EVALUATING OF DEEP LEARNING MODELS FOR EARLY DETECTION IN MEAT CLASSIFICATION: A STUDY ON BEEF AND PORK DETECTION

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ABSTRACT

Accurate classification of beef and pork images is essential for developing reliable automated food inspection systems, particularly because these meats exhibit high visual similarity in color distribution, texture, and muscle fiber patterns. Although deep learning methods have been increasingly applied to meat classification, many previous studies evaluate only a single model or use different experimental configurations, making it difficult to determine which architecture provides the most stable and generalizable performance. Therefore, a standardized comparative evaluation of multiple deep learning architectures is necessary. This study evaluates the performance of several Convolutional Neural Network (CNN) architectures for binary meat image classification using RGB digital images. Four CNN models, namely InceptionV3, VGG16, Res-Net50, and Xception were assessed under identical preprocessing pipelines and hyperparameter settings to ensure a fair comparison. The dataset consisted of 400 original images, which were expanded to 6,400 images through augmentation. Preprocessing included cropping, resizing to 224×224 pixels, normalization, and data augmentation to improve variability and generalization. Model performance was evaluated using accuracy, precision, recall, and F1-score on unseen test data. Experimental results show that InceptionV3 achieved the most balanced performance with a test accuracy of 72% and an F1-score of 0.70. These findings indicate that InceptionV3 provides a more stable architecture for beef and pork image classification and support the development of image-based automated meat authentication systems.

Keywords: *Beef, Convolutional Neural Network, Image Classification, Pork.*

I. INTRODUCTION

Meat is a vital source of animal-based protein and plays a central role in the dietary patterns of many populations. Among various meat types, beef is particularly valued for its high nutritional content and is widely consumed worldwide [1]. However, because beef has a higher market price than other meats, especially pork [2], [3], adulteration practices such as mixing pork into beef products have become a recurring problem. These fraudulent activities not only cause economic losses but also raise ethical, religious, and public health concerns [4]. In Indonesia, multiple cases of meat adulteration have been reported, affecting both fresh meat and processed products. The visual similarity between beef and pork in terms of texture and color makes it extremely difficult for consumers to differentiate them through simple observation [5], [6], [7]. Consequently, there is a growing need for a fast, accurate, and scalable technological solution to detect meat adulteration effectively.

To address this issue, this study employs digital image-based modelling combined with deep learning techniques for automated meat classification [8], [9], [10]. Image-based modelling provides a non-invasive and scalable alternative to traditional laboratory-based authentication methods. Conventional techniques such as spectroscopy, chemical analysis, or sensor-based detection often require specialized instruments, controlled laboratory environments, and time-consuming calibration procedures, which limit their practicality for large-scale or real-time inspection.

In contrast, image-based approaches rely on readily available RGB imaging devices and computational analysis, enabling rapid and cost-effective detection without requiring physical sampling or complex laboratory preparation. Visual characteristics such as color distribution, muscle fiber patterns, and surface texture contain discriminative information that can be effectively captured through digital imaging. By leveraging these visual cues, computer vision systems can perform automated inspection in a manner that is both efficient and scalable for real-world applications.

Within this framework, CNNs serve as powerful computational models capable of learning hierarchical visual representations directly from raw image data. CNN architectures automatically extract discriminative features such as edges, texture patterns, and spatial structures, allowing the model to distinguish subtle visual differences between beef and pork images without requiring manual feature engineering. This capability makes CNN-based image analysis particularly suitable for developing automated and deployable meat authentication systems [11], [12], [13], [14], [15].

This research focuses on developing a deep learning framework for beef and pork classification using four well-established CNN architectures: InceptionV3, VGG16, ResNet50, and Xception. Each model acts as a computational simulation that processes images under identical hyperparameter conditions, allowing comparative analysis of their generalization ability. To enhance robustness and reduce overfitting, preprocessing and data augmentation techniques are applied to simulate diverse real-world imaging conditions.

Digital image modelling has been extensively utilized in engineering and computer vision due to its ability to represent and analyze visual data through computational analysis. In meat classification, these techniques facilitate the modelling of texture, color, and spatial structures that differentiate meat species. CNN-based deep learning further extends this capability by hierarchically modelling image representations.

Each CNN architecture in this study embodies a distinct feature learning mechanism. VGG16 provides deep yet homogeneous feature hierarchies. ResNet50 models residual learning to overcome vanishing gradients. Xception introduces depthwise separable convolutions for efficient parallel simulation of spatial and channel features. Prior studies have demonstrated the potential of CNNs for meat classification tasks [8], [16], [17], [18], [19], [20], [21], [22], [23], [24] but limitations in dataset diversity and model robustness remain.

Therefore, this study aims to develop a deep learning framework capable of distinguishing between beef and pork. By evaluating multiple deep learning models under a controlled experimental setup with identical preprocessing pipelines and hyperparameter configurations, this research seeks to identify the architecture that provides the most reliable balance between classification accuracy and generalization capability for meat image recognition.

Based on this objective, the study addresses the following research questions:

RQ1: How do different CNN architectures (InceptionV3, VGG16, ResNet50, and Xception) perform in distinguishing beef and pork images under standardized experimental conditions?

RQ2: Which CNN architecture provides the most stable generalization performance when evaluated on unseen meat image data?

RQ3: Which architecture offers the best balance between accuracy, precision, recall, and F1-score for automated meat classification?

Answering these questions contributes to the development of intelligent food inspection systems by identifying the most suitable deep learning architecture for image-based meat authentication.

II. LITERATURE REVIEWS

Deep learning has become a dominant paradigm in artificial intelligence due to its capability to automatically learn hierarchical feature representations from large-scale datasets. Among various deep learning techniques, CNN have demonstrated superior performance in image classification tasks by extracting spatially invariant features such as edges, textures, and color gradients [25]. CNN-based approaches have been widely applied across various domains, including object recognition, medical image analysis, industrial inspection, and food quality assessment [26], [27], [28]. In food authentication research, CNN models have increasingly been utilized to analyze visual characteristics of meat products, including color distribution, muscle fiber structure, and surface texture patterns.

Several CNN architectures have been explored in previous studies for visual classification tasks, each offering distinct architectural characteristics that influence feature extraction capability and classification performance. InceptionV3 introduces multi-branch convolutional modules that enable efficient multi-scale feature extraction through factorized convolutions [12]. Such architectures are particularly effective in capturing complex spatial patterns in image datasets. VGG16 employs a simpler architecture composed of stacked 3×3 convolutional layers, which facilitates stable hierarchical feature learning and has been widely adopted as a baseline model in many image recognition studies [15]. ResNet50 addresses the vanishing gradient problem through residual connections, enabling deeper network architectures to be trained effectively while maintaining convergence stability [29]. Meanwhile, Xception extends the Inception framework by employing depthwise separable convolutions, improving computational efficiency while preserving strong feature representation capability [30].

Previous studies have demonstrated the potential of machine learning and deep learning approaches for meat authentication and classification. Several works have applied advanced computational methods to distinguish meat types or detect adulteration based on chemical composition, spectral analysis, or visual characteristics [31], [32], [33]. These studies confirm that machine learning models can extract discriminative patterns from different types of data sources. However, the reported performances vary significantly due to differences in dataset size, preprocessing strategies, and experimental configurations. In many cases, prior studies focus on a single model or analytical technique, making it difficult to determine whether the observed performance is method-specific or influenced by experimental conditions. Furthermore, inconsistencies in preprocessing pipelines and evaluation protocols limit the ability to perform meaningful cross-study comparisons. These limitations raise concerns regarding model generalization, particularly when datasets are relatively small or collected under controlled acquisition environments.

A summary of representative studies related to meat classification using machine learning and deep learning techniques is presented in Table 1.

Table 1. Comparison of previous studies on meat classification

Study	Method/Model	Input Data	Task	Performance	Limitation
Mazola et al. (2023) [34]	Multielement Analysis + Machine Learning (CART, MLP, Naïve Bayes, Random Forest, SMO)	Chemical element composition	Beef cuts classification	MLP achieved 96% accuracy, while CART obtained 70% accuracy	Requires laboratory-based chemical analysis, expensive equipment, and limited scalability for rapid on-site meat authentication
Barragán et al. (2020) [35]	Vis–NIR Spectroscopy + PLS-DA + Support Vector Machine (SVM)	Spectral reflectance data	Classification of barley-fed vs corn-fed beef	>94% accuracy for binary classification; performance drops to ~70% for ground samples	Performance depends on spectral preprocessing and decreases when multiple diet classes are included
Siddique et al. (2023) [36]	FTIR Spectroscopy + PCA + Multiclass SVM (M-SVM)	Infrared spectral data	Detection of lard adulteration	Overall classification accuracy 71–81% depending on adulteration ratio	Requires spectroscopy instruments; spectral similarity between lipids may reduce discrimination capability

As summarized in Table 1, previous studies on meat authentication can be broadly categorized into three main approaches: chemical composition analysis, spectroscopic techniques, and machine learning-based classification methods. Chemical and spectroscopic approaches often provide high analytical accuracy because they rely on detailed compositional measurements. However, these techniques typically require specialized laboratory equipment, complex sample preparation procedures, and controlled experimental conditions, which limit their scalability for rapid or large-scale inspection applications.

In contrast, image-based deep learning approaches offer a non-invasive and more practical alternative by utilizing readily available RGB images to analyze visual patterns in meat products. Such approaches enable automated inspection systems that can potentially be deployed in real-world environments without extensive laboratory infrastructure. Nevertheless, existing studies in meat image classification often focus on evaluating a single CNN architecture, making it difficult to assess whether the reported performance improvements originate from the model design itself or from experimental configurations. Therefore, a standardized comparative evaluation of multiple CNN architectures under identical preprocessing pipelines and experimental settings is necessary to better understand their relative performance and generalization capability in meat image classification tasks.

III. RESEARCH METHOD

This research was conducted through six sequential stages: image data collection, image preprocessing, dataset partitioning, model training, and model evaluation, as illustrated in Figure 1. Each stage represents a computational process aimed at evaluating the behavior and performance of CNN architectures.

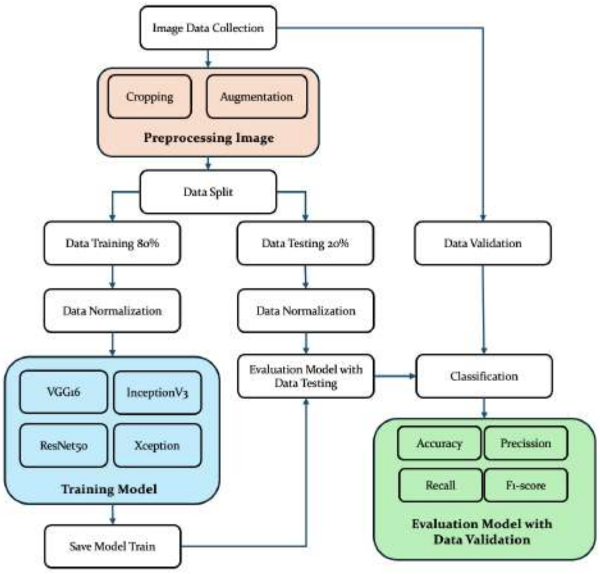

Figure 1. Research stages of the proposed CNN framework

A. *Image Data Collection*

Image data collection involves gathering, selecting, and organizing images according to the objectives of this study. The dataset employed was adapted from prior research and comprises 400 images with a resolution of 720×720 pixels. These images are categorized into three classes: beef, pork, and goat, as illustrated in Figure 2 [5], [24]. The figure presents representative samples of the original dataset, showing the visual characteristics of each meat type, including differences in color distribution, surface texture, and muscle fiber structure.

a b c

Figure 2. Original image samples: (a) beef, (b) pork, and (c) mutton

For the purpose of this study, only beef and pork images were used to establish a balanced binary classification problem, while goat images were excluded from the experimental analysis. Although the original dataset contains three meat categories, the exclusion of goat images allows the experiment to focus specifically on distinguishing between beef and pork, which exhibit highly similar visual characteristics and therefore present a more challenging classification task.

Although the dataset size is relatively small for deep learning applications, it still captures representative visual patterns of the two meat classes used in this study. To address this limitation, data augmentation techniques were applied during preprocessing to artificially increase the number of training samples and simulate variations in orientation, illumination, and spatial positioning. This approach helps improve model robustness and reduces the likelihood of overfitting.

Nevertheless, the relatively limited dataset may introduce potential bias, particularly if the images originate from similar acquisition conditions or controlled environments. Such limitations may affect the model's ability to generalize to more diverse real-world scenarios. Therefore, the findings of this study should be interpreted within the scope of the available dataset. Future studies are encouraged to incorporate larger and more diverse datasets collected under varying imaging conditions to further enhance the robustness and generalization capability of deep learning models for meat classification.

Following the data collection stage, preprocessing was performed to standardize image characteristics and prepare the dataset for model training. This stage improves feature extraction reliability and ensures dataset consistency, which is essential for stable model convergence. Cropping and resizing operations were conducted using Python-based image processing libraries to standardize the input images before they were used in the CNN training process.

B. *Data Preprocessing*

Preprocessing is a crucial stage that ensures the image data are clean, standardized, and suitable for deep learning modelling [37]. This stage improves data consistency, minimizes visual noise, and enables the CNN architectures to focus on discriminative visual features during learning. Two primary preprocessing techniques were applied in this study: image cropping and image augmentation.

Cropping is the process of removing irrelevant parts of an image to retain only the region of interest that contains meaningful visual information. In this study, cropping was performed manually to focus on the main portion of the meat sample. Raw images often include unwanted background or non-uniform illumination that can distract the CNN from learning relevant spatial features. By isolating the meat region, the model receives cleaner and more representative input data, enhancing the accuracy of feature extraction. This technique allows the model to emphasize intrinsic characteristics such as color distribution, fiber texture, and surface structure, which are critical for distinguishing beef and pork. The resulting cropped images are shown in Figure 3, which illustrates the focus adjustment process used before model training.

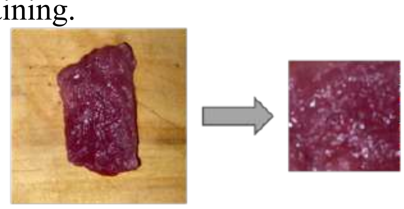

Figure 3. Cropped image results

Image augmentation was implemented to artificially expand the dataset and introduce simulated variability in imaging conditions [38], [39], [40]. This technique improves the model's ability to generalize by generating new image samples from existing data through controlled transformations. It effectively simulates real-world variations in viewing angles, lighting, and object positioning, thus enhancing robustness against environmental diversity. Several augmentation operations were applied, including rotation, scaling, translation (shifting), and horizontal flipping. Rotation introduces orientation variability to simulate camera angle changes, scaling mimics different object distances and sizes, translation shifts the image along the X or Y axis to simulate framing differences, and horizontal flipping produces mirrored variations, enriching spatial diversity.

The relationship between the original dataset D and the augmented dataset D'can be expressed as:

$$D' = n \times D \qquad (1)$$

where n is the number of augmentation operations applied to each original image. In this study, n=8, meaning that each image was transformed into eight augmented variations. This resulted in a total of 3,200 images per class, effectively expanding the dataset and reducing overfitting risk.

Through this process, the CNN models were trained on data that represent various lighting conditions, orientations, and spatial perspectives. Examples of augmented images are shown in Figure 4.

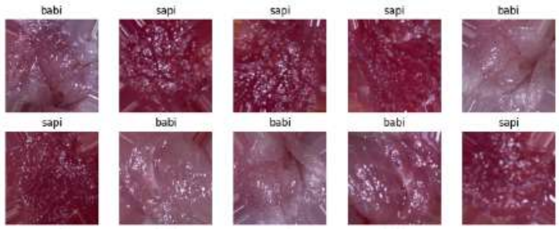

Figure 4. Example results of image augmentation for dataset expansion

C. Data Split

The next stage involves dividing the dataset into three subsets: training, validation, and testing. This partitioning ensures that the simulation model is trained, fine-tuned, and evaluated using independent data segments, thereby preventing overfitting and enhancing the model's generalization ability [41].

The dataset division follows an 80:10:10 ratio, where 80% of the data is used for training, 10% for validation, and 10% for final testing. This procedure simulates the real-world process of model evaluation by exposing the CNN architectures to unseen data at different phases of the experiment [42], [43], [44]. The data split for each class is shown in Table 2.

Table 2. Distribution of image data subsets

Classes	Total Data		
	Training Data 80%	Validation Data 10%	Test Data 10%
Pork meat	2,880	320	320
Beef Meat	2,880	320	320

The number of samples allocated to each subset can be formulated as:

$$N_{subset} = R_{subset} \times N_{total} \qquad (2)$$

where N_{subset} is the number of images in each data segment, R_{subset} represents the corresponding ratio, N_{total} is the total number of images per class.

The training set is used to optimize network parameters and learn discriminative visual features. The validation set supports hyperparameter tuning and helps prevent overfitting during model development, while the test set is reserved exclusively for the final evaluation to measure the model's generalization capability on unseen data.

Although this fixed data split strategy is widely used in deep learning experiments, performance estimation may still vary depending on the dataset partitioning. Future studies may consider employing k-fold cross-validation to provide a more robust statistical evaluation, particularly when working with relatively limited datasets. The use of data augmentation during training introduces additional variability in the training samples, which may lead to slightly lower training accuracy compared to validation accuracy. This behavior is commonly observed when strong augmentation is applied to improve model robustness.

D. Training Model

Four convolutional neural network (CNN) architectures, namely InceptionV3, VGG16, ResNet50, and Xception were employed in this study for automated classification of beef and pork images. Each model serves as a deep learning architecture designed to learn and generalize discriminative visual features. The dataset was divided into two classes, and all input images were resized to 224×224 pixels to match the standard input dimensions required by the CNN architectures [24], [29], [30], [32], [45], [46], [47]

During classification, each model processes an input image x_i with a true class label y_i and generates a predicted output $\hat{y}_i$. The learning objective is to minimize the categorical cross-entropy loss, which measures the divergence between the true and predicted class probabilities. The loss function is defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log\left(\hat{y}_{i,c}\right) \quad (3)$$

where:

N = total number of samples,

C = number of classes (2),

$y_{i,c}$ = binary indicator (1 if sample i belongs to class c, 0 otherwise), and

$\hat{y}_{i,c}$ = predicted probability of class c.

Model optimization was performed using the Adam optimizer with a learning rate (η) of 0.001, following the update rule:

$$\theta_{t+1} = \theta_t - \eta\frac{\hat{v}_t}{\sqrt{\hat{m}_t} + \epsilon} \quad (4)$$

where θ_t represents the model parameters at iteration t, and $\hat{m}_t$, $\hat{v}_t$ denote the bias-corrected first and second moment estimates, respectively. The optimization ensures smooth convergence while maintaining training stability across all architectures.

All CNN architectures were trained using identical hyperparameters, namely ReLU activation, Adam optimizer, batch size = 32, and learning rate 0.001 to ensure a fair performance comparison under controlled simulation conditions. During training, each model produced a probability distribution for both meat classes, and the class with the highest probability value was selected as the final predicted label. Each CNN architecture represents a distinct simulation strategy for hierarchical image representation. InceptionV3 incorporates parallel convolutional modules with multiple receptive fields, enabling multi-scale feature extraction and improving computational efficiency. [29], [30] VGG16 utilizes uniform 3×3 convolutional filters arranged in deep sequential layers to construct robust hierarchical representations of texture and color features [48], [49] ResNet50 employs residual connections that alleviate the vanishing gradient problem, allowing efficient training of deeper architectures with stable convergence [24], [47], [50] Xception extends the Inception concept by implementing depthwise separable convolutions, thereby enhancing computational efficiency through the separation of spatial and channel processing [51]. After completing the training phase, each CNN model was evaluated using quantitative performance metrics, namely accuracy, precision, recall, and F1-score to determine its classification effectiveness. These architectures were selected to compare accuracy, generalization capability, and computational efficiency under standardized experimental conditions. The evaluation results were then used to identify the most suitable model for deployment in intelligent and automated food inspection systems.

E. Evaluation Model

The purpose of model assessment is to gauge how well the created image categorization system performs [52], [53], [54], [55]. The purpose of this study is to evaluate the model's ability to identify and differentiate between the meat classes of beef and pig. To make sure the model works on both training and previously unknown data, the assessment procedure is an essential step. Researchers can determine each examined model's advantages and disadvantages by properly evaluating it.

Four primary assessment criteria are employed in this study: F1-score, recall, accuracy, and precision [24], [56], [57]. The proportion of properly categorized cases among all test samples is referred to as accuracy. The precision metric quantifies the percentage of actual positive predictions among all the model's positive predictions. Conversely, recall is the percentage of real positive instances that were found out of all positive cases. The F1-score provides a thorough evaluation of model efficacy, especially in situations when there is a class imbalance, by combining accuracy and recall into a single statistic by computing their harmonic mean. The Adam optimizer, which was chosen for its dependability and effectiveness in convergent convergence across a variety of datasets, was used to train the model at a learning rate of 0.001. All input pictures were scaled to 224x224 pixels to meet the input parameters required by the CNN architectures used. This scaling step improves computing performance and preserves consistency without appreciably compromising classification accuracy. Strong performance may be achieved by the model when the parameters are set correctly. To identify the top-performing architecture, the accuracy, precision, recall, and F1-score values from each model were compared [57], [58]. To choose the best model for the unique features of the meat picture dataset, this comparison is essential. Additionally, to support both quantitative and qualitative assessments, the evaluation results are shown using tables and graphical representations. These visual aids facilitate the formation of more impartial and solid opinions. The model with the best performance was selected for final implementation based on this analysis.

The evaluation stage measures the classification performance of each CNN model. Four key metrics were used: accuracy, precision, recall, and F1-score[60], [61], [62], [63].

These metrics quantify both the correctness and reliability of the model's predictions, formulated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1\text{ - }score = 2\, x \frac{Precision\ x\ Recall}{Precision + Recall} \quad (8)$$

where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively. All CNN models were trained using identical hyperparameters, namely ReLU activation, Adam optimizer, and a learning rate of 0.001 to ensure a fair comparison of their performance. Each model's results were analyzed both numerically and visually through tables and comparative charts to capture differences in accuracy and robustness. The CNN architecture demonstrating the best balance between accuracy, precision, recall, and F1-score was selected as the optimal model for further implementation in the intelligent food inspection system.

IV. RESULTS AND DISCUSSIONS

The evaluation of the four convolutional neural network (CNN) architectures, namely InceptionV3, VGG16, ResNet50, and Xception was carried out to analyze their learning behavior and classification performance in distinguishing beef and pork images. Each model was trained using identical hyperparameters, including the ReLU activation function, Adam optimizer, and a learning rate of 0.001, to ensure a fair comparison under consistent experimental conditions. Table 3 presents the average training and validation accuracy results obtained for each architecture, while Figure 5 illustrates a comparative overview of the model performance during the training phase.

Table 3. Model training evaluation

Architecture	Optimizer	Learning Rate	Avg. Training Accuracy	Avg. Validation Accuracy
InceptionV3	Adam	0.001	89%	96%
VGG16	Adam	0.001	82%	91%
ResNet50	Adam	0.001	50%	48%
Xception	Adam	0.001	96%	99%

As shown in Table 3, notable variations were observed among the architectures in terms of training and validation performance. InceptionV3 demonstrated strong learning capability, achieving an average training accuracy of 89% and a validation accuracy of 96%. The slightly higher validation accuracy may be attributed to the application of data augmentation during training, which introduces additional variability in the training samples while the validation dataset contains unaltered images.

In contrast, ResNet50 recorded the lowest performance, with 50% training accuracy and 48% validation accuracy, suggesting that the residual network structure may not have been well suited to the characteristics of the dataset or that additional hyperparameter tuning was required. Xception, on the other hand, achieved the highest training and validation accuracy of 96% and 99%, respectively, indicating its strong capability to capture complex visual features through depthwise separable convolutions.

However, such extremely high training performance should be interpreted with caution. Given the relatively limited size of the dataset, the model may have learned dataset-specific patterns rather than generalizable visual features. This phenomenon is commonly associated with overfitting, where the model memorizes training samples instead of learning robust representations that generalize well to unseen data. As discussed in the testing results, the performance of Xception decreased when evaluated on the test dataset, suggesting that the model's high training accuracy did not translate into consistent generalization performance.

Figure 5 provides a graphical comparison of these training results, showing the relative strengths of each architecture during the learning process. It can be observed that InceptionV3 and Xception significantly outperformed the other two architectures during training, highlighting their efficiency in capturing complex texture and color features in meat images.

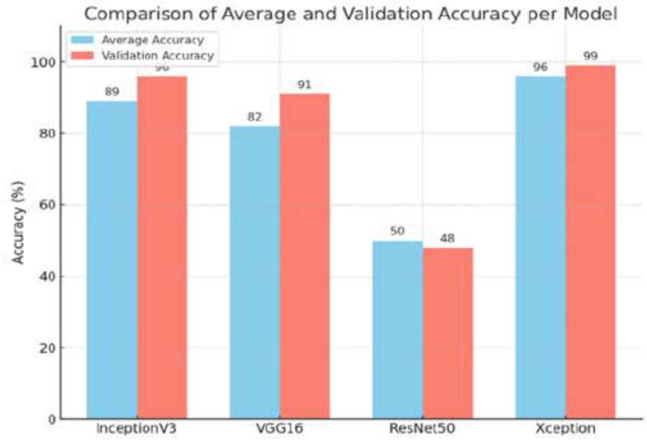

Figure 5. Performance comparison chart of model training

To further evaluate the models, four performance metrics, namely accuracy, precision, recall, and F1-score were calculated during the testing phase using 320 unseen images for each CNN model. The results are summarized in Table III, while Figure 6 visualizes the comparative outcomes. The testing phase provides a more reliable indication of model generalization because the models are evaluated using completely unseen data.

Table 4. Model performance evaluation results

Architecture	Accuracy	Precision	Recall	F1-score
InceptionV3	72%	0.7	0.7	0.7
VGG16	50%	0.2	0.5	0.3
ResNet50	68%	0.7	0.7	0.6
Xception	62%	0.7	0.6	0.6

As summarized in Table 4, InceptionV3 achieved the best overall testing performance, with an accuracy of 72% and balanced precision, recall, and F1-score values (each at 0.7). This result indicates relatively strong generalization and stability when classifying previously unseen meat images. The balanced metric values confirm that InceptionV3 maintained a good trade-off between true positive rate and false positive control, suggesting that this architecture provides the most reliable performance among the evaluated models.

In contrast, VGG16 showed limited adaptability with a testing accuracy of 50%, precision of 0.2, recall of 0.5, and F1-score of 0.3, suggesting that it struggled to handle intra-class variations in meat texture and color. This limitation may be related to the relatively simple sequential convolutional structure of VGG16, which may not capture complex multi-scale texture patterns as effectively as more advanced architectures. Meanwhile, Xception, despite achieving the highest training accuracy, attained only 62% testing accuracy and an F1-score of 0.6, indicating potential overfitting where the model learns dataset-specific patterns that do not generalize effectively to unseen samples.

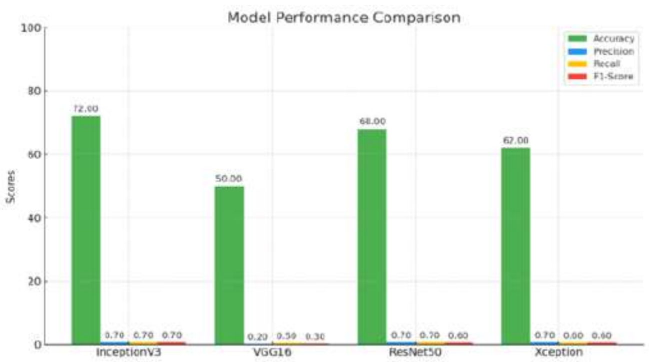

Figure 6. Model performance evaluation chart

Figure 6 illustrates the comparative accuracy, precision, recall, and F1-scores across all architectures, reinforcing that InceptionV3 offers the most stable and balanced performance profile among the tested models. The convergence behavior of InceptionV3 indicates that it efficiently captures discriminative features while minimizing noise sensitivity. This advantage may be attributed to its multi-branch convolutional structure, which allows the model to extract visual features at multiple spatial scales simultaneously. Misclassification between beef and pork images mainly occurs due to the high visual similarity between the two meat types. Both meats exhibit comparable color distributions and muscle fiber structures, particularly under varying illumination conditions. These similarities reduce the discriminative capability of convolutional filters, making it challenging for the models to consistently distinguish between the two classes.

To further interpret the model's behavior, Figure 7 compares the average training, validation, and testing accuracy of each CNN. Xception, on the other hand, achieved the highest training and validation accuracy of 96% and 99%, respectively, indicating its strong capability to capture complex visual features through depthwise separable convolutions. This architectural design enables efficient extraction of spatial and channel-wise features, which may enhance the model's ability to represent fine-grained texture patterns in meat images. InceptionV3, by contrast, maintained consistent accuracy across all phases (training 89%, validation 96%, testing 72%), indicating robust generalization and stable model performance. VGG16 showed moderate training and validation performance (82%, 91%) but failed to generalize effectively during testing (50%), while ResNet50 exhibited unstable performance across the evaluation stages, achieving relatively low training and validation accuracy (50% and 48%), but improving to 68% during testing. This behavior may indicate that the model did not converge optimally during training under the fixed hyperparameter settings used in this study.

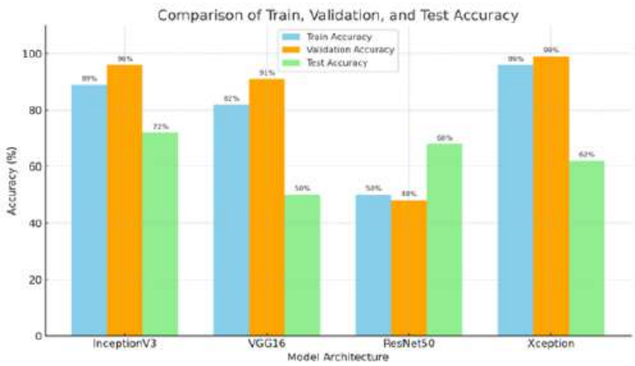

Figure 7. Comparison chart of training, validation, and testing accuracy of CNN models

Overall, these results demonstrate that InceptionV3 offers the best balance between training efficiency, accuracy, and generalization capability. Although Xception achieved superior performance during training, its high variance between training and testing indicates sensitivity to overfitting. The comparative analysis confirms that InceptionV3 provides a reliable and computationally efficient model for meat image classification and is therefore identified as the most suitable architecture for further deployment in automated food inspection systems.

The superior performance of InceptionV3 can be attributed to its multi-scale convolutional architecture. The parallel convolutional filters enable the model to capture visual features at different spatial resolutions, which is particularly beneficial for meat images where discriminative patterns such as muscle fibers and texture variations appear at multiple scales.

Several recent studies have explored the application of machine learning and deep learning techniques for meat authentication and classification; however, the reported accuracies vary substantially depending on the type of input data, acquisition modality, and model configuration. Mazola et al. (2023) [34] applied several supervised learning algorithms, including CART, Random Forest, and Multilayer Perceptron (MLP), to authenticate beef cuts based on multielement composition, achieving accuracies ranging from 70% (CART) to 96% (MLP). Barragán et al. (2020) [35] employed visible and near-infrared spectroscopy (Vis-NIRS) combined with discriminant analysis techniques to classify beef based on feeding regimes, reporting accuracies exceeding 94% for binary classification, but dropping to approximately 70% when ground beef samples were analyzed. Similarly, Siddique et al. (2023) [36] implemented Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN) models to detect poultry breast myopathies, with SVM achieving 71.04% accuracy for mild woody breast classification.

In contrast, the present study introduces a CNN-based modelling framework that utilizes image-level data under identical preprocessing pipelines and hyperparameter configurations across four architectures, namely InceptionV3, VGG16, ResNet50, and Xception. Among these models, InceptionV3 achieved the most balanced performance with an accuracy of 72% and an F1-score of 0.70. While the obtained accuracy is comparable to several previously reported results in AI-based meat classification studies, the proposed approach differs in its reliance on visual image data rather than spectroscopy or chemical composition analysis. This distinction enables a more practical and scalable framework that reduces dependence on specialized laboratory instruments while maintaining competitive classification performance.

Table 5. Comparison of current study with previous works

Study	Method / Model	Input Type	Accuracy (%)	Remarks
[34] Mazola et al.	Multielement Analysis + ML (CART, MLP, Naïve Bayes, Random Forest, SMO)	Chemical element composition	MLP achieved 96% accuracy, while CART obtained 70% accuracy	Requires laboratory-based chemical analysis
[35] Barragán et al.	Vis–NIR Spectroscopy + PLS-DA + SVM	Spectral reflectance data	>94% accuracy for binary classification; performance drops to ~70% for ground samples	Accuracy decreases for ground meat samples
[36] Siddique et al.	FTIR Spectroscopy + PCA + Multiclass SVM	Infrared spectral data	Overall classification accuracy 71–81% depending on adulteration ratio	Spectral overlap affects discrimination capability
This Study	CNN (InceptionV3, VGG16, ResNet50, Xception)	RGB digital images	72 (InceptionV3)	Image-based approach without laboratory instrumentation

As shown in Table 5, the proposed CNN model based on the InceptionV3 architecture achieved an accuracy of 72%, achieved an accuracy comparable to the lower range of previously reported results by Mazola et al. (70%), Barragán et al. (70%), and Siddique et al. (71%). Although these previous studies employed different data modalities, including chemical composition analysis, spectral measurements, and bioelectrical impedance, their approaches generally relied on specialized laboratory equipment and hardware calibration.

In contrast, the present study utilizes standardized RGB digital images as input data, enabling a more practical and accessible framework for automated meat classification. By relying solely on visual features extracted through deep convolutional networks, the proposed approach reduces dependency on laboratory instrumentation while maintaining competitive classification performance. These findings suggest that image-based CNN modelling offers a scalable and reproducible alternative for meat authentication tasks, with strong potential for integration into intelligent food inspection systems.

V. CONCLUSION

This study presented a comparative evaluation of four CNN architectures, namely InceptionV3, VGG16, ResNet50, and Xception for automated classification of beef and pork images. All models were trained and evaluated under identical experimental settings using standardized preprocessing pipelines and hyperparameter configurations to ensure a fair comparison. The experimental results indicate that InceptionV3 achieved the most balanced performance, obtaining a testing accuracy of 72% and an F1-score of 0.70. In contrast, Xception achieved the highest training accuracy but exhibited clear signs of overfitting when evaluated on unseen test data, while VGG16 and ResNet50 showed comparatively lower classification performance. This work provides a standardized comparative evaluation framework that enables a fair assessment of CNN architectures under identical preprocessing pipelines and hyperparameter configurations.

From a theoretical perspective, this study provides empirical insights into the comparative behavior of different CNN architectures when applied to meat image classification under standardized experimental conditions. The results suggest that higher model complexity does not necessarily lead to better generalization performance, particularly when training datasets are relatively limited. Instead, architectures that balance feature extraction capability and model stability, such as InceptionV3, may offer more reliable performance for practical image classification tasks.

From a practical perspective, the findings demonstrate the potential of image-based deep learning approaches as scalable alternatives to conventional laboratory-based meat authentication methods. Unlike spectroscopy or chemical analysis techniques that require specialized equipment, the proposed approach relies on RGB digital images and computational models, enabling more accessible and cost-effective deployment. This capability opens opportunities for developing automated meat inspection systems that can assist food quality control in markets, supply chains, and food processing industries.

However, this study has several limitations, particularly the relatively small dataset size and the use of fixed image resolution, which may limit the model's ability to generalize across diverse imaging conditions. Future research may address these limitations by expanding the dataset with more diverse samples collected under varying environmental conditions. In addition, incorporating k-fold cross-validation could provide a more robust statistical evaluation of model performance. Further studies may also explore hybrid or ensemble learning strategies and integrate explainable AI techniques to enhance model robustness, interpretability, and practical deployment in automated food inspection systems.

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