beef, fresh mutton, and rotten mutton which made the distribution equal and consistent for all categories. This balanced design was critical to building and testing models effectively. Besides that, 3,256 images were used for meat species classification to differentiate between beef and mutton. This dataset was balanced as well, to have a most fair model training and testing. The dataset was divided into 75% for training and 25% for validation. The Pre-processing steps included resizing the images and normalization of pixel values to keep its uniformity across the dataset. The models that this study was based on were custom CNN, ResNet-50, k-NN, and SVM. We use these models to predict the meat quality and species classification. Both cases showcased the efficiency of deep learning, with models such as custom CNNs and ResNet-50 being able to take advantage of their ability to extract intricate features from the high-resolution images. The model was validated in the four categories: accuracy, precision, recall and F_1-score. Custom CNN and ResNet-50 models displayed increased accuracy compared to conventional machine learning techniques such as k-NN and SVM for meat quality grading tasks where subtlety of differences between the meat quality and species levels were present.

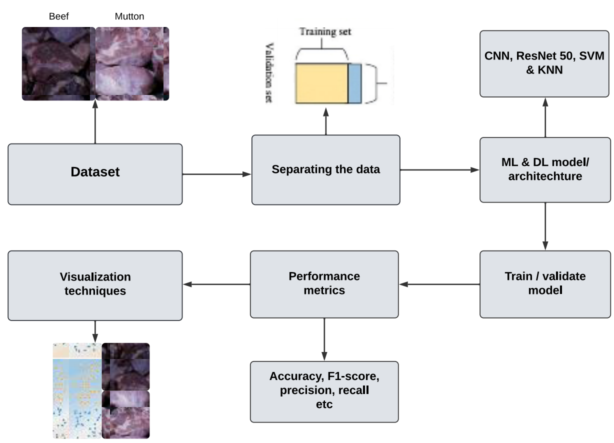

FIGURE 8. Workflow of meat quality and species classification system.

Fig. 8 outlines the workflow for the meat quality and species classification system, beginning with a dataset of beef and mutton images, categorized by freshness as either fresh or rotten. The images undergo essential preprocessing steps, including resizing to images and normalization, ensuring uniformity for analysis. The dataset is split into training and validation sets to facilitate model development and evaluation. Various traditional machine learning and deep learning models such as custom CNN, ResNet-50, k-NN, and SVM are trained to classify both meat quality and species. Cross-validation techniques are employed to optimize the models, ensuring they perform well on unseen data. The validation set is used to assess model performance through metrics like accuracy, precision, recall, and F_1-score, which indicate how well the models classify meat quality and species. Visualization techniques are then used to present the results, providing clear insights into the effectiveness of the classification system.

A. ANALYSIS OF MEAT SPECIES CLASSIFICATION

In this analysis, we evaluated the performance of several machine learning models, including custom CNN, ResNet-50, k-NN, and SVM, for the task of meat species classification. The dataset used for this task consisted of 3,256 images, evenly distributed between two meat species categories—beef and mutton. To ensure consistent results, images were preprocessed by resizing them to 512×512 pixels and normalizing their pixel values. This preprocessing step was crucial to standardize the input and ensure that the models could effectively differentiate between visual characteristics such as texture, color, and marbling.

The custom CNN exhibited outstanding performance, achieving a remarkable accuracy of 99% in the task of meat freshness and species classification as shown in Fig. 8. This high level of accuracy was attributed to the carefully designed architecture of the model, which was specifically tailored to handle the complexities of classifying meat species. Such used a CNN of stacked convolutional layers, the initial layer has 32 filters in order to learn local patterns (such as edges), later greater values up to 512 to capture more complex features. These patterns were important for discerning the visual differences in meat texture, amount of marbling or other characteristics that set beef apart from mutton. The convolutional layers use 3×3 kernels with 'same' padding, which keeps the spatial dimension of the input as it is and protects border information which is important for accurate classification. A 2×2 Max Pooling layer is applied after each block to lower the spatial dimension of feature maps and avoid overfitting but also not lose important features. We include a dropout layer (0.25 and 0.4) for regularization, which helps making the model more robust by preventing overfitting problems. These learned features are then synthesized by dense layers, the first of which contains 1,500 neurons to cope with the data complexity. The last layer is a soft max, and we get the probability of detecting beef and mutton. This resulted in custom CNN having precision, recall, and F_1-score of 0.99 (min misclassification), for both meat classes. That custom CNN significantly outperformed traditional machine learning models as well as other state-of-the-art deep learning approaches in meat species classification underscores its improved feature extraction and generalization ability, which would make it a better-suited model for this problem.

ResNet-50, another deep learning model, also delivered strong performance, achieving an accuracy of 98% as shown in Fig. 9. While it trailed slightly behind CNN, ResNet-50 showed excellent results in terms of precision and recall.

For beef classification, ResNet-50 achieved a precision of 0.99 and a recall of 0.98, with an F_1-score of 0.98. For mutton classification, the precision was 0.98 and the recall was 0.99, leading to an F_1-score of 0.98. ResNet-50's residual learning capabilities allowed it to retain and leverage important features, contributing to its high classification accuracy, especially when handling intricate and varied textures in the meat samples. Although its performance was marginally lower than CNN's, ResNet-50 proved to be highly effective at distinguishing between beef and mutton.

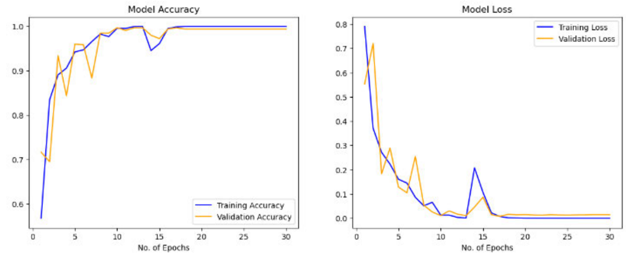

FIGURE 9. Accuracy and loss graphs for CNN model in meat species classification.

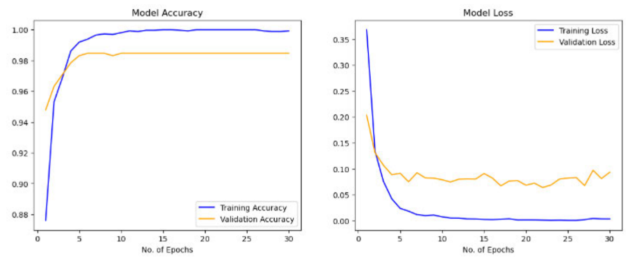

FIGURE 10. Accuracy and loss graphs for ResNet-50 model in meat species classification.

SVM emerged as another competitive model, achieving an accuracy of 97%. While SVM did not outperform the deep learning models, it showed impressive results, particularly when distinguishing between clear-cut visual categories. For beef, SVM recorded a precision of 0.98, a recall of 0.96, and an F_1-score of 0.97. Similarly, for mutton, the precision was 0.96, the recall was 0.98, and the F_1-score was 0.97. The model's ability to define clear decision boundaries through hyperplane separation allowed it to perform well, though it struggled to match the more intricate pattern recognition capabilities of custom CNN and ResNet-50, especially when dealing with fine-grained visual distinctions.

By contrast, k-NN showed the worst performance by reaching an accuracy of 86%. It also did quite poorly with mutton, which is likely one of the harder categories to segment, as indicated by its low recall (0.81) and large number of false negatives. Mutton had an accuracy of 0.91, but the F_1 -score was lower at 0.86 as well because the keras model also failed to predict mutton images properly. k-NN gave us 0.83 precision, 0.92 recall and 0.87 F_1-score with beef classification. This confirmed k-NN's inadequacy for more complicated classification problems. With only distance-based metrics, k-NN failed to capitalize on the subtle differences between beef and mutton — it was unable to identify the highly detailed visual patterns required for identifying species accurately.

Overall, Custom CNN and ResNet-50 emerged as the most effective models for meat species classification. CNN's deep learning architecture enabled it to consistently achieve higher accuracy, precision, recall, and F_1-scores, making it the best performing model for this task. ResNet-50 followed closely, providing strong results, and confirming its utility in classification tasks requiring detailed pattern recognition. SVM also performed admirably, though it lacked the nuanced feature extraction capabilities of the deep learning models. k-NN, while useful in simpler classification tasks, fell short when faced with the complex texture and marbling patterns required for accurate species identification in this context. These results highlight the clear advantage of deep learning approaches, particularly custom CNN, and ResNet-50, in achieving superior performance in meat species classification. The comparative performance of these models for both meat species is summarized in Table 3. The table provides a detailed comparison of the accuracy, precision, recall, and F_1-scores achieved by each model across these classification tasks.

B. ANALYSIS OF MEAT QUALITY CLASSIFICATION

In the task of meat freshness classification, four models—custom CNN, ResNet-50, SVM, and k-NN –were evaluated for their ability to differentiate between fresh and rotten meat across both beef and mutton categories. The dataset comprised 1,336 images, evenly distributed across four classes: fresh beef, fresh mutton, rotten beef, and rotten mutton. The objective was to assess the models' capacity to accurately classify meat freshness based on the visual characteristics presented in the high-resolution images.

The accuracy achieved by the custom CNN was also competitive and it gave an outstanding performance of 99% accuracy in meat freshness classification as shown in Fig.11. The exceptional performance of the model was largely due to its well-designed architecture aimed at capturing subtle visual variations in meat. In terms of architecture, the Custom CNN model leveraged successive convolutional layers with 32 filters intensified up to 512, which helped it in capturing low level and high-level features from the images. The ability to distinguish between fresh and rotten meat based on minor texture, color, and other visual cues among a wide range of features was crucial. For the convolutional layers, we used 3×3 kernels with same padding even this does not influence result if kernel size 5,7 or 11 it doesn't provide increase in final performance and make training slower, but the point was to keep images spatial dimensions equal as they were initially no important boundary information would lose due convolutional processing. After each convolutional block, there was a Max Pooling layer with a pool size of 2×2 to reduce spatial dimensions and computational expenses while maintaining key features and reducing the risks of overfitting. Few Dropout layers were also added in different positions with the rate set to 0.25 and 0.4 to regularize the model and reduce overfitting even further. These dense layers processed the high-level features that were represented by convolutional and max-pooling layers, with capacity to maintain representation of complex input data in 1,500 neurons of the first fully connected layer. The final SoftMax layer then produced the probabilities for the classification of fresh and rotten meat.

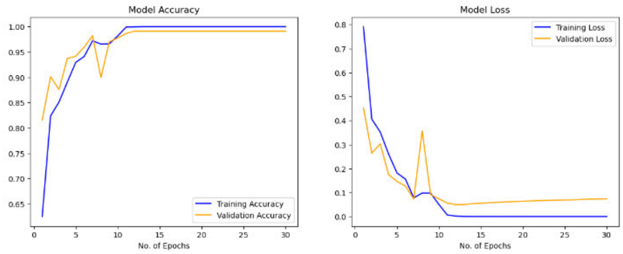

FIGURE 11. **Accuracy and loss graphs for custom CNN model in meat quality classification.**

The custom CNN achieved near-perfect precision, recall, and F_1-scores for each meat category, with 0.99 for fresh beef, 1.00 for fresh mutton, 0.99 for rotten beef, and 0.98 for rotten mutton. These exceptional results underscored the custom CNN's effectiveness in classifying meat freshness, as it consistently outperformed traditional machine learning models and other deep learning architectures by leveraging its robust feature extraction and generalization capabilities.

ResNet-50 also performed exceptionally well, achieving an accuracy of 98% as shown in Fig. 12. Although slightly behind custom CNN, ResNet-50 maintained high precision and recall across all categories. For fresh beef and mutton, precision and recall values were both high, with ResNet-50 achieving a precision of 0.97 for fresh beef and 0.98 for fresh mutton. The model performed similarly well on the rotten meat classes, achieving a precision of 0.99 for rotten beef and 0.99 for rotten mutton, though there was a slight decrease in recall for rotten mutton (0.97). The high performance of ResNet-50 highlights its ability to handle the complex patterns present in meat imagery, though it is slightly lower recall compared to CNN suggests that it may struggle in some edge cases involving more subtle visual cues of freshness or spoilage.

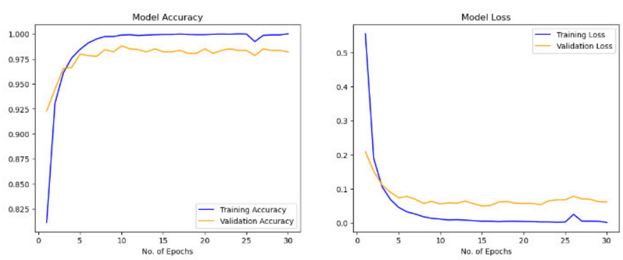

FIGURE 12. **Accuracy and loss graphs for ResNet-50 model in meat quality classification.**

SVM also delivered strong performance, achieving an overall accuracy of 96%. The precision and recall for fresh beef and mutton were 0.94 and 0.96, respectively, while for rotten beef and mutton, SVM achieved values around 0.97 for both precision and recall. While SVM performed well overall, particularly in classifying rotten meat, it was slightly less accurate than custom CNN and ResNet-50 in distinguishing

TABLE 3. Evaluation of custom CNN, Resnet-50, *k-NN*, and SVM models for meat species and meat freshness classification.

Class Name	Custom CNN			ResNet-50			k-NN			SVM		
	Precision	Recall	F_1-score	Precision	Recall	F_1-score	Precision	Recall	F_1-score	Precision	Recall	F_1-score
Fresh Beef	0.99	1.00	1.00	0.97	0.98	0.97	0.75	0.86	0.80	0.94	0.96	0.95
Fresh Mutton	1.00	0.99	1.00	0.98	0.99	0.98	0.83	0.84	0.84	0.96	0.95	0.95
Rotten Beef	0.99	0.98	0.99	0.99	0.99	0.99	0.89	0.84	0.86	0.97	0.97	0.97
Rotten Mutton	0.98	0.99	0.99	0.99	0.97	0.98	0.86	0.78	0.82	0.97	0.97	0.97
Beef	0.99	0.99	0.99	0.99	0.98	0.98	0.83	0.92	0.87	0.98	0.96	0.97
Mutton	0.99	0.99	0.99	0.98	0.99	0.98	0.91	0.81	0.86	0.96	0.98	0.97

the fine-grained visual differences between fresh and spoiled meat. This model's reliance on decision boundaries may have led to minor misclassifications in cases where visual characteristics were not as distinct.

k-NN on the other hand gave slightly lesser accuracy, which was 83%. It did well on fresh mutton — a precision of 0.83 and recall of 0.84 – but not so great with fresh beef, only managing a low precision of 0.75 for that category. By contrast, k-NN performed well on rotten meat examples just some of the time – it recalled rotten mutton at 0.78 and rotten beef at 0.84. This result showed that k-NN was not perfect to find the subtle differences for meat freshness classification using distance metric. The discrepancies in the classes show that k-NN does not manage complex image classification tasks very well, especially on more visually demanding dataset like the meat one.

Overall, custom CNN and ResNet-50 emerged as the most effective models for meat freshness classification, with custom CNN slightly outperforming ResNet-50 in terms of accuracy and consistency across all metrics. SVM provided a strong alternative, particularly in cases where computational resources are limited, while k-NN's performance demonstrated the need for more advanced feature extraction methods to improve accuracy in such tasks.

The comparative performance of these models for both meat freshness classification is summarized in Table 3. The table provides a detailed comparison of the accuracy, precision, recall, and F_1-scores achieved by each model across these classification tasks.

C. ANALYSIS OF BEEF QUALITY CLASSIFICATION WITH IoT DEVICE GAS SENSORS

In this study, we employed an IoT-based system equipped with gas sensors—MQ135, MQ4, and MQ136—to monitor and classify beef meat quality over a 48-hour period. The system was designed with three LED indicators: green for fresh beef, yellow for beef that is neither fresh nor spoiled, and red for rotten beef. Gas sensor readings were recorded at 12-hour intervals, with the goal of observing the transition from fresh to spoiled beef as it occurred. At 0 hours, the sensor readings were low across all samples, indicating that the beef was fresh. For example, for Beef Sample 1, the MQ135 sensor measured a reading of 6.348 ppm, MQ4 recorded 0.411 ppm, and MQ136 recorded 0.455 ppm. These low readings consistently activated the green LED, confirming that the beef was in its freshest state at the beginning of the monitoring period. Across all samples, the initial readings for MQ135 ranged from 5.08 ppm to

7.074 ppm, MQ4 varied between 0.411 ppm and 0.693 ppm, and MQ136 showed values from 0.333 ppm to 0.46 ppm, representing the fresh state of the beef. At the 12-hour mark, the sensor readings began to increase slightly, indicating the early stages of beef degradation. For instance, MQ135 for Beef Sample 1 rose to 21.372 ppm, MQ4 increased to 0.894 ppm, and MQ136 reached 0.543 ppm. This gradual rise in gas concentrations activated the yellow LED, signaling that the beef was beginning to lose its freshness but had not yet spoiled.

Across other beef samples, MQ135 ranged between 13.135 ppm and 19.028 ppm, MQ4 between 0.502 ppm and 0.791 ppm, and MQ136 between 0.366 ppm and 0.544 ppm during this 12-hour period, reflecting the beginning of the degradation process. By the 24-hour interval, the sensor readings continued to increase more noticeably. For Beef Sample 1, MQ135 recorded a reading of 86.183 ppm, MQ4 reached 18.184 ppm, and MQ136 registered 7.827 ppm. The yellow LED remained active, indicating that the beef was still in a transitional state. However, the elevated sensor readings suggested that the beef was moving closer to spoilage. Other beef samples followed a similar trend, with MQ135 readings ranging from 80.138 ppm to 233.34 ppm, MQ4 fluctuating between 13.574 ppm and 82.275 ppm, and MQ136 between 7.278 ppm and 64.891 ppm, demonstrating significant increases that corresponded with the ongoing deterioration of freshness. Between 36 and 48 hours, the sensor readings showed a dramatic rise, confirming that the beef had spoiled. For Beef Sample 1, MQ135 registered a sharp increase to 230.234 ppm, MQ4 reached 186.018 ppm, and MQ136 recorded 123.98 ppm. This phase triggered the red LED, indicating that the beef had fully spoiled. Other beef samples displayed similarly high readings, with MQ135 values ranging from 155.221 ppm to 238.389 ppm, MQ4 between 185.93 ppm and 239.695 ppm, and MQ136 from 110.292 ppm to 175.252 ppm. These elevated values demonstrated a significant release of gases associated with beef spoilage, confirming that the beef was no longer fresh.

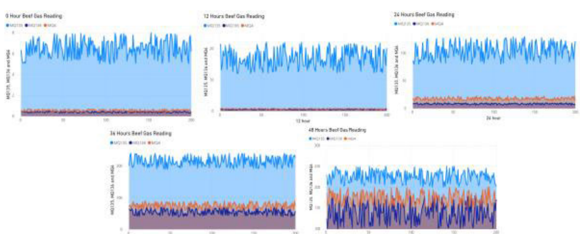

FIGURE 13. 0 hour to 48-hour gas sensor reading for beef quality classification.

The hourly analysis of the gas sensor data allowed for precise classification of beef quality, as visualized in Fig. 13, which shows the gas sensor readings over the 0 to 48-hour period for beef quality classification, and Fig. 14, which provides detailed readings for the MQ4, MQ135, and MQ136 sensors used in the classification. At 0 hours, the fresh state of the beef was confirmed by the lowest sensor readings, with the green LED constantly triggered.

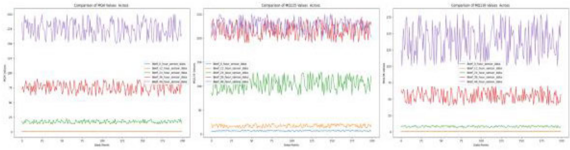

FIGURE 14. MQ4, MQ135 and MQ136 gas sensor reading for beef quality classification.

Within about 12 to 36 hours, the slight bump in gas quantities turned on the yellow LED – which meant went from fresh beef to less-fresh beef. At 48 hours, the gas levels spiked enough to trigger the red LED, indicating that the beef was bad. The gas sensor readings at each time interval are comprehensively summarized in Table 4, which presents the data collected from the MQ135, MQ4, and MQ136 sensors at 0, 12, 24, 36, and 48 hours. That offers an apparent insight into the evolution of gas concentrations through time, i.e., from fresh to spoiled beef. The gas sensor system based IoT was shown to be a useful technology for monitoring freshness and spoilage of beef in real-time, an important strategy mechanism that detects the gases awareness during the stance of ripening.

D. ANALYSIS OF MUTTON QUALITY CLASSIFICATION WITH IoT DEVICE GAS SENSORS

In this analysis, an IoT-based system equipped with gas sensors–MQ135, MQ4, and MQ136–was used to assess the quality of mutton meat over a period of 48 hours. The LED indicators (green, yellow, and red) were integrated into the IoT system to show the current freshness of mutton in real time. With green LED, mutton was fresh; yellow with which it is a phase from fresh to spoilage, and finally red gave the information that perchance the meat has already rotten. The gas sensor readings are monitored at intervals of two hours, giving a step-by-step representation of what happened to the mutton after it was purchased. The sensor readings revealed that mutton remained to be fresh for all samples at 0 hour. E.g., on Sample 1 the MQ135 sensor showed a value of 8.915 ppm, while MQ4 measured 0.531 ppm, and MQ136 recorded 0.445 ppm. Similar readings were observed across the other samples, with MQ135 values ranging from 6.112 to 8.915 ppm, MQ4 between 0.47 and 0.699 ppm, and MQ136 values from 0.333 to 0.479 ppm. These low sensor readings triggered the green LED, confirming the freshness of the mutton at the start of the observation period. As time progressed to 12 hours, sensor readings began to increase slightly, indicating the early stages of mutton degradation. In Sample 1, the MQ135 sensor showed a reading of 14.561 ppm, MQ4 increased to 2.913 ppm, and MQ136 measured 0.468 ppm. Similar patterns were observed across other samples, with MQ135 values ranging from 14.649 to 28.611 ppm, MQ4 between 1.058 and 2.979 ppm, and MQ136 from 0.307 to 0.587 ppm. These intermediate

TABLE 4. Gas sensor reading for beef quality.

S/L	0 hour			12 hours			24 hours			36 hours			48 hours		
	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136
1	0.44	6.34	0.45	0.89	21.37	0.54	18.18	86.18	7.82	72.31	200.9	64.25	186	230.2	123.95
2	0.54	5.37	0.46	0.65	13.13	0.366	13.57	80.13	9	76.9	233.3	59.76	155.2	205.7	100.67
3	0.468	5.08	0.42	0.878	14.76	0.546	13.78	87.31	8.41	67.06	239.7	58.64	158.2	209.2	137.16
4	0.461	5.112	0.45	0.72	14.76	0.498	19.18	118.5	8.34	73.05	212.2	65	198	231.4	157.67
5	0.639	5.203	0.39	0.502	14.76	0.543	15.05	110.4	9.31	80.85	195.1	60.67	185	224.6	124.38
6	0.42	5.08	0.36	0.56	14.76	0.4	20.8	94	9.82	87.18	196.9	45.8	190.6	204.2	133.54
7	0.46	7.07	0.41	0.76	14.76	0.41	20.73	113.17	7.27	73.24	214.9	45.6	175.7	219.4	171
8	0.6	6.18	0.43	0.786	18.79	0.41	18.68	80.29	6.37	77.64	238.3	43.52	191.2	239.6	175.25
9	0.67	5.81	0.33	0.56	13.27	0.54	18.53	88	7.8	69.6	235.9	64.89	166.6	220.4	117.8
10	0.69	6.96	0.34	0.79	19	0.33	17.67	84.9	7.69	82.27	238.3	43.05	185.9	229.4	110.29

sensor values activated the yellow LED, signaling that the mutton was starting to lose its freshness but was not yet spoiled. The gradual rise in gas concentrations at this stage suggested that the quality of the mutton was transitioning. Between 24 and 36 hours, the sensor data revealed a more pronounced rise in gas concentrations, especially in the readings for MQ135 and MQ4. In Sample 1, MQ135 recorded 123.692 ppm, MQ4 reached 20.583 ppm, and MQ136 was at 9.463 ppm. Other samples followed a similar pattern, with MQ135 readings ranging from 106.897 to 144.009 ppm, MQ4 between 15.79 and 25.986 ppm, and MQ136 between 9.069 and 12.609 ppm. These increasing sensor values corresponded with the yellow LED, indicating that the mutton was in a middle stage of degradation, moving closer to spoilage. By the time the mutton reached the 48-hour mark, the gas sensor readings had increased significantly, signaling spoilage. For Sample 1, MQ135 recorded 234.255 ppm, MQ4 measured 166.316 ppm, and MQ136 reached 43.094 ppm. Across other samples, the MQ135 values ranged from 204.31 to 265.832 ppm, MQ4 between 165.691 and 193.322 ppm, and MQ136 from 1.222 to 77.426 ppm. These elevated readings activated the red LED, indicating that the mutton was now classified as rotten.

The sharp increase in gas emissions during this phase highlighted the spoilage process, with MQ135 and MQ4 showing substantial rises, confirming that the quality of the mutton had deteriorated significantly.

The progression of gas concentrations over time is illustrated in Fig. 15, showing the gas sensor readings for mutton quality classification from 0 to 48 hours, and Fig. 16, which details the specific readings from MQ4, MQ135, and MQ136 sensors for mutton quality classification. The detailed sensor readings captured by the IoT device provided

TABLE 5. Gas sensor reading for mutton quality.

S/L	0 hour			12 hours			24 hours			36 hours			48 hours		
	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136	MQ-4	MQ-135	MQ-136
1	0.531	8.91	0.44	2.913	14.56	0.46	20.58	123.69	9.46	110.4	227.3	76.42	166.3	234.2	43.09
2	0.54	7.161	0.36	1.40	17.85	0.307	20.40	106.97	10.51	98.7	237.2	78.34	171.1	235.6	0.18
3	0.613	6.811	0.43	2.97	26.486	0.587	21.65	133.75	12.30	99.61	238.2	52.17	182.1	221.7	15.62
4	0.538	6.74	0.46	1.78	14.64	0.382	21.86	133.56	9.06	116.3	212.2	58.65	184.74	221.9	0.486
5	0.672	8.52	0.45	1.05	28.61	0.581	21.99	106.89	9.745	84.68	227.3	50.02	179.9	231.8	49.206
6	0.47	6.66	0.43	2.68	22.72	0.477	16.39	144	9.64	98.39	235.6	77.78	167.7	243.7	62.76
7	0.625	6.708	0.36	1.98	25.88	0.36	19.49	147.65	12.60	103.6	249.2	71.7	165.6	265.8	41.35
8	0.699	6.112	0.47	2.606	26.69	0.515	25.98	115.3	9.54	88.48	217.5	50.01	193.3	248.1	32.83
9	0.569	6.438	0.33	2.27	28.5	0.433	15.79	139.16	10.36	88.47	204.3	68.03	185.3	231.4	1.222
10	0.68	6.514	0.35	1.107	15.13	0.411	22.12	128.8	11.61	119.4	225.7	75.1	189.8	242.1	77.42

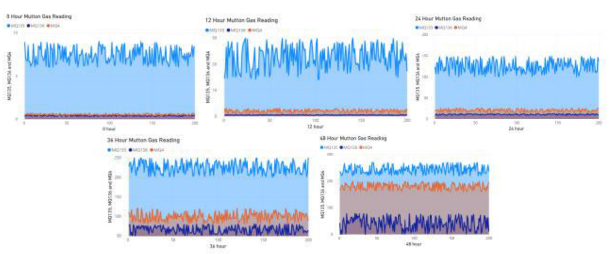

FIGURE 15. 0 hour to 48-hour gas sensor reading for mutton quality classification.

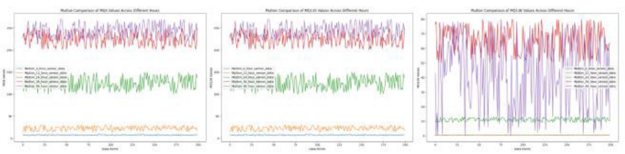

FIGURE 16. MQ4, MQ135 and MQ136 gas sensor reading for mutton quality classification.

a reliable method for real-time classification of mutton freshness.

The lowest gas sensor readings, and the triggering of the green LED both consistently confirmed an on fresh state at 0 hour. At 12–36 hours after the meat were exposed to harvested fruit odors, a certain rise in gas levels suggesting the transition from ripened to overripe state; consequently, a yellow LED light was switched ON. However, after 48 hours the substantial increase in gas emissions set off the red LED indicating that the mutton had indeed turned rancid. Our research on the detection of mutton freshness is a success, and we verified that the change in volatile organic compounds over time could accomplish real-time monitoring and classification via this IoT system. A summary of the detailed Gas Sensor reads for each interval is provided in Table 5, to give a better understanding of spoilage on time scale from Fresh mutton to Mutton at end of storage.

E. COMPARATIVE EVALUATION OF DEEP LEARNING AND TRADITIONAL MACHINE LEARNING MODELS FOR MEAT SPECIES AND MEAT FRESHNESS CLASSIFICATION

In this study, we conducted a comprehensive evaluation of four models: custom CNN, ResNet-50, SVM, and k-NN, focusing on their performance in meat species and freshness classification tasks. These models were trained and tested using high-resolution images of beef and mutton to assess their ability to accurately classify both species (beef or mutton) and quality (fresh or rotten). The goal of this comparative analysis was to identify the most effective model for real-time meat classification in an IoT-based system. Deep learning models, particularly CNNs, are well-suited for image classification tasks due to their ability to automatically extract and learn hierarchical features directly from raw image data. CNNs excel in capturing visual patterns such as texture, color, and shape, which are essential for distinguishing between different meat species and quality levels. Unlike traditional machine learning models that rely on handcrafted features, CNNs autonomously learn a range of features, from simple edges to complex textures, making them ideal for tasks requiring fine-grained image analysis, such as meat classification. ResNet-50, another deep learning model, leverages residual learning to enhance feature extraction, allowing it to handle deeper networks while avoiding the vanishing gradient problem. This enables ResNet-50 to perform well on complex image datasets, although it slightly trails behind the custom CNN in certain tasks. On the other hand, traditional machine learning models like SVM and k-NN, while useful in some simpler classification tasks, fall short when dealing with the complex and subtle visual distinctions required for accurate meat classification. SVM relies on hyperplane separation to classify data points, which may not capture the nuanced differences in image data as effectively as CNNs. k-NN, which uses distance-based metrics, struggles particularly with large datasets and complex features, as it lacks the capacity for advanced feature extraction. Among the models evaluated, the custom CNN demonstrated superior performance, achieving an impressive accuracy of 99% in both meat species and freshness classification tasks. The exceptional performance of the custom CNN is attributed to its carefully designed architecture, which includes additional layers to enhance feature extraction and generalization capabilities. The custom CNN model features a series of convolutional layers, starting with 32 filters and progressively increasing to 512 filters in the deeper layers. This architecture allows the model to extract both basic and complex patterns from the images, such as subtle differences in meat texture and marbling, which are essential for distinguishing between beef and mutton or fresh and rotten meat. Each convolutional layer employs a 3×3 kernel with 'same' padding, ensuring that the spatial dimensions of the images are preserved, which is crucial for retaining boundary information that aids in accurate classification. Max Pooling layers with a 2×2 pool size follow each convolutional block, reducing the size of feature maps while maintaining important features, thus preventing overfitting, and lowering computational complexity. To further improve the model's robustness, Dropout layers are incorporated at different stages of the network, with dropout rates set at 0.25 and 0.4. These layers help prevent overfitting by randomly deactivating neurons during training, ensuring that the model generalizes well to unseen data. The final dense layers synthesize the learned features, with the first dense layer comprising 1,500 neurons, providing the model with significant capacity to handle the complexity of the input data. The SoftMax layer at the output produces class probabilities, allowing for accurate classification between the meat species and freshness categories. While the custom CNN emerged as the best-performing model, ResNet-50 also showed strong performance, achieving an accuracy of 98%. ResNet-50 performed particularly well in distinguishing between beef and mutton, with high precision and recall scores, though it slightly lagged behind the custom CNN, especially in terms of recall for some edge cases. Its residual learning framework helped it retain important features, making it effective for complex classification tasks, albeit with a slightly lower accuracy than CNN. SVM demonstrated good performance, achieving an accuracy of 96%.

It performed well in distinguishing between clear-cut categories, such as fresh vs. rotten meat, with precision and recall values comparable to those of the deep learning models. However, its reliance on decision boundaries limited its ability to handle more intricate visual distinctions, such as the subtle differences in meat texture and marbling that are better captured by CNN and ResNet-50. k-NN, however, exhibited the weakest performance, with an accuracy of 86%. The model particularly struggled with mutton classification, where its recall dropped to 0.81, indicating a high number of false negatives. k-NN's performance in differentiating between fresh and rotten meat was also suboptimal, as its distance-based metrics were not effective at capturing the subtle visual features necessary for accurate classification in this task. The results are visually demonstrated in Fig. 17, which shows the confusion matrix for both meat species and meat freshness classification tasks. In our study, the custom CNN emerged as the best performing model for meat species and freshness classification, demonstrating exceptional accuracy and robustness as shown in Fig. 18. We included this unique custom CNN architecture into an IoT system for real-time meat classification because of its exceptional performance. The apparatus takes pictures of meat samples using the ESP32-CAM module, and then a Raspberry Pi 3 with a customized CNN model processes those images.

This setup allows for real-time classification of meat species and freshness, with the results displayed directly on

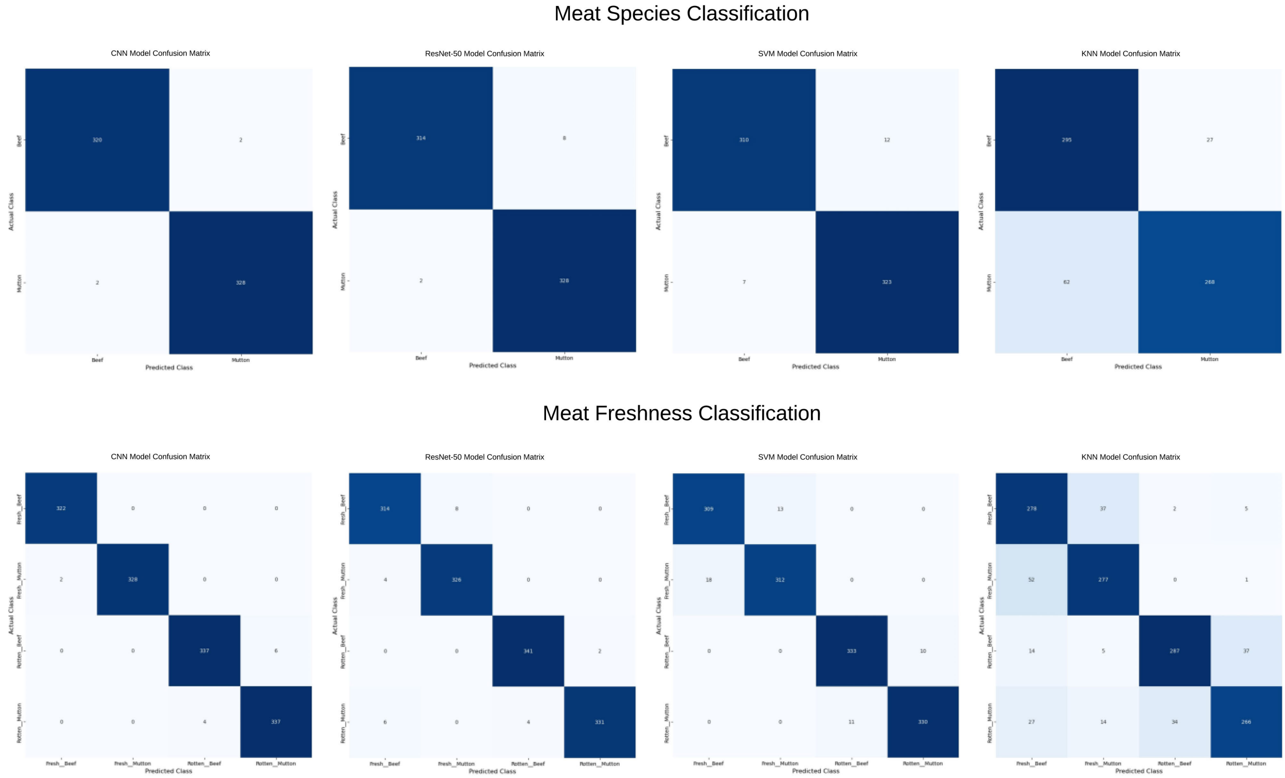

FIGURE 17. **Confusion matrix for custom CNN, ResNet-50, SVM and *k*-NN models in meat species and meat freshness classification.**

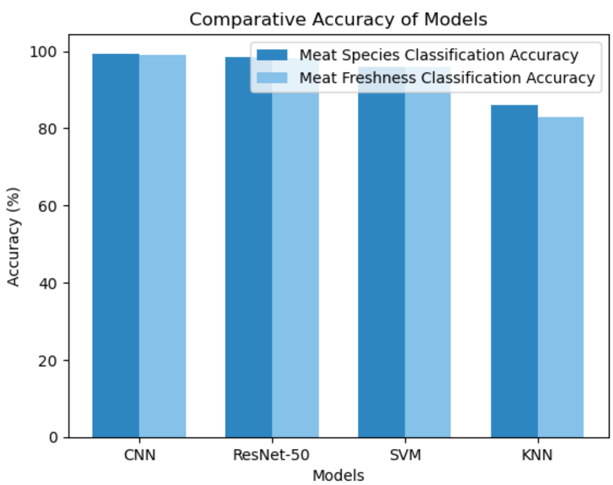

FIGURE 18. **Comparative accuracy of models for meat species and freshness classification.**

the IoT device's screen. The use of the custom CNN ensures high accuracy and reliability in meat quality monitoring, making it a practical solution for applications in food safety and quality control. To conclude, the deep learning models, particularly the custom CNN, demonstrated clear superiority over traditional machine learning models in meat species and freshness classification tasks. The custom CNN's ability to automatically extract and learn complex image features made it the most effective model, surpassing ResNet-50, SVM, and k-NN in terms of accuracy and reliability. Additionally, the custom CNN's integration into an IoT-based system, using the ESP32-CAM module and Raspberry Pi 3 for real-time image capture and classification, further emphasizes its practical utility. This solution provides an efficient and dependable system for real-time meat quality monitoring, validating the custom CNN's role as the best-performing model in our study.

VI. CONCLUSION AND FUTURE WORK

In this study, we developed and evaluated a comprehensive system for meat species and freshness classification, leveraging both traditional machine learning models and advanced deep learning architectures. The results of our comparative analysis demonstrated the clear superiority of deep learning models, particularly the custom CNN, in achieving high accuracy and reliability in both classification tasks. The custom CNN outperformed ResNet-50, SVM, and k-NN models by effectively extracting complex visual features from high-resolution images, allowing for precise differentiation between meat species and freshness states. The custom CNN's carefully designed architecture, with multiple layers and enhanced feature extraction capabilities, allowed it to capture intricate patterns in meat textures and marbling, making it the best-performing model. With an accuracy of 99%, it surpassed ResNet-50's performance (98%) and exhibited a clear advantage over traditional machine learning models such as SVM (96%) and k-NN

(86%). Its ability to generalize well to unseen data, coupled with regularization techniques such as Dropout layers, ensured robust performance across a variety of scenarios. Furthermore, the integration of the custom CNN into an IoT-based system highlights its practical applicability. The system, equipped with an ESP32-CAM module for image capture and a Raspberry Pi 3 for processing, successfully classified meat species and freshness in real time. This real-time capability, combined with the system's accuracy and reliability, provides an efficient and scalable solution for ensuring meat quality and safety in various settings. The IoT device displays results instantly, offering immediate feedback on meat freshness and species classification, making it a valuable tool for the food industry. In addition to the image-based classification provided by the custom CNN, the IoT system incorporated gas sensors–MQ135, MQ4, and MQ136–to further enhance meat freshness classification. These sensors measure Gases like ammonia (NH3), methane (CH4), and hydrogen sulfide (H2S), which are emitted during meat spoilage. The MQ135 sensor is sensitive to a range of air quality pollutants, including volatile organic compounds (VOCs), which are crucial indicators of meat spoilage. The MQ4 detects methane, a byproduct of protein degradation, while the MQ136 sensor measures hydrogen sulfide, which is often associated with rotting meat. These gas sensors provide real-time feedback through LED indicators (green for fresh, yellow for transitioning, and red for spoiled meat) based on gas concentration thresholds, adding an extra layer of precision to the overall classification system.

While our system has proven highly effective, several directions for future work can further enhance its capabilities. Firstly, we plan to expand the dataset by including a variety of meats beyond beef and mutton, increasing both the data size and diversity. This expansion will also include extending the freshness and spoilage time frames to better capture the degradation process over longer periods. We also aim to explore additional deep learning and traditional machine learning models, testing advanced architectures to improve classification accuracy further. By evaluating a broader range of models, we hope to identify the most effective algorithms for image classification tasks related to meat species and freshness classification. Additionally, future work will focus on deploying the best-performing model in web and mobile applications, allowing for broader accessibility and real-time monitoring capabilities. This will enable users to assess meat quality remotely through their devices, enhancing the system's scalability and usability in the food industry. This future development will provide a comprehensive solution for real-time meat classification, supporting food safety and quality assurance across various sectors. In conclusion, this research lays the foundation for future advancements in real-time food quality monitoring, offering significant potential to improve food safety, reduce waste, and increase consumer confidence through reliable and scalable technological solutions.

REFERENCES

[1] Z. W. Bhuiyan, S. A. R. Haider, A. Haque, M. R. Uddin, and M. Hasan, 2024, "IoT based meat freshness classification using deep learning," IEEE Dataport, doi: 10.21227/tz42-s971.

[2] S. Gc, B. Saidul, Y. Zhang, D. Reed, M. Ahsan, E. Berg, and X. Sun, "Using deep learning neural network in artificial intelligence technology to classify beef cuts," *Frontiers Sensors*, vol. 2, p. 5, Jun. 2021.

[3] D. Kolosov, L.-C. Fengou, J. M. Carstensen, N. Schultz, G.-J. Nychas, and I. Mporas, "Microbiological quality estimation of meat using deep CNNs on embedded hardware systems," *Sensors*, vol. 23, no. 9, p. 4233, Apr. 2023.

[4] A. Bajpai, H. Rai, and N. Tiwari, "An efficient CNN-based method for classification of red meat based on its freshness," in *Proc. Int. Conf. Mach. Learn., IoT Big Data*. Singapore: Springer, Mar. 2023, pp. 393–405.

[5] T. Hidayat, D. U. E. Saputri, and F. Aziz, "Meat image classification using deep learning with ResNet152V2 architecture," *Jurnal Techno Nusa Mandiri*, vol. 19, no. 2, pp. 131–140, Sep. 2022.

[6] Z. W. Bhuiyan, S. A. Redwanul Haider, A. Haque, M. Hasan, and M. R. Uddin, "Meat freshness classifier with machine and AI," in *Proc. IEEE Region 10 Symp. (TENSYMP)*, Sep. 2023, pp. 1–5.

[7] A. F. Juannata, D. R. Wijaya, and W. Wikusna, "Electronic nose and neural network algorithm for multiclass classification of meat quality," in *Proc. Int. Conf. Data Sci. Appl. (ICoDSA)*, Jul. 2022, pp. 128–132.

[8] R. R. Mohamed and W. Hashim, "Food freshness detection using smart machine learning classification," *J. Pharmaceutical Negative Results*, vol. 13, no. 9, pp. 7410–7426, 2023.

[9] H. Ayaz, M. Ahmad, M. Mazzara, and A. Sohaib, "Hyperspectral imaging for minced meat classification using nonlinear deep features," *Appl. Sci.*, vol. 10, no. 21, p. 7783, Nov. 2020.

[10] A. Abuzaid and A. Atia, "Exploring and classifying beef retail cuts using transfer learning," in *Proc. IEEE 9th Int. Conf. Sci. Electron., Technol. Inf. Telecommun. (SETIT)*, May 2022, pp. 461–467.

[11] N. Kointarangkul and Y. Limpiyakorn, "Detection of Wagyu beef sources with image classification using convolutional neural network," *Proc. SPIE*, vol. 11913, pp. 116–120, Aug. 2021.

[12] L. Zhou, C. Zhang, F. Liu, Z. Qiu, and Y. He, "Application of deep learning in food: A review," *Comprehensive Rev. Food Sci. Food Saf.*, vol. 18, no. 6, pp. 1793–1811, Nov. 2019.

[13] Y. Yuan and X. Chen, "Vegetable and fruit freshness detection based on deep features and principal component analysis," *Current Res. Food Sci.*, vol. 8, Feb. 2024, Art. no. 100656.

[14] N. Jmour, S. Zayen, and A. Abdelkrim, "Convolutional neural networks for image classification," in *Proc. Int. Conf. Adv. Syst. Electric Technol. (IC_ASET)*, Mar. 2018, pp. 397–402.

[15] S. Shin, Y. Lee, S. Kim, S. Choi, J. G. Kim, and K. Lee, "Rapid and non-destructive spectroscopic method for classifying beef freshness using a deep spectral network fused with myoglobin information," *Food Chem.*, vol. 352, Aug. 2021, Art. no. 129329.

[16] H. Liao and L. Chen, "Meat freshness recognition based on improved ResNet34 model," *Proc. SPIE*, vol. 12645, pp. 672–678, May 2023.

[17] S. Agustin and R. Dijaya, "Beef image classification using K-nearest neighbor algorithm for identification quality and freshness," *J. Phys., Conf. Ser.*, vol. 1179, no. 1, Jul. 2019, Art. no. 012184.

[18] X. Ren, Y. Wang, Y. Huang, M. Mustafa, D. Sun, F. Xue, D. Chen, L. Xu, and F. Wu, "A CNN-based E-nose using time series features for food freshness classification," *IEEE Sensors J.*, vol. 23, no. 6, pp. 6027–6038, Mar. 2023.

[19] L. Guo, T. Wang, Z. Wu, J. Wang, M. Wang, Z. Cui, and X. Chen, "Portable food-freshness prediction platform based on colorimetric barcode combinatorics and deep convolutional neural networks," *Adv. Mater.*, vol. 32, no. 45, 2020, Art. no. 2004805.

[20] J. Xinhua, X. Heru, Z. Lina, G. Xiaojing, W. Guodong, and B. Jie, "Nondestructive detection of chilled mutton freshness based on multi-label information fusion and adaptive BP neural network," *Comput. Electron. Agricult.*, vol. 155, pp. 371–377, Dec. 2018.

[21] V. J. Ajaykumar and P. K. Mandal, "Modern concept and detection of spoilage in meat and meat products," in *Meat Quality Analysis*. New York, NY, USA: Academic, 2020, pp. 335–349.

[22] A. Taheri-Garavand, S. Fatahi, M. Omid, and Y. Makino, "Meat quality evaluation based on computer vision technique: A review," *Meat Sci.*, vol. 156, pp. 183–195, Oct. 2019.

[23] A. Arsalane, A. Klilou, N. E. Barbri, and A. Tabyaoui, "Artificial vision and embedded systems as alternative tools for evaluating beef meat freshness," in *Proc. IEEE 6th Int. Conf. Optim. Appl. (ICOA)*, Apr. 2020, pp. 1–6.

[24] A. Li, C. Li, M. Gao, S. Yang, R. Liu, W. Chen, and K. Xu, "Beef cut classification using multispectral imaging and machine learning method," *Frontiers Nutrition*, vol. 8, Oct. 2021, Art. no. 755007.

[25] Y. Shi, X. Wang, M. S. Borhan, J. Young, D. Newman, E. Berg, and X. Sun, "A review on meat quality evaluation methods based on non-destructive computer vision and artificial intelligence technologies," *Food Sci. Animal Resour.*, vol. 41, no. 4, pp. 563–588, Jul. 2021.

[26] A. Kaya, A. S. Keçeli, C. Catal, and B. Tekinerdogan, "Sensor failure tolerable machine learning-based food quality prediction model," *Sensors*, vol. 20, no. 11, p. 3173, Jun. 2020.

[27] Y. L. Brasil, J. P. Cruz-Tirado, and D. F. Barbin, "Fast online estimation of quail eggs freshness using portable NIR spectrometer and machine learning," *Food Control*, vol. 131, Jan. 2022, Art. no. 108418.

[28] E. Sehirli and K. Arslan, "An application for the classification of EGG quality and haugh unit based on characteristic EGG features using machine learning models," *Expert Syst. Appl.*, vol. 205, Nov. 2022, Art. no. 117692.

[29] S. Huh, H.-J. Kim, S. Lee, J. Cho, A. Jang, and J. Bae, "Utilization of electrical impedance spectroscopy and image classification for non-invasive early assessment of meat freshness," *Sensors*, vol. 21, no. 3, p. 1001, Feb. 2021.

[30] I. M. P. De Vargas-Sansalvador, M. M. Erenas, A. Martínez-Olmos, F. Mirza-Montoro, D. Diamond, and L. F. Capitan-Vallvey, "Smartphone based meat freshness detection," *Talanta*, vol. 216, Aug. 2020, Art. no. 120985.

[31] S. Park, S.-J. Hong, S. Kim, J. Ryu, S. Roh, and G. Kim, "Classification of fresh and frozen-thawed beef using a hyperspectral imaging sensor and machine learning," *Agriculture*, vol. 13, no. 4, p. 918, Apr. 2023.

[32] A. Arsalane, N. El Barbri, A. Tabyaoui, A. Klilou, K. Rhofir, and A. Halimi, "An embedded system based on DSP platform and PCA-SVM algorithms for rapid beef meat freshness prediction and identification," *Comput. Electron. Agricult.*, vol. 152, pp. 385–392, Sep. 2018.

[33] R. Farinda, Z. R. Firmansyah, C. Sulton, I. S. Wijaya, and F. Bimantoro, "Beef quality classification based on texture and color features using SVM classifier," *J. Telematics Inform.*, vol. 6, no. 3, pp. 201–213, 2018.

[34] S. Sutarman, D. Avianto, and A. P. Wibowo, "Vision-based chicken meat freshness recognition system using RGB color moment features and support vector machine," *Sci. Inf. Technol. Lett.*, vol. 4, no. 2, pp. 65–74, Nov. 2023.

[35] A. Arsalane, A. Klilou, and N. E. Barbri, "Performance evaluation of machine learning algorithms for meat freshness assessment," *Int. J. Electr. Comput. Eng.*, vol. 14, no. 5, p. 5858, Oct. 2024.

[36] M. I. Mladenov, "Model-based approach for assessment of freshness and safety of meat and dairy products using a simple method for hyperspectral analysis," *J. Food Nutrition Res.*, 2020.

[37] J. Johnson, D. Atkin, K. Lee, M. Sell, and S. Chandra, "Determining meat freshness using electrochemistry: Are we ready for the fast and furious?" *Meat Sci.*, vol. 150, pp. 40–46, Apr. 2019.

[38] T. Wang, F. Shen, H. Deng, F. Cai, and S. Chen, "Smartphone imaging spectrometer for EGG/meat freshness monitoring," *Anal. Methods*, vol. 14, no. 5, pp. 508–517, Feb. 2022.

[39] V. S. Kartika, M. Rivai, and D. Purwanto, "Spoiled meat classification using semiconductor gas sensors, image processing and neural network," in *Proc. Int. Conf. Inf. Commun. Technol. (ICOIACT)*, Mar. 2018, pp. 418–423.

[40] X. Weng, X. Luan, C. Kong, Z. Chang, Y. Li, S. Zhang, S. Al-Majeed, and Y. Xiao, "A comprehensive method for assessing meat freshness using fusing electronic nose, computer vision, and artificial tactile technologies," *J. Sensors*, vol. 2020, pp. 1–14, Sep. 2020.

[41] A. Denih and I. Anggraeni, "Beef freshness detection device based on gas and color sensors using the K-nearest neighbor method," in *Proc. 13th Annu. Int. Conf. Ind. Eng. Oper. Manage.*, 2023.

[42] A. Feyzioglu and Y. S. Taspinar, "Beef quality classification with reduced E-Nose data features according to beef cut types," *Sensors*, vol. 23, no. 4, p. 2222, Feb. 2023.

[43] P. F. M. Pereira, P. H. de Sousa Picciani, V. Calado, and R. V. Tonon, "Electrical gas sensors for meat freshness assessment and quality monitoring: A review," *Trends Food Sci. Technol.*, vol. 118, pp. 36–44, Dec. 2021.

[44] R. R. Mohamed, R. Yaacob, M. A Mohamed, T. A. T. Dir, and F. A Rahim, "Food freshness using electronic nose and its classification method: A review," *Int. J. Eng. Technol.*, vol. 7, no. 3.28, p. 49, Aug. 2018.

[45] J. Chen, J. Gu, R. Zhang, Y. Mao, and S. Tian, "Freshness evaluation of three kinds of meats based on the electronic nose," *Sensors*, vol. 19, no. 3, p. 605, Jan. 2019.

[46] S. Grassi, S. Benedetti, M. Opizzio, E. di Nardo, and S. Buratti, "Meat and fish freshness assessment by a portable and simplified electronic nose system (Mastersense)," *Sensors*, vol. 19, no. 14, p. 3225, Jul. 2019.

[47] I. M. Nolasco-Perez, L. A. C. M. Rocco, J. P. Cruz-Tirado, M. A. R. Pollonio, S. Barbon, A. P. A. C. Barbon, and D. F. Barbin, "Comparison of rapid techniques for classification of ground meat," *Biosyst. Eng.*, vol. 183, pp. 151–159, Jul. 2019.

[48] T. Liu, W. Zhang, M. Yuwono, M. Zhang, M. Ueland, S. L. Forbes, and S. W. Su, "A data-driven meat freshness monitoring and evaluation method using rapid centroid estimation and hidden Markov models," *Sens. Actuators B, Chem.*, vol. 311, May 2020, Art. no. 127868.

[49] S. N. Mohtasim, J. Jahan Khan, M. Mahmudul Islam, M. K. Sarker, M. R. Uddin, and M. Hasan, "IoT-based crop monitoring and disease detection," in *Proc. 5th Int. Conf. Sustain. Technol. Ind. 5.0 (STI)*, Dhaka, Bangladesh, Dec. 2023, pp. 1–6, doi: 10.1109/sti59863.2023.10464923.

[50] M. M. K. Sohag, M. A. U. Rahman, M. I. Shochcho, M. R. Mahmud, D. M. Shams, M. Samiha, M. R. Uddin, and M. Hasan, "Fruit quality detection and monitoring system," in *Proc. IEEE 13th Int. Conf. Control Syst., Comput. Eng. (ICCSCE)*, Penang, Malaysia, Aug. 2023, pp. 111–114, doi: 10.1109/iccsce58721.2023.10237165.

ZARIF WASIF BHUIYAN was born in Dhaka, in August 2001. He has always demonstrated a profound curiosity and passion for learning, traits that have significantly shaped his academic and professional trajectory. From an early age, he developed a keen interest in technology, particularly in the fields of data science, machine learning, and computer vision, which later became the focal points of his academic pursuits and career development. During his undergraduate studies at Independent University, Bangladesh (IUB), he quickly immersed himself in the rapidly expanding field of data science. His aptitude for problem-solving and technical proficiency earned him recognition from both faculty and peers. Through his active involvement in various data science projects, he has not only honed his skills but also established a strong academic reputation. His work, characterized by innovation and analytical rigor, furthered his understanding of complex systems and advanced technologies. Upon completing his undergraduate degree, he began his professional career as a Data Scientist at a prominent software company. In this capacity, he applied his expertise to address complex, real-world challenges, contributing to the development of data-driven solutions in machine learning, predictive analytics, and data modeling. His role enabled him to gain valuable industry experience and deepen his practical knowledge of the field. At the end of 2024, his academic journey took a new turn when he joined IUB as a Graduate Research Assistant (RA). In this role, he collaborates on various research projects, focusing on cutting-edge developments in machine learning, computer vision, and data science. His research contributions have already garnered significant attention, with multiple publications in prestigious conferences. Notably, he has authored two papers presented at the ICACTCE'24 Conference and one at the IEEE TENSYMP Conference in 2023. His work, which spans a variety of domains, demonstrates his versatility and expertise in applying advanced computational techniques to solve complex problems.

SYED ALI REDWANUL HAIDER has been always involved in dynamic activities, including sports and voluntary work. From an early age, he has been embracing a disciplined lifestyle with social engagement and physical activity. His passion for sports, such as football, cricket, and martial arts, motivated him to participate in competitive events. Having fully pledged science-based O and A levels, he carried out his undergraduate studies in CSE from IUB with remarkable IOT based ML projects. Through this process, he found the opportunity to proceed with his career further on technology sector. Since September 2023, he has been involved in tech industry, as a Python Developer at a reputed company. He contributed advanced technological solutions from ERP to the IoT based projects. His project involved web development with React.js and Django, Flask for the IoT based projects, and Odoo for ERP solutions. Aside from that, he has been involved in research at Independent University, Bangladesh, expanding his expertise in cutting-edge technology, such as the IoT. His achievements extend to the academic and professional realms. He has also participated in many IoT based competitions which have remarkable positions making his passion grow further. His journey reflects on his consistency whether it's about developing AI and machine learning-based meat classifier or achieving sports success. He developed the philosophy of his life in a very rational manner while growing up in a close-knit joint family. He draws strength from the love and support of his parents, uncles, cousins, and friends. The strength of his community groomed him with a strength of being modest and passionate hardworking character with a visionary mindset. This environment made him a challenge loving person with resilience. He approaches life's hurdles as steppingstones toward his dreams, living with a conviction that peace and success come through perseverance.

ADIBA HAQUE was born in Dhaka, in February 2000. She received the Bachelor of Science degree in computer science and engineering from Independent University, Bangladesh (IUB), in May 2023. From a young age, she had an interest in music and other creative activities. Coming from that environment she developed a passion for exploring adventurous sectors which involved music, participating in cultural activities and school competitions. This gave her the opportunity to explore her talents in various sectors. After completing her secondary and higher secondary from the Viqarunnisa Noon School and College. During her undergrads, she was recognized for her dedication and academic achievements of participating in numerous projects based competitions. She has published and presented a paper at the prestigious IEEE TENSYMP Conference in Canberra, Australia, in 2023, which has been her major milestone in her career. Her relationship with her family provided her with strong motivation, helping her develop a clear philosophy of success throughout her life. Her career has been full of milestones where she was involved in countless voluntary events and cultural competitions. Her participation in tech festivals and coding competitions was remarkable where she showcased her commitment to learning and technological innovation. Guided by her personal philosophy, "experience and explore the world all you can. For happiness, one must live only once," she embraces every opportunity for growth and discovery. Since May 2024, she has been a Software Developer at a reputed educational technology company, while also conducting research at IUB, where she contributes to cutting-edge advancements in technology. Her journey is marked by her boundless potential, perseverance, and dedication, making her a standout figure in both her personal and professional life.

MOHAMMAD REJWAN UDDIN (Member, IEEE) received the B.Sc. and M.Sc. degrees from Independent University, Bangladesh (IUB), in 2011 and 2016, respectively. He began his academic journey as a Graduate Research Assistant with the GERC IUB Laboratory for Applied Research on Power Electronics-Based Systems, in 2015, subsequently working as a Senior Research Associate, in 2016. He has been an Adjunct Lecturer with the Department of Electrical and Electronic Engineering (EEE), IUB, since September 2018. Additionally, he has held various roles within the School of Engineering and Technology (SETS), most notably as the Technical Supervisor of the Fab Laboratory, IUB, from January 2018 to December 2018. He is actively involved in consulting for both government and non-government organizations in device development and is the Director of the Solar Boat Irrigation Project, a government-funded initiative aimed at developing solar-powered boats for irrigation and recreational purposes. His work on this project includes a focus on high-frequency (HF) controllers and solar inverters for 3-phase induction motors. His research interests include the design, manufacturing, and control techniques of power electronic systems and components, with applications spanning a wide range of industries. He has received numerous awards, including the SECS Award for International Publications and the Challenge Fund Award of \$30,000 from the Prime Minister's Office for an innovative idea, and accolades, such as Winner at the National Project Competition on Green Energy and Technology and 1st Runner-Up at the Inter-University Innovation Competition during National Electricity Week in 2015. He has authored three journal articles and 32 conference papers, all indexed by IEEE and is the co-author of an IEEE prize paper. With 477 citations and 82 publications, his contributions to the field continue to gain recognition.

MAHADY HASAN received the bachelor's degree in computer science from Independent University, Bangladesh (IUB), in 2001, the master's degree in information technology from The University of Sydney, in 2004, and the Ph.D. degree in spatial database from the Department of Computer Science and Engineering, University of New South Wales (UNSW), in 2010. Before joining IUB as an Assistant Professor, he gained valuable academic and industry experience, having served at UNSW, Australian Pacific College, and James Cook University, Australia. He has been with IUB, since 2004, where he has made significant contributions to the development of the university's Computer Science and Engineering (CSE) Department. He is currently an Associate Professor and the Head of the Department of Computer Science and Engineering. In addition, he is the Director of the FAB Laboratory and leads the industrial automation wing at the RIoT Center, IUB. He has authored 133 papers in reputable journals and conferences, which have collectively garnered 692 citations. His scholarly work includes several book chapters, journal articles, and conference papers published in prestigious academic platforms. His research interests include software engineering, big data, data analytics, and engineering education. His contributions to these fields have earned him widespread recognition and he continues to inspire future generations of students and researchers. Through his leadership, he has spearheaded initiatives aimed at promoting green technology entrepreneurship and advancing societal impact through technological innovation. These efforts have further solidified his position as a transformative figure in academia and industry. His ongoing work in these areas is contributing to the development of sustainable and impactful technologies, enhancing his reputation as a leader in both education and applied research.