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Leveraging Portable Digital Microscopes and CNNs for Chicken Meat Quality Evaluation with AlexNet and GoogleNet

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ABSTRACT

The global consumption of chicken meat has surged due to its affordability, versatility, and perceived health benefits, making quality and safety crucial for public health and consumer trust. This study developed a non-destructive, real-time method for classifying chicken meat quality by integrating portable digital microscopes with Convolutional Neural Networks (CNNs). High-resolution images were captured using a 1,000× WiFi-enabled digital microscope and analyzed with two advanced CNN architectures, AlexNet and GoogLeNet, to categorize chicken meat into four classes: fresh, carrion, rotten, and formalinized. The methodology included systematic sampling and image preprocessing techniques—such as histogram equalization, noise reduction, and color space transformation—to enhance image quality and model performance. A dataset of 2,000 images was split into training and validation sets, with 600 images reserved for testing. Models were optimized using various hyperparameters, including optimizers Stochastic Gradient Descent with Momentum (SGDM), Adaptive Moment Estimation (Adam), Root Mean Square Propagation (RMSProp), and learning rates (0.0001, 0.00005). Results showed that GoogLeNet, optimized with RMSProp and a 0.00005 learning rate, achieved the highest testing accuracy of 99.15%, outperforming AlexNet's 98.65%. The study highlighted that adaptive optimizers and lower learning rates significantly improve model accuracy and stability. Confusion matrix analysis confirmed high precision in classifying most categories, with minor errors in the rotten category. This approach enhances food safety standards, reduces the distribution of low-quality meat, minimizes food waste, and improves supply chain traceability. The CNN-based system offers the poultry industry a rapid, accurate, and cost-effective solution for automating meat quality assessments, boosting consumer confidence, and supporting global sustainability goals.

Keywords: Chicken meat, CNN, digital microscope, image classification

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INTRODUCTION

The global consumption of chicken meat has witnessed a remarkable surge over recent decades, establishing it as the most consumed meat worldwide, surpassing traditional staples such as beef and pork (Gržinić et al., 2023; Rao, 2015; Sporchia et al., 2023). This trend stems from chicken's affordability, versatility in culinary applications, and its perceived health benefits, further bolstered by rising incomes and urbanization in developing countries, making poultry a staple protein source essential for global food security. Consequently, poultry farming has expanded to meet this growing market demand.

However, the escalation in chicken meat consumption has concurrently amplified concerns regarding meat quality and safety. Ensuring the integrity of chicken meat is paramount, as it directly impacts public health and consumer confidence. Pathogenic contamination, largely due to improper handling and processing, poses severe health risks, including foodborne illnesses (Akhlaghi et al., 2024; Gržinić, 2023). Additionally, the widespread use of antibiotics in poultry farming to promote growth and prevent disease has raised alarms about antibiotic resistance, further complicating food safety dynamics (Akhlaghi et al., 2024). Consumers are becoming increasingly vigilant about these issues, demanding greater transparency and assurance regarding the safety and quality of chicken meat products (Akhlaghi et al., 2024; Gržinić, 2023). This heightened awareness underscores the urgent need for effective quality assessment methods that can ensure the safety and reliability of chicken meat in the supply chain.

Traditional methods for assessing meat quality, including sensory evaluation and chemical analysis, present several significant drawbacks. Sensory evaluation, while useful, is inherently subjective and relies heavily on the expertise and consistency of human assessors, which can lead to variability and potential biases in quality assessments (Damez & Clerjon, 2011; Wu et al., 2022). Chemical analysis methods, although objective, are often time-consuming, expensive, and require specialized training and equipment, making them impractical for routine and large-scale quality monitoring (Damez & Clerjon, 2011; Wu et al., 2022). Moreover, these conventional techniques may not sufficiently address the multifaceted nature of meat quality, particularly in detecting microbial contamination or adulterants that can compromise food safety (Adam, 2021; Akhlaghi et al., 2024; Rebezov et al., 2022; Şahin et al., 2025). In contrast, an automated, CNN-based approach offers faster, more accurate evaluations, reducing reliance on intensive labor and subjective judgment.

Recent advancements in machine learning, particularly in the realm of CNNs, coupled with portable imaging technologies, offer promising avenues to address these challenges. CNNs have revolutionized image processing and classification tasks by enabling the extraction of intricate features from visual data without the need for manual intervention (Alzubaidi et al., 2021; Damez & Clerjon, 2011; Mienye & Swart, 2024). Their application in non-destructive food quality assessments has demonstrated significant potential, allowing for rapid and accurate classification of meat quality based on image data (Alzubaidi et al., 2021; Damez & Clerjon, 2011; Mienye & Swart, 2024). For example, CNNs have been effectively employed to classify the quality of chicken meat through the analysis of hyperspectral images, which capture a broad spectrum of wavelengths and provide detailed insights into the meat's composition (L. Zhou et al., 2019; Mienye & Swart, 2024). These technological innovations not only enhance the precision of quality assessments but also substantially reduce the time and labor associated with traditional methods (Hwang et al., 2025; Suthar et al., 2024). By enabling real-time, high-accuracy detection of quality attributes, CNN-based systems help prevent the distribution of substandard products, thereby minimizing food waste and improving traceability within the supply chain.

The integration of portable digital microscopes with CNNs represents a significant leap forward in the automation and efficiency of meat quality evaluation. Portable digital microscopes are cost-effective, easy to deploy, and capable of capturing high-resolution images that reveal microstructural details of meat samples (Hwang et al., 2025; Xu et al., 2024). When combined with CNNs, these devices facilitate the real-time, non-destructive analysis of chicken meat, enabling the classification of various quality parameters such as freshness, spoilage, and the presence of adulterants (Hwang et al., 2025; Xu et al., 2024). This synergy not only streamlines the quality assessment process but also aligns with broader sustainability goals by reducing the likelihood of sending poor-quality products to market, which in turn curbs unnecessary waste and bolsters trust through transparent tracking of product integrity. The ability to monitor meat quality in real-time ensures that only safe and high-quality products reach consumers, thereby safeguarding public health and reducing environmental impact through more efficient resource utilization (Damez & Clerjon, 2011; Suthar et al., 2024).

Despite the promising advancements, the application of CNNs and portable imaging devices in meat quality assessment is still evolving, with several challenges remaining. One of the primary challenges is ensuring the generalizability of CNN models across different breeds, storage conditions, and imaging devices. Variations in these factors can significantly affect the performance and accuracy of classification models, necessitating extensive training datasets that encompass diverse scenarios (Damez & Clerjon, 2011; Xu et al., 2024). Additionally, the optimization of CNN hyperparameters, such as learning rates and optimizers, is crucial for achieving optimal performance but remains a complex and often trial-and-error process (Mienye & Swart, 2024). Furthermore, the practical implementation of these technologies in real-world settings requires addressing technical challenges related to device calibration, lighting variations, and data standardization to ensure consistent and reliable performance (Hwang et al., 2025; Suthar et al., 2024).

To address these challenges, this study aims to develop a robust CNN-based classification model utilizing images captured by a portable digital microscope to accurately evaluate chicken meat quality. By leveraging advanced CNN architectures such as

AlexNet and GoogleNet, the research seeks to enhance the accuracy and reliability of meat quality assessments while maintaining cost-effectiveness and operational simplicity. The study further investigates the impact of different optimizers and learning rates on model performance, striving to identify the optimal configuration that maximizes classification accuracy and minimizes computational overhead. Through comprehensive evaluation using a substantial dataset, the research endeavors to validate the efficacy of the proposed method in diverse and realistic conditions, thereby contributing to the advancement of non-destructive, automated meat quality assessment technologies.

METHODOLOGY

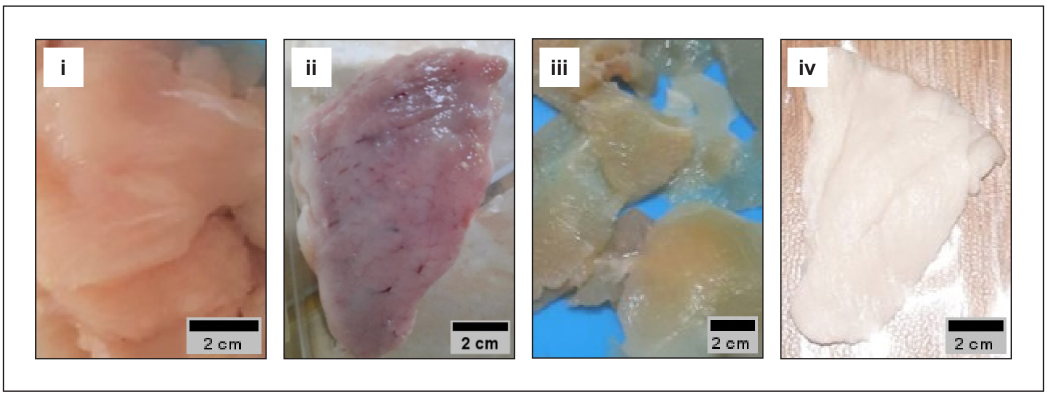
Sample Collection and Preparation

Chicken meat samples were sourced from local chicken farmers in Malang, East Java, Indonesia, predominantly consisting of commercial broiler chickens (Ross 308) to ensure a diverse representation of quality categories. The sampling procedure adhered to standardized protocols as outlined by the United States Department of Agriculture (USDA) and International Organization for Standardization (ISO), specifically referencing United States Department of Agriculture – Food Safety and Inspection Service (USDA-FSIS) (2021) and ISO 22000:2018 (ISO, 2018), which emphasize systematic sampling from various parts of the poultry carcass to account for variability in quality attributes such as color, texture, and moisture content (Taheri-Garavand et al., 2019). The procedure was organized as follows:

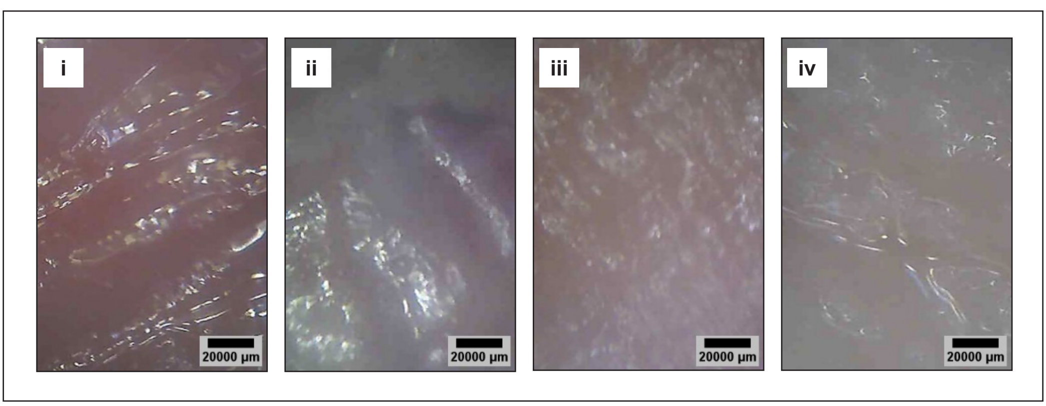
1. Each sample was categorized into one of four quality classes: (a) fresh chicken, (b) carrion chicken, (c) rotten chicken, and (d) formalinized chicken.
2. Fresh chicken was defined as meat cut within 24 hours post-slaughter, exhibiting bright yellowish-white coloration, clean and shiny skin, and no visible blood traces in muscle fibers.
3. Carrion chicken comprised meat from chickens that died without undergoing the slaughter process, displaying red-patched skin, bleeding in the head and neck, and reddish muscle fibers.
4. Rotten chicken was characterized by greenish-gray discoloration indicative of mold and bacterial growth, resulting from storage for six days in a chiller refrigerator at 2–4°C.
5. Formalinized chicken was obtained by immersing fresh chicken meat in a 10% formalin solution (Merck, Germany) for 24 hours at room temperature, resulting in sticky skin and pale meat (Söderqvist et al., 2024).
6. Each sample was filleted to a uniform size (no more than 7 cm in length and 1 cm in thickness) to ensure consistency in image acquisition.
7. A total of 2,000 digital images were captured, with 500 images per quality category. The dataset was then divided into training and validation sets at a ratio of 70:30, and an additional 600 images were reserved for testing. By ensuring a comprehensive

sampling strategy, this methodology establishes a robust foundation for accurate, real-time classification that surpasses traditional subjective or time-consuming methods, ultimately benefiting the poultry industry through more reliable quality assurance.

The types of chicken meat quality categories can be seen in Figure 1, which consists of four classes, namely fresh chicken, carrion chicken, rotten chicken, and formalinized chicken.



(a)



(b)

Figure 1. Image acquisition results in several types of chicken meat quality: (a) Chicken meat before the image acquisition process, (i) fresh sample, (ii) carrion sample, (iii) rotten sample, and (iv) formalinized sample; (b) Image acquisition at 1,000 × magnification level, (i) fresh sample, (ii) carrion sample, (iii) rotten sample, and (iv) formalinized sample

Image Acquisition and Preprocessing

High-resolution images of the chicken meat samples were acquired using an W04 Wi-Fi Portable Digital Microscope (China), Model W04 Wi-Fi Portable Digital Microscope-1000, equipped with a Complementary Metal–Oxide–Semiconductor (CMOS) image sensor, magnification range of 50–1,000×, and a resolution of 960 × 540 pixels. Potential limitations of this microscope include minor variations in magnification accuracy at higher zoom levels and the possibility of inconsistent focusing under suboptimal lighting conditions. Key steps were as follows:

1. The microscope was connected wirelessly to an Android 5.0 smartphone running HVviewing software, enabling seamless image capture under controlled lighting conditions.
2. An 8 SMD 3528 white light source with a sensitivity of 3V/lux-second was employed to ensure consistent illumination across all samples (Figure 2).
3. CNN models were developed and trained using MATLAB R2021a on an Acer NITRO 5 AN515-52 laptop with an 8th-generation Intel Core i5 processor, 16GB RAM, and a 4GB NVIDIA GeForce GTX 1050 GPU. This setup provided sufficient computational power for high-resolution image data analysis and CNN optimization.
4. Histogram equalization was applied to improve image contrast (Xiong et al., 2021).
5. Noise reduction using Gaussian filters minimized image noise and artifacts (Weli & Abdullah, 2024).
6. Color space transformation converted images from RGB to Lab* color space to facilitate better feature extraction (Lin et al., 2019).
7. Data augmentation (rotation, flipping, scaling) was employed to increase training data diversity, thus preventing overfitting and enhancing model robustness (Dhanya et al., 2022; Natho et al., 2025).

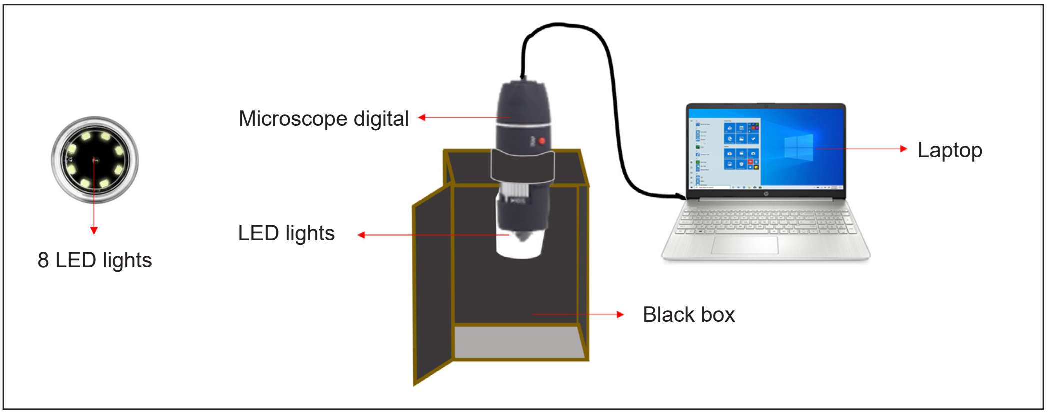


Figure 2. Image acquisition setup using a WiFi digital microscope capturing chicken meat samples under controlled lighting conditions
Note. LED = Light-emitting diode

CNN Model Selection and Hyperparameter Optimization

The study utilized two state-of-the-art CNN architectures, AlexNet and GoogleNet, to perform feature extraction and classification of chicken meat quality. These models were chosen due to their proven efficacy in image classification tasks and their ability to handle complex feature hierarchies without extensive manual intervention (Alzubaidi et al., 2021; Mienye & Swart, 2024). The architectural models used in this study are AlexNet and GoogleNet. Known for its simplicity and effectiveness in image classification, AlexNet consists of five convolutional layers followed by three fully connected layers, utilizing ReLU activation and dropout for regularization (Alzubaidi et al., 2021). GoogleNet features a more complex architecture with inception modules that allow for parallel convolutional operations, enhancing the network's ability to capture diverse features from the images (Mienye & Swart, 2024).

To optimize the performance of the CNN models, various hyperparameters were systematically tuned, i.e., optimizers, learning rate, epochs and batch size. Three optimizers were evaluated—SGDM, Adam, and RMSProp. Adam was found to perform the best in preliminary studies due to its adaptive learning rate capabilities, which facilitate faster convergence (Li et al., 2022). Two learning rates were tested—0.0001 and 0.00005. A smaller learning rate of 0.00005 was preferred as it provided higher accuracy and stability in the training process (Yoon & Kang, 2023). An optimal epoch of 30 and a batch size of 20 were determined through sensitivity analysis to balance training time and model performance. These careful optimizations ensure that the system can be implemented efficiently in real-world conditions, speeding up decision-making processes and thereby reducing the time window in which suboptimal meat might enter the market.

Evaluation Metrics Analysis

The performance of the CNN models was evaluated using a comprehensive set of metrics to ensure robust and reliable classification results. The primary metrics employed included accuracy, sensitivity, specificity, and confusion matrix. For accuracy, the proportion of correctly classified instances out of the total instances. Sensitivity is needed for the model to correctly identify positive instances within each class, and specificity is needed to correctly identify negative instances. Confusion Matrix provided a detailed breakdown of true positive, false positive, true negative, and false negative classifications for each quality category.

The dataset was split into 70% for training and 30% for validation, ensuring that the model was trained on a diverse set of samples and validated against unseen data to assess generalization. An independent test set of 600 images, not included in the training or validation sets, was used to evaluate the final model performance, thereby providing an unbiased assessment of the model's accuracy and reliability. By leveraging such standardized evaluation protocols, this methodology fosters confidence in the model's real-world applicability, supporting the poultry industry's need for a scalable tool that can be seamlessly integrated into existing quality control workflows.

CNN was used as a modeling method for the classification of chicken meat quality as shown in Figure 3. After the CNN model was built, the CNN model was tested using 600 testing data taken on meat samples outside the training and validation data samples. This study used two pre-trained CNN models, i.e., AlexNet and GoogLeNet. The optimizer variations used in this study included SGDM, Adam, and RMSProp. Variations in learning rate were also carried out at values of 0.0001 and 0.00005. The best CNN model testing process was carried out using the confusion matrix method, using testing data. Such a data-driven, efficient methodology not only surpasses traditional methods in speed and consistency but also supports enhanced traceability and resource management by enabling precise quality checks at critical points in the supply chain.

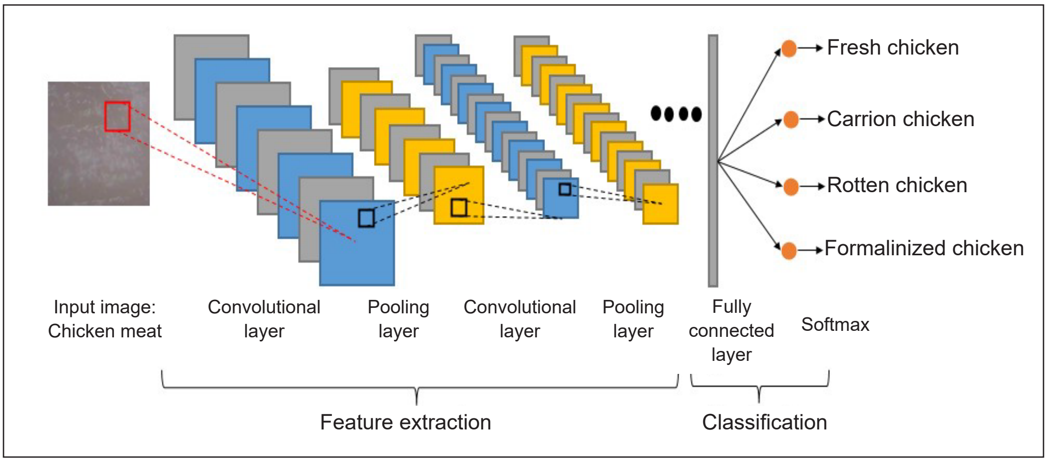


Figure 3. Convolutional Neural Network structure to classify four types of chicken meat quality

RESULTS AND DISCUSSION

Classification Performance

The primary objective of this study was to evaluate the effectiveness of two state-of-the-art CNN architectures, AlexNet and GoogLeNet, in classifying chicken meat quality into four distinct categories: fresh, carrion, rotten, and formalinized. The classification performance was assessed using a comprehensive dataset comprising 2,000 images for training and validation (70:30 split) and an independent test set of 600 images. Table 1 summarizes the validation and testing accuracies achieved by each CNN model combined with different optimizers and learning rates. The highest testing accuracy of 99.15% was achieved using GoogLeNet with the RMSProp optimizer and a learning rate of 0.00005.

The results indicate that both CNN architectures are highly effective in classifying chicken meat quality, with overall testing accuracies exceeding 95% across most configurations. Notably, GoogLeNet outperformed AlexNet in most scenarios, achieving a maximum testing accuracy of 99.15% compared to AlexNet's highest accuracy of 98.65%. This aligns with previous studies highlighting the superior feature extraction capabilities

Table 1
CNN performance based on validation and testing data accuracy

Pre-trained CNN	Optimizer	Learning rate	Validation accuracy (%)	Testing accuracy (%)
GoogLeNet	SGDM	0.0001	96.17	96.82
	SGDM	0.00005	92.00	95.17
	Adam	0.0001	99.00	96.32
	Adam	0.00005	97.17	96.82
	RMSProp	0.0001	98.50	97.85
	RMSProp*	**0.00005**	**97.83**	**99.15**
AlexNet	SGDM	0.0001	97.67	96.50
	SGDM	0.00005	94.50	96.17
	Adam	0.0001	98.00	95.67
	Adam*	**0.00005**	**98.50**	**98.65**
	RMSProp	0.0001	95.50	91.32
	RMSProp	0.00005	94.00	94.50

Note. CNN = **C**onvolutional **N**eural **N**etwork; SGDM = Stochastic Gradient Descent with Momentum; Adam = Adaptive Moment Estimation; RMSProp = Root Mean Square Propagation; * = Optimizer and learning-rate pairing yielded optimal performance

of deeper and more complex architectures like GoogLeNet in image classification tasks (Aguilar et al., 2018; Mienye & Swart, 2024). This level of performance surpasses traditional sensory or chemical assessments, providing the poultry industry with a rapid, objective, and more accurate tool for ensuring product quality.

Comparison of CNN Architecture

The comparative analysis between AlexNet and GoogLeNet reveals significant differences in their classification performances. GoogLeNet consistently achieved higher accuracies across various optimizer and learning rate settings compared to AlexNet. GoogLeNet top performance (99.15%) with RMSProp and a learning rate of 0.00005, along with validation accuracies as high as 99.00%, underscores the advantages of deeper and more complex architectures capable of capturing diverse features (Aguilar et al., 2018; Mienye & Swart, 2024). These improvements mean that producers and processors can identify quality issues earlier and more reliably, allowing them to take corrective action before inferior products reach consumers.

Optimizer and Learning Rates

The study evaluated three different optimizers (SGDM, Adam, and RMSProp) and two learning rates (0.0001 and 0.00005) to determine their effects on the CNN models' performance. Adam and RMSProp, with their adaptive learning rate capabilities, yielded superior results compared to SGDM. RMSProp, in particular, produced the highest testing accuracy of 99.15%. A lower learning rate of 0.00005 consistently resulted in improved accuracy and training stability, aligning with literature suggesting that fine-tuning hyperparameters enhances model performance (Kingma & Ba, 2014; Loshchilov & Hutter, 2016). Such optimized models can be seamlessly integrated into quality control workflows, improving the speed and consistency of assessments. By ensuring that only top-quality meat moves forward, this reduces the chance of spoilage in the supply chain, thereby minimizing waste and contributing to better traceability as each batch's quality is verified before distribution.

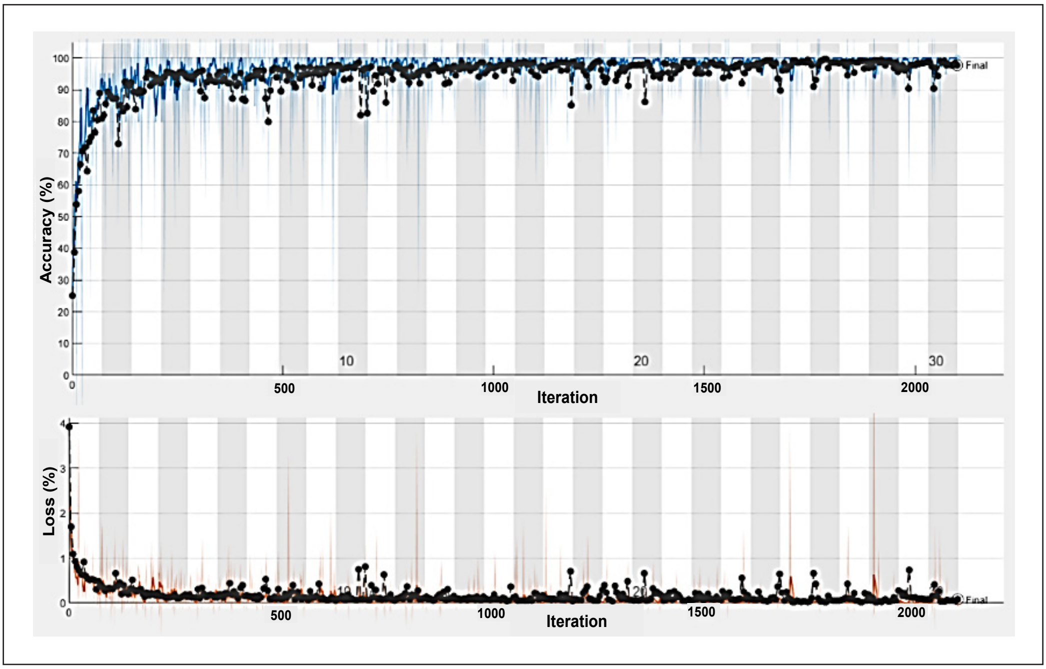
Training and Validation

The training and validation processes were closely monitored to assess the convergence behavior and potential overfitting of the models. Figure 4 illustrates the accuracy and loss curves for the best-performing configurations of GoogLeNet and AlexNet, respectively. Monitoring training and validation processes revealed stable convergence and minimal overfitting. GoogLeNet stabilized around epoch 8 and AlexNet by epoch 5, indicating efficient training. The rapid convergence and stable learning curves attest to the suitability of the chosen architectures and hyperparameters, as well as the efficacy of preprocessing and augmentation steps. This training efficiency also suggests that the system can be deployed in real-world conditions without excessive computational demands, supporting scalability and wider adoption. As a result, even smaller producers or distributors can employ this technology, enhancing industry-wide standards and ensuring high-quality meat reaches consumers.

Confusion Matrix Analysis

Confusion matrices were employed to provide a detailed breakdown of the classification performance across the four meat quality categories. Figure 5 present the confusion matrices for the best-performing GoogLeNet and AlexNet models, respectively. Confusion matrices were used to analyze classification performance across the four categories. GoogLeNet accurately classified 99.30% of fresh, carrion, and formalinized samples, and AlexNet also demonstrated strong performance, albeit with slightly more misclassifications in the rotten category. The primary confusion involved rotten and fresh classes, likely due to subtle visual similarities. Carrion and formalinized classes were occasionally confused, indicating overlapping color and texture features.

These results indicate that both models perform exceptionally well in classifying most categories, with GoogLeNet slightly outperforming AlexNet in overall accuracy. The Rotten category remains the most challenging, particularly for AlexNet, which experienced higher misclassification rates compared to GoogLeNet. This aligns with literature suggesting that more complex architectures like GoogLeNet can better handle subtle differences



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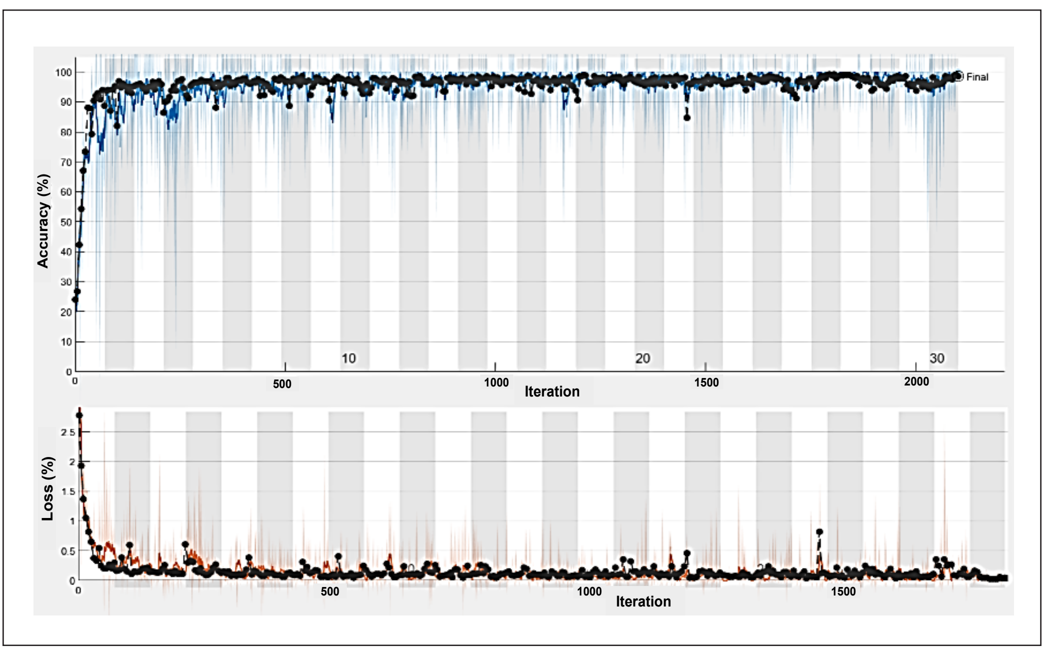
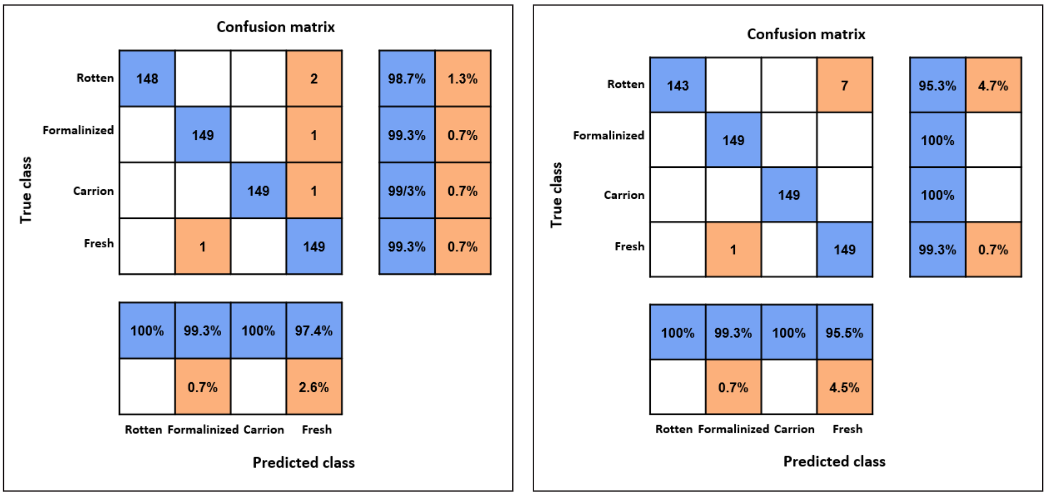


(b)

Figure 4. CNN's learning process for the classification of types of chicken meat quality: (a) GoogLeNet with RMSProp optimizer and learning rate of 0.00005; (b) AlexNet with Adam optimizer and learning rate of 0.00005
Note. CNN = **C**onvolutional **N**eural **N**etwork; RMSProp = Root Mean Square Propagation; Adam = Adaptive Moment Estimation



(a) (b)

Figure 5. The results of the confusion matrix on testing data: (a) GoogLeNet with RMSProp optimizer and learning rate of 0.00005; (b) AlexNet with Adam optimizer and learning rate of 0.00005
Note. RMSProp = Root Mean Square Propagation; Adam = Adaptive Moment Estimation

in image features (Aguilar et al., 2018; Mienye & Swart, 2024). Despite these minor misclassifications, the overall high precision of the models ensures that the poultry industry can rely on this tool to maintain quality standards. By flagging questionable products early, the system helps prevent low-quality items from entering the supply chain, reducing waste and enhancing traceability because each product can be monitored, identified, and, if necessary, removed at an earlier stage.

Error Analysis and Misclassification Patterns

An in-depth error analysis was conducted to understand the misclassification patterns and underlying causes. The primary misclassifications observed were between the rotten and fresh categories, as well as between carrion and formalinized categories. For both CNN models, the rotten category had the lowest classification accuracy. In GoogLeNet, 2 out of 150 rotten samples were misclassified as fresh, while in AlexNet, 7 out of 150 were misclassified as fresh. These misclassifications could be attributed to the visual similarities between severely spoiled meat and fresh meat under certain imaging conditions, such as lighting variations or surface moisture levels. This finding is consistent with studies that highlight challenges in distinguishing between similar visual attributes in food quality assessments (Aguilar et al., 2018; Mienye & Swart, 2024). Minor misclassifications occurred between carrion and formalinized categories. For instance, GoogLeNet misclassified 1 carrion sample as formalinized, and AlexNet did not misclassify any carrion samples. These errors may result from overlapping visual features, such as redness in carrion meat and discoloration in formalinized meat, which can confuse the CNN models. Similar patterns have been observed in other food quality classification studies, where certain quality attributes present overlapping visual characteristics that pose challenges for automated classification systems (Aguilar et al., 2018). Minor misclassifications occurred between carrion and formalinized categories. For instance, GoogLeNet misclassified 1 carrion sample as formalinized, and AlexNet did not misclassify any carrion samples. Minor misclassifications between carrion and formalinized categories may stem from visual similarities in redness and discoloration. Techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) (Saadallah et al., 2022) could further refine the models by highlighting which image features lead to errors, guiding improvements in preprocessing or model architecture. By continually refining and improving model accuracy through such feedback loops, this approach ensures ongoing adaptability and robustness, making it more effective at preventing off-quality products from reaching consumers and sustaining a transparent, trustworthy supply chain.

Model Robustness and Generalization

Testing on an independent dataset validated the model's robustness, with GoogLeNet achieving 99.15% and AlexNet 98.65% accuracy. This indicates strong generalization and suggests that the models can perform well under varied conditions. While the study focused on a single dataset, future work could explore cross-dataset validation to ensure broad applicability. Diversifying the dataset with samples from multiple regions, breeds, and storage conditions could further enhance robustness and make the technology even more attractive for global adoption.

The high performance of the models suggests that the dataset was sufficiently diverse, capturing a wide range of quality attributes and variations within each category. This diversity is crucial for training CNNs to recognize and accurately classify subtle differences in meat quality, enhancing their generalization performance (Elmasry & Abdullah, 2024; L. Zhou et al., 2019). The models' ability to maintain high accuracy on an independent test set indicates their potential for real-world implementation in poultry supply chains. By integrating these CNN models with portable digital microscopes, it is feasible to deploy automated, real-time quality assessment systems that can operate reliably in various environmental conditions, thereby ensuring consistent meat quality and safety (Hwang et al., 2025; Xu et al., 2024). Such systems can be instrumental in enhancing operational efficiency, reducing reliance on labor-intensive traditional methods, and providing immediate feedback for quality control processes.

The training process for both CNN models was efficient, with GoogLeNet converging faster than AlexNet due to its deeper architecture and more sophisticated feature extraction mechanisms. The use of adaptive optimizers like RMSProp and Adam significantly reduced the number of epochs required for convergence, aligning with findings that adaptive learning rate methods enhance training efficiency and model performance (Szegedy et al., 2015). This efficiency is particularly advantageous for practical deployments where computational resources and time are constrained. Throughout the training process, both models exhibited stable learning curves, with minimal fluctuations in accuracy and loss metrics. This stability is indicative of the models' resilience to overfitting and their ability to consistently learn relevant features from the image data (Alzubaidi et al., 2021; Mienye & Swart, 2024). The balanced training and validation curves suggest that the models maintained a healthy generalization capacity, avoiding the pitfalls of overfitting that can plague complex neural network architectures.

The successful implementation of high-performing models on a relatively modest computational setup (Acer NITRO 5 AN515-52 laptop with an NVIDIA GeForce GTX 1050 GPU) suggests that the proposed system is scalable and can be adapted to various hardware configurations. This scalability is essential for practical deployment in diverse settings, ranging from small-scale farms to large poultry processing facilities (Natho et al., 2025). The use of pre-trained CNN models facilitates transfer learning, allowing for rapid adaptation to new environments and meat types with minimal retraining, thereby enhancing the system's flexibility and applicability (Saadallah et al., 2022). Despite the high accuracies achieved, certain limitations were noted. The rotten category exhibited slightly lower accuracy, particularly in AlexNet, indicating a need for further refinement in distinguishing highly spoiled meat from fresh samples. Additionally, the study was conducted under controlled laboratory conditions, which may not fully replicate the variability encountered in real-world environments (Nayeem et al., 2025).

The models' impressive performance in accurately classifying chicken meat quality has direct implications for the poultry industry. Unlike traditional methods that are subjective, time-intensive, or costly, this CNN-based approach delivers rapid, objective, and repeatable evaluations. By implementing this system, producers can detect low-quality meat at an earlier stage, ensuring that only safe, high-quality products reach the market. This not only builds consumer confidence but also reduces waste by preventing substandard meat from advancing through the supply chain. Moreover, improved traceability results from consistent, documented quality assessments, allowing stakeholders to quickly identify and address issues. These factors collectively support industry-wide upgrades in safety, efficiency, and resource management, ultimately encouraging the technology's scalable and global implementation.

Precise identification of meat quality can significantly reduce food waste by ensuring that only genuinely spoiled or adulterated meat is discarded while retaining consumable products. This efficient utilization of resources aligns with global sustainability goals, promoting environmental stewardship by minimizing the environmental footprint associated with poultry farming and meat processing (Kilibarda et al., 2023; Suthar et al., 2024). By implementing automated quality assessment systems, the poultry industry can achieve more sustainable operations, reducing both economic and environmental losses linked to food waste. The integration of portable digital microscopes and CNNs facilitates enhanced traceability within the poultry supply chain. Real-time monitoring and documentation of meat quality at various stages of processing and distribution ensure that any issues can be swiftly identified and addressed. This traceability not only enhances food safety by enabling quick identification of contamination sources but also fosters accountability and transparency, thereby increasing stakeholder trust and industry credibility (B. Zhou et al., 2016; El-tahlawy et al., 2025; Suthar et al., 2024).

CONCLUSION

This study successfully demonstrated the integration of portable digital microscopes with advanced CNNs for the accurate classification of chicken meat quality. It provides a robust framework for developing automated, real-time quality assessment systems that align with global food safety and sustainability objectives. By employing two state-of-the-art CNN architectures, AlexNet and GoogLeNet, the research achieved high classification accuracies, with GoogLeNet outperforming AlexNet by attaining a testing accuracy of 99.15% compared to AlexNet's 98.65%. These results affirm that this CNN-based approach surpasses traditional, labor-intensive, and time-consuming methods in both speed and objectivity, providing the poultry industry with a more efficient tool for routine quality assessments. The findings highlight the critical role of optimizer selection and learning rate tuning in enhancing model performance. Adaptive optimizers such as RMSProp and Adam significantly improved classification accuracies and training stability, aligning with existing literature that underscores the effectiveness of these optimizers in complex image processing applications. Additionally, the utilization of a lower learning rate (0.00005) was instrumental in achieving higher accuracy and preventing overfitting, ensuring robust model performance. Beyond mere accuracy improvements, the proposed technology contributes to reducing food waste and improving traceability by quickly identifying low-quality meat before it advances through the supply chain. This early detection prevents substandard products from reaching consumers, thereby minimizing discard rates and enabling stakeholders to maintain detailed quality records that enhance transparency. Implementing such a system not only bolsters consumer confidence and meets regulatory requirements but also fosters a more sustainable and accountable industry. In terms of real-world implementation, the cost-effective, portable nature of the digital microscope-CNN framework supports scalability across different operational scales—from large processing plants to smaller farms. By facilitating timely, data-driven decisions about product quality, this approach is poised to streamline existing workflows, reduce reliance on specialized personnel, and integrate seamlessly into diverse supply chain environments.

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