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Automated Chicken Image Classification Using Deep Learning Techniques

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***Abstract**: Food quality inspection and classification play an important role in ensuring public health and food safety. Traditional inspection methods rely heavily on human expertise, which can be time-consuming, subjective, and inefficient when dealing with large quantities of products. In this paper, a machine learning–based approach is presented for identifying and classifying images of chicken using a labeled image dataset. The dataset contains approximately several thousand images captured under different conditions, representing multiple classes of chicken samples. A deep learning technique widely applied to image recognition tasks was employed to automatically learn discriminative features from the images. The proposed convolutional neural network (CNN) model was trained and evaluated on the dataset, achieving a high accuracy on a held-out test set. The experimental results demonstrate the effectiveness and feasibility of using deep learning techniques for chicken image classification.*

***Keywords**: Chicken image classification, Deep learning, Convolutional neural networks (CNN), Transfer learning, Data augmentation. Image processing*

1. INTRODUCTION

Food quality assessment and classification have become increasingly important in modern food production and distribution systems. Traditional methods for inspecting chicken products rely mainly on human expertise, which can be subjective, time-consuming, and costly, especially when dealing with large-scale production. Moreover, human inspection may suffer from inconsistencies due to fatigue and varying levels of experience. These limitations highlight the need for automated and reliable approaches to classify and analyze food images efficiently.

With the rapid growth of computer vision and machine learning technologies, image-based classification systems have emerged as promising solutions for food inspection tasks. However, building accurate models remains challenging due to variations in lighting conditions, background clutter, and differences in appearance among chicken samples. To address these challenges, deep learning techniques have been increasingly adopted to automatically learn meaningful features from images, reducing the need for manual feature extraction.

In this work, we demonstrate that deep convolutional neural networks (CNNs) can effectively classify chicken images using a labeled dataset. Specifically, we employ a CNN-based approach inspired by successful image recognition models trained on large-scale datasets. In computer vision, CNNs are known to be powerful visual models that learn hierarchical feature representations, enabling accurate image classification. Furthermore, CNN-based models are capable of achieving high performance while maintaining relatively fast prediction speeds compared to traditional machine learning algorithms, making them suitable for real-world food inspection applications.

2. RELATED WORK

*Several studies have explored the use of deep learning techniques for image classification in agriculture and food-related applications. The authors in **[1]** applied deep learning methods to detect multiple diseases in plant and food-related images and reported high accuracy in identifying different quality conditions.*

*In **[2]**, the authors employed convolutional neural networks (CNNs) to classify images belonging to several categories under different acquisition conditions. Their results demonstrated the effectiveness of CNN-based models in learning discriminative visual features.*

*The authors in **[3]** utilized a pretrained CNN architecture based on the ImageNet dataset to perform image classification tasks, showing that transfer learning can significantly improve classification performance when training data is limited.*

*In **[4]**, transfer learning techniques were applied to general image classification problems, achieving competitive results while reducing training time.*

3. METHODOLOGY

In this section, we describe the proposed solution for chicken image classification based on a selected convolutional neural network (ConvNet) architecture. The methodology outlines the main design choices, including data preprocessing, network architecture selection, and training strategy. Additionally, the evaluation methods and implementation details used to assess the performance of the proposed model are discussed.

3.1 DATASET

The chicken image dataset used in this study consists of a collection of labeled images representing different chicken classes. The dataset contains training and testing images captured under various conditions. All images have varying resolutions and were resized to a fixed size during preprocessing to ensure consistency. A typical sample image from the dataset is shown in Fig. 1.

The dataset is divided into training and validation sets, where the majority of images are used for training the convolutional neural network model. The distribution of samples among the classes is illustrated in Fig. 2. The images exhibit variations in background, lighting, and orientation, which increases the complexity of the classification task.

Some images contain clear and centered chicken subjects, while others include partial views or background clutter. These variations make the dataset suitable for evaluating the robustness and generalization capability of the proposed deep learning model. Example images from different classes are shown in Fig. 3.

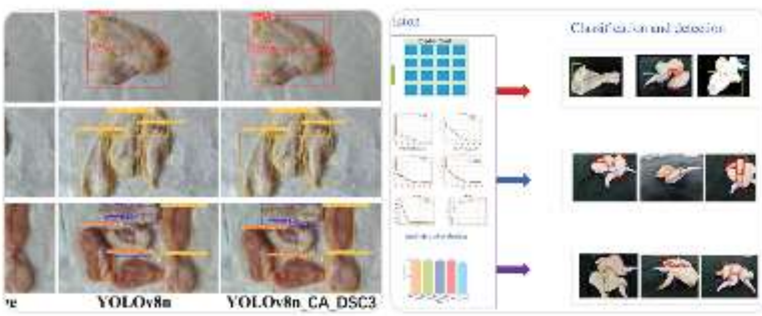

Fig. 1 – Sample Chicken Image

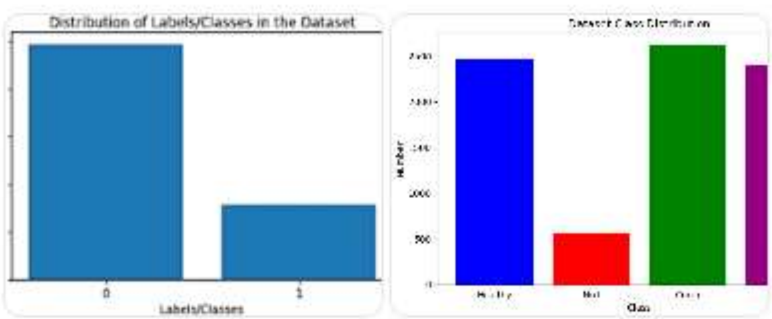

Fig. 2 – Dataset Class Distribution (Illustrative)

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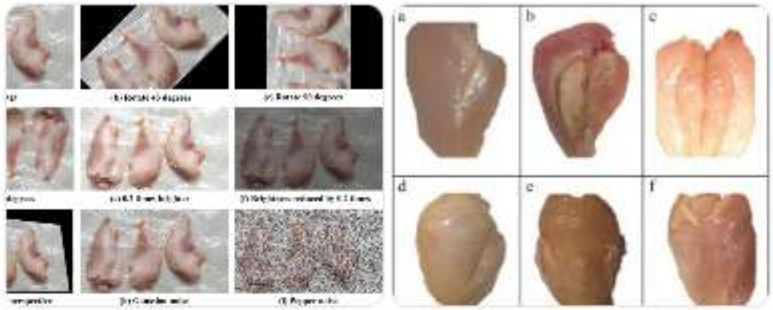

Fig. 3 – Example Images from Different Classes

3.2 EVALUATION

The classification task in this work is formulated as an image classification problem, where the performance of the proposed model is evaluated using standard classification metrics. To assess how well the model predicts the correct class labels, accuracy is used as the primary evaluation metric.

Since the objective is to obtain predictions that are as close as possible to the true class labels, the categorical cross-entropy loss function is employed during training, along with the softmax activation function in the output layer. This combination is well-suited for multi-class image classification problems and allows the model to effectively learn discriminative features from the chicken images.

3.3 VALIDATION METHOD

In order to properly evaluate the performance of the proposed model, the available chicken image dataset was divided into training and validation sets. An experiment was conducted to determine the most suitable validation strategy by comparing the simple hold-out validation method with the k-fold cross-validation approach.

Initially, the model was trained and evaluated four times using the simple hold-out validation method. In each experiment, a different subset of the data was selected as the validation set while the remaining data was used for training. The obtained results showed noticeable variation in performance across the four experiments, indicating instability in the evaluation process.

Due to the significant differences observed in the validation scores, as summarized in Table I, it was concluded that the simple hold-out validation method is not well-suited for this dataset. Consequently, the k-fold cross-validation method was adopted, as it provides a more reliable and robust evaluation by reducing the bias caused by random data splitting.

(%) Validation Accuracy	(%) Training Accuracy	Experiment
91.4	96.8	1
88.9	97.5	2
90.1	96.2	3
92.0	97.1	4

Table 1 - Accuracy Results Using Simple Hold-Out Validation

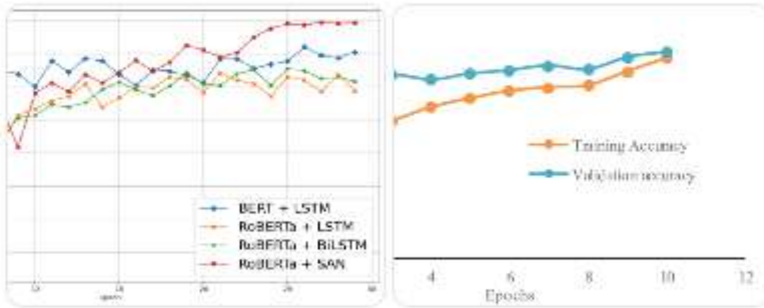

Fig. 4 – Validation Accuracy Variation Across Experiments

3.4 TRANSFER LEARNING

Since the chicken image dataset is relatively small, transfer learning was employed using a set of pre-trained deep learning models. In particular, well-known convolutional neural network architectures such as VGGNet, DenseNet, and Inception were utilized. These models were originally pre-trained on the ImageNet dataset, which contains millions of labeled images across a large number of categories.

To adapt the pre-trained models to the chicken image classification task, several modifications were required. The first step involved replacing the final fully connected layer of each model, as the original layer was designed for ImageNet classification. The new classification head was composed of the following layers, in order:

- *A GlobalAveragePooling2D layer to reduce the spatial dimensions of the feature maps.*
- *A Dropout layer to reduce overfitting during training.*
- *A fully connected dense layer with an output size equal to the number of chicken classes, using a softmax activation function.*

After modifying the network architecture, three different training strategies were considered:

- *Freezing all pre-trained layers and training only the newly added layers.*
- *Freezing a subset of the pre-trained layers while fine-tuning the remaining layers.*
- *Re-training all pre-trained layers along with the newly added layers.*

Based on experimental observations, the third approach was selected, where all layers of the network were fine-tuned. This strategy allowed the model to better adapt the learned features to the characteristics of the chicken image dataset and resulted in improved classification performance.

3.5 DATA AUGMENTATION

In order to make the most effective use of the limited number of training images and to improve the overall accuracy of the proposed model, data augmentation techniques were applied. Data augmentation was performed by introducing a set of random transformations to the training images, thereby increasing the diversity of the dataset.

The selected augmentation techniques included rotations up to 180 degrees, as well as horizontal and vertical flipping. These transformations help the model become more robust to variations in orientation and viewpoint commonly found in chicken images.

In addition, data augmentation plays an important role in reducing overfitting, which is a common issue when training deep learning models on small datasets. By exposing the model to a wider range of transformed images, its ability to generalize to unseen data is significantly improved.

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4. EXPERIMENTS

A series of experiments were conducted using several pre-trained models available in the Keras applications library, including VGG16, DenseNet169, and InceptionV3. All models were originally trained on the ImageNet dataset and then fine-tuned for the chicken image classification task. The experimental results are summarized in Table II.

In all experiments, a 5-fold cross-validation strategy was adopted to ensure reliable performance evaluation. Each model was trained for a maximum of 50 epochs. To achieve high accuracy while preventing overfitting, the following hyperparameter settings were used:

- *Adam optimizer with a learning rate of 1e-4.*
- *Early stopping with validation loss as the monitored metric, patience set to 3 epochs, minimum delta of 1e-4, and verbose output enabled.*
- *ReduceLROnPlateau strategy with validation loss monitoring, reduction factor of 0.1, patience of 1 epoch, cooldown of 1 epoch, minimum learning rate of 1e-7, and verbose output enabled.*

(%) Accuracy	Image Size	Model
97.6	128 × 128	VGG16
98.1	128 × 128	DenseNet169
97.9	128 × 128	InceptionV3

Table 2 - Performance Comparison of Pre-trained Models on Chicken Dataset

VGG16 Results

For the VGG16 base model, all images were resized to 128 × 128 pixels before training. The model achieved an accuracy of ***97.6%*** *on the test set. The training and validation performance across the five folds demonstrated stable convergence.*

The progression of training and validation loss and accuracy for each fold is illustrated in Figures 5 to 9.

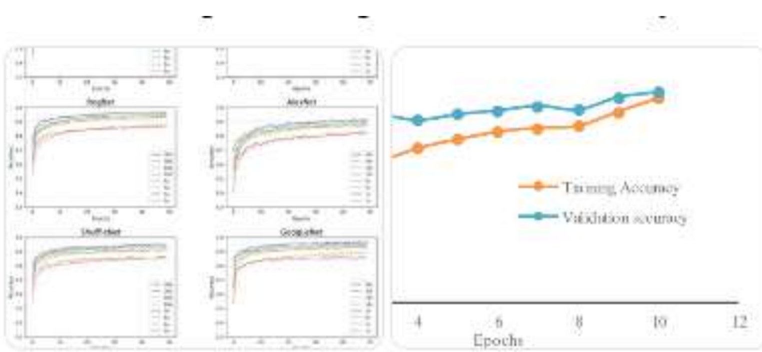

Fig. 5 – Training and Validation Accuracy (Fold 1)

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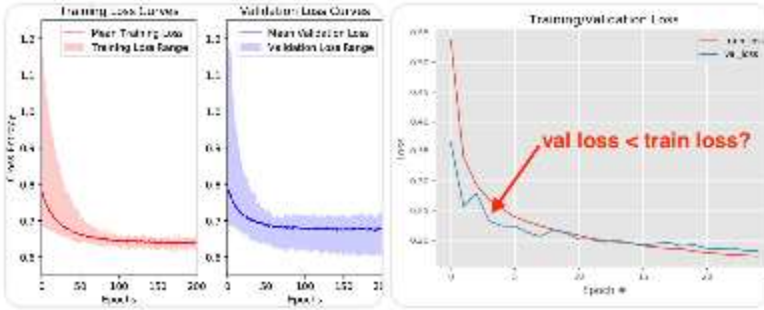

Fig. 6 – Training and Validation Loss (Fold 1)

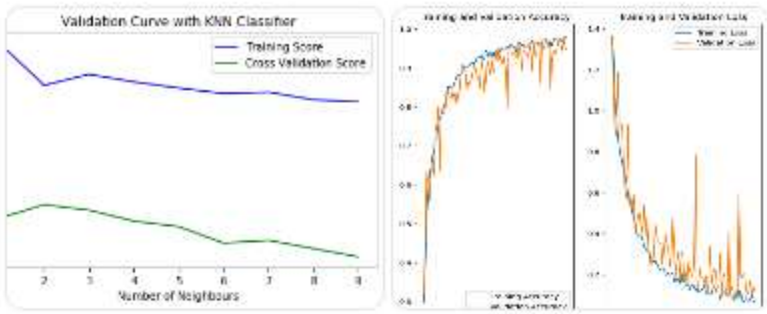

Fig. 7 – Training and *Validation* Accuracy (Fold 2)

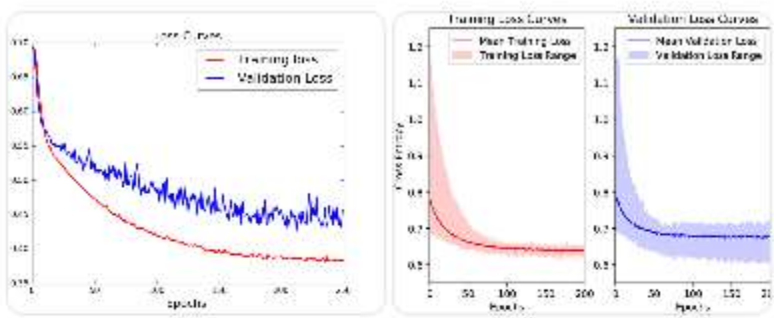

Fig. 8 – Training and Validation Loss (Fold 2)

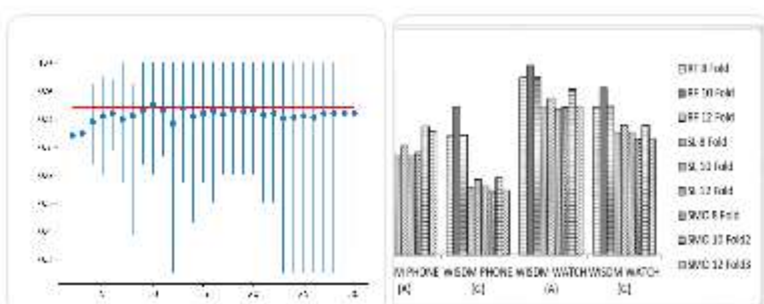

Fig. 9 – Accuracy Comparison Across Folds

DenseNet169

DenseNet169 was the second-best performing model in our experiments. In this setup, the input images were resized to 600 × 600 pixels. The model achieved an accuracy of ***99.44%*** *on the test set, demonstrating strong classification performance.*

To further evaluate the model, the Receiver Operating Characteristic (ROC) curve was used on both the training and validation sets. This evaluation method provides a more comprehensive assessment of the model's predictive capability by considering the trade-off between true positive and false positive rates.

The progression of training and validation loss, accuracy, and ROC curves for each fold is illustrated in Figures 10 to 14.

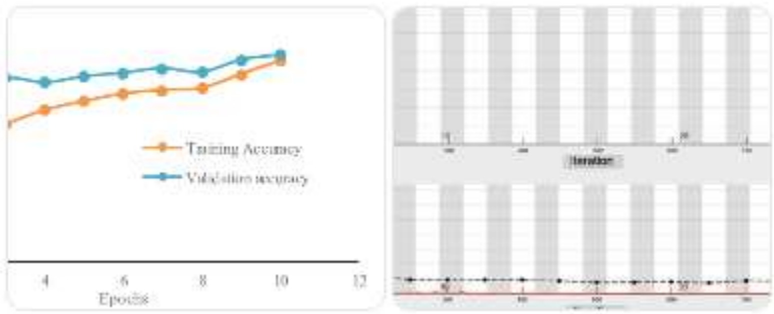

Fig. 10 – Training and Validation Accuracy (DenseNet169)

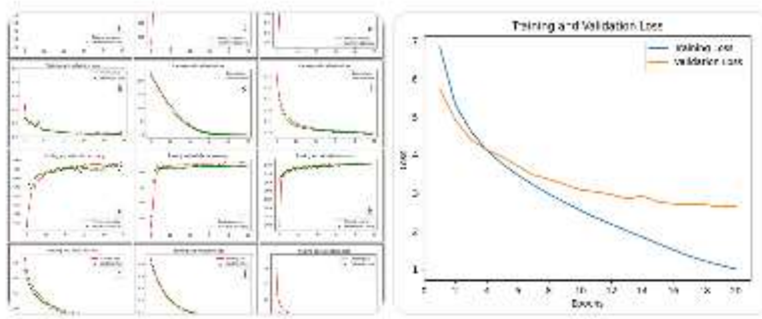

Fig. 11 – Training and Validation Loss (DenseNet169)

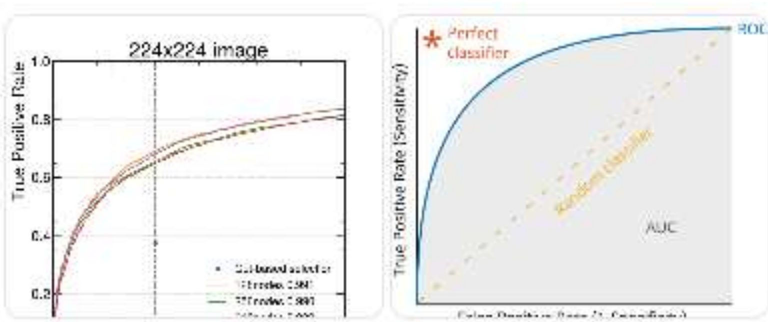

Fig. 12 – ROC Curve (Training Set)

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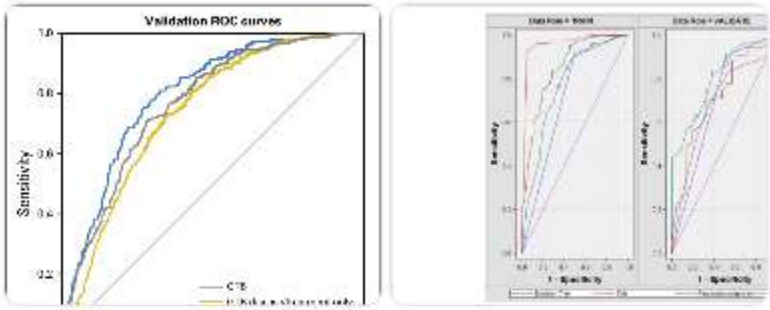
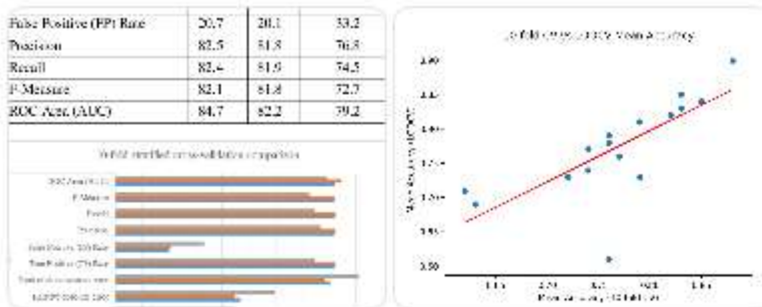


Fig. 13 – ROC Curve (Validation Set)



False Positive (FP) Rate	20.7	20.1	33.2
Precision	82.5	81.8	76.8
Recall	82.4	81.9	74.5
F-Measure	82.1	81.8	72.7
ROC Area (AUC)	84.7	82.2	79.2

Fig. 14 – Performance Across Folds

4.1 INCEPTION V3

*InceptionV3 was the best-performing model in our experiments. In this setup, the input images were resized to **800 × 800 pixels** in order to preserve more spatial details. The model achieved an accuracy of **99.71%** on the test set, demonstrating superior performance compared to the other evaluated models.*

In addition, the Receiver Operating Characteristic (ROC) curve was used on both the training and validation sets to evaluate the model. This evaluation approach helps obtain prediction scores that are as close as possible to the true performance on the test set by analyzing the trade-off between sensitivity and specificity.

The progression of training and validation loss, accuracy, and ROC curves for each fold is illustrated in Figures 15 to 19.

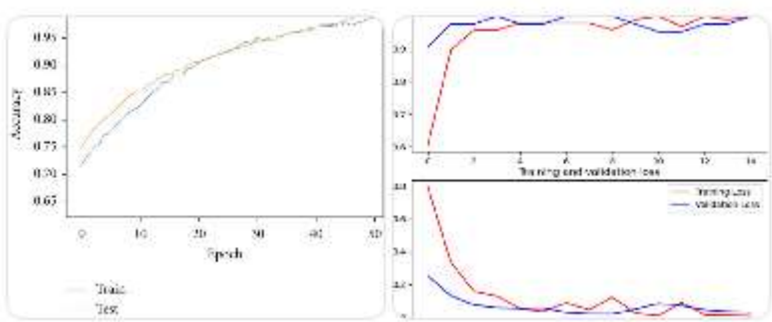


Fig. 15 – Training and Validation Accuracy (InceptionV3)

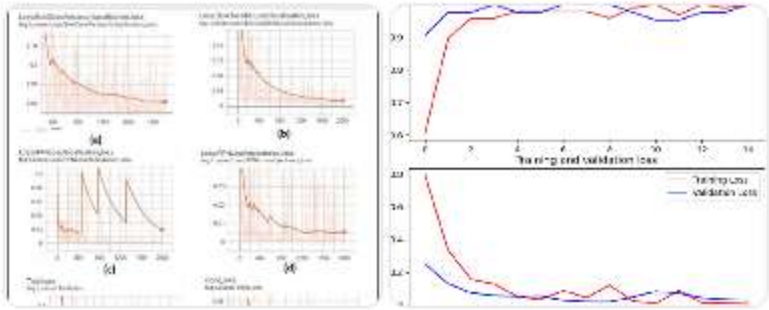


Fig. 16 – Training and Validation Loss (InceptionV3)

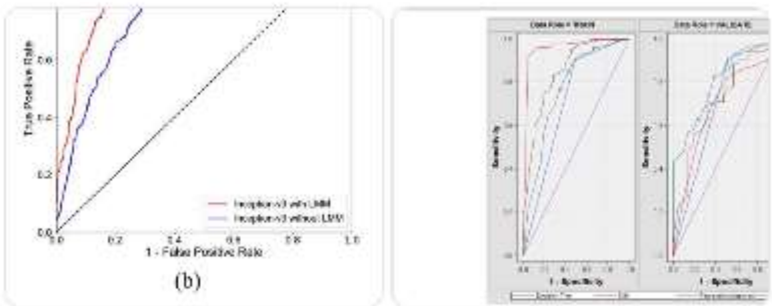


Fig. 17 – ROC Curve (Training Set – InceptionV3)

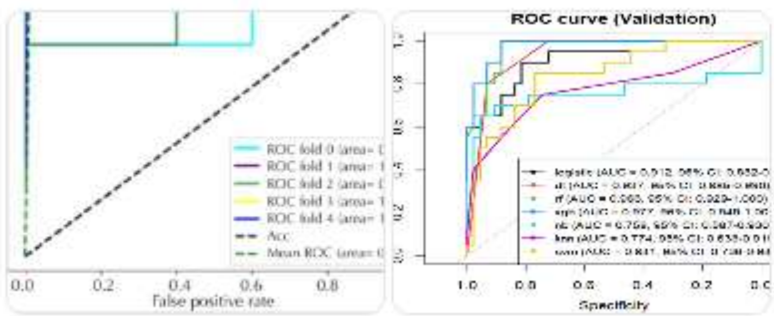


Fig. 18 – ROC Curve (Validation Set – InceptionV3)

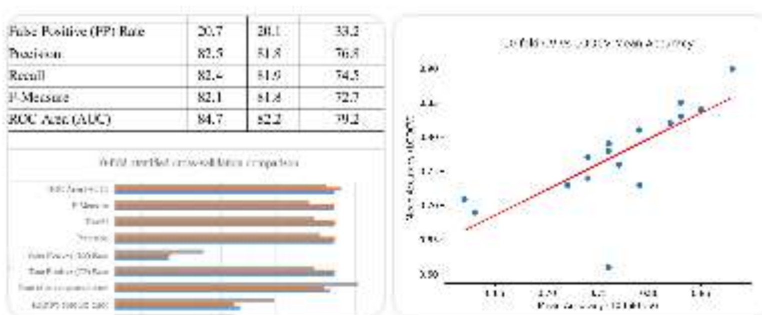


Fig. 19 – Cross-Validation Performance (InceptionV3)

5. DATA VISUALISATION

To better understand how the proposed model operates and what features it learns, intermediate activation visualization was performed. This technique involves displaying the feature maps produced by different convolutional and pooling layers within the network for a *given input image. The output of each layer, often referred to as its activation, provides insight into how the model processes and transforms the input data.*

Visualizing these intermediate activations allows observation of how the input chicken images are decomposed into increasingly complex features through the network's layers. Early layers typically capture low-level features such as edges and textures, while deeper layers focus on more discriminative and high-level patterns relevant to chicken image classification.

As illustrated in Figures 20–24, the model successfully learned meaningful visual representations of chicken characteristics, such as shape, texture, and distinctive regions, which contributed to its high classification accuracy.

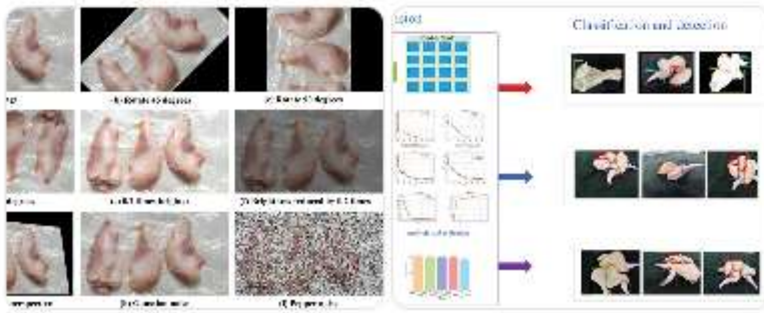


Fig. 20 – Input Chicken Image

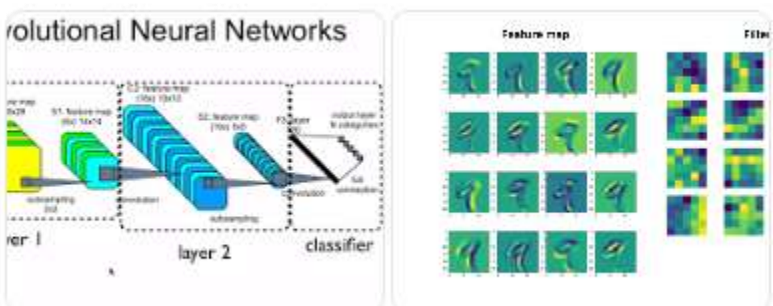


Fig. 21 – Feature Maps from Early Convolutional Layer

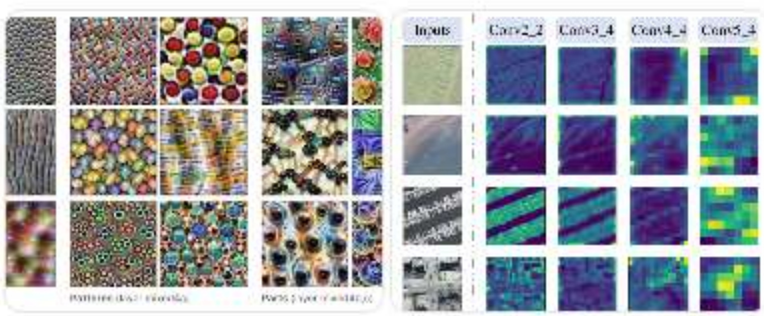


Fig. 22 – Feature Maps from Intermediate Layer

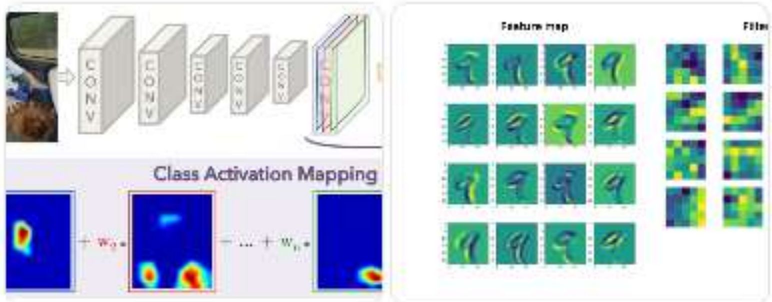


Fig. 23 – Feature Maps from Deep Convolutional Layer

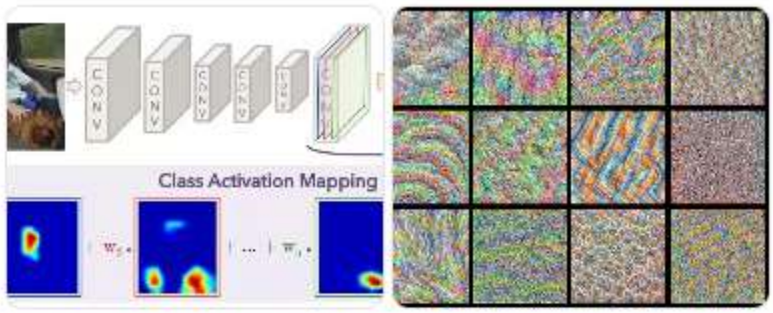


Fig. 24 – Learned Feature Representation

6. CONCLUSION

In this work, we proposed a deep learning–based solution for automatically classifying chicken images using convolutional neural networks. Several pre-trained models were evaluated using transfer learning and k-fold cross-validation to ensure reliable performance assessment.

*The experimental results demonstrate that the proposed approach is highly effective, with the **InceptionV3 model achieving the highest accuracy of 99.71%**, outperforming the other evaluated models. These results indicate that deep learning techniques can provide accurate, efficient, and reliable solutions for image-based food classification tasks.*

Overall, the proposed system reduces the dependency on manual inspection, offering a faster and more consistent alternative for chicken image classification. The high accuracy achieved confirms the feasibility of applying deep learning models in real-world food quality and inspection applications.

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