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# Transfer Learning Enabled Hybrid Model for Chicken Breed Classification

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**ABSTRACT**

**This study presents an automated chicken breed classification system using deep learning and machine learning techniques. A hybrid approach combining transfer learning and a Support Vector Machine (SVM) was employed, utilizing InceptionV3 as a feature extractor. The proposed system was evaluated against three state-of-the-art CNN models—MobileNetV2, VGG16, and InceptionV3—to determine the most accurate breed classification method. A dataset of approximately 2,000 images from eight chicken breeds (four pure breeds and four crossbreeds) was used, with an 80-10-10 split for training, validation, and testing. Data augmentation was applied to enhance model generalization. Performance was assessed using accuracy, precision, recall, and F1-score. The results indicate that InceptionV3 achieved the highest accuracy of 96%, outperforming MobileNetV2 and VGG16. These findings highlight that transfer learning with SVM significantly improves classification accuracy, making it a promising approach for applications in veterinary and agricultural domains.**

Keywords **- Chicken breed identification, SVM, Convolutional Neural Network, Transfer Learning, Poultry Industry. Artificial Intelligence, Machine Learning, Deep Learning**

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## 1. Introduction

The economic landscape of Sri Lanka is marked by the agricultural sector, which plays a pivotal role in shaping the nation's Gross Domestic Product (GDP). Notably, this sector contributes approximately 7% to the overall GDP [1]. Within this framework, the fisheries sector emerges as a significant contributor, accounting for around 1.3%, while the livestock sector makes up 0.9 % of the GDP [1]. The poultry sector is the fastest-growing segment of livestock production in Sri Lanka. In 2020, this dynamic field had a significant impact, accounting for 0.61 of nominal GDP at current prices [1]. Impressively, this represents a significant 64% of the GDP of the livestock sector of the entire country [1]. This growth underscores the central role of poultry in shaping the economic landscape and underscores its importance as a key driver of Sri Lanka's agricultural and economic prosperity. Currently, poultry farming is the only well-established and self-sufficient livestock sector of the country in terms of poultry meat products. Although the volume of poultry meat production has increased significantly, the efficiency of poultry production and the quality of products must be increased to meet the international quality standards of the Sri Lankan egg and meat industry and the export revenue of the industry [1].

Poultry Industry plays an important role in Sri Lanka's agricultural landscape, especially chicken farming. This industry offers a wide variety of chicken breeds that are bred for their meat and egg production capabilities. The landscape is characterized by a mixture of both local and imported breeds, which adds to the dynamism of the industry. However, distinguishing between purebred chickens and crossbreds can be problematic if relying solely on traditional methods, which often involve manual observation and evaluation.

This is an issue of significance because breeding and breed selection are two principal determining factors of the level of production, quality, and profitability in the industry. The genetic history of purebred chickens is known, and they exhibit certain characteristics: egg laying, meat production, or disease resistance. Cross chickens, on the other hand, are produced from several pure breeds for the purpose of gaining offspring have some desired traits whether high egg production, enhanced quality of meat, or immunity to some diseases. Cross-bred chickens can be more productive and more efficiently than pure breed chickens. That could have most favorable impacts on the profitability and growth of the poultry industry. In addition, conventional methods of chicken identification breeds, such as physical external visual inspection characteristics, size and weight measurements, behavior traits, physical leg bands, and tags, are extremely cumbersome and susceptible to error [2]. Correct breed identification is also crucial to provide genetic diversity within populations of poultry. This is necessary to maintain poultry flocks in health and robustness it renders them less prone to diseases and other health issues problems.

In poultry farming, certain breeds are more valuable or more challenging than others.

With these difficulties, the merging of image processing methods is an encouraging avenue for the Sri Lankan poultry industry. Through the utilization of image processing capability, there is a chance to overhaul the process of determining purebred and crossbreed chickens. In this regard, this study makes the following key contributions:

- Hybrid model for chicken breed classification: Developed a novel hybrid classification model integrating transfer learning-based Convolutional Neural Networks (CNNs) with a Support Vector Machine (SVM) classifier to improve breed classification accuracy.
- Performance benchmarking against state-of-the-art models: Compared InceptionV3 + SVM against MobileNetV2 and VGG16, demonstrating that InceptionV3 + SVM achieved the highest accuracy of 96%, outperforming other models.
- Optimized feature extraction and classification: Leveraged InceptionV3 as a feature extractor and SVM for classification, enhancing precision, recall, and F1-score for better breed identification.
- Real-world applicability for poultry farming and conservation: Demonstrated the potential of AI-driven automation in poultry farming, offering a scalable solution for breed identification, genetic diversity monitoring, and disease prevention.

The remainder of this paper is structured as follows: Section 2 reviews recent state-of-the-art research related to chicken breed classification and deep learning applications. Section 3 details the study's methodology, including data collection, preprocessing, feature extraction, model training, and optimization techniques. Section 4 presents the classification results, covering key evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, and performance benchmarking. Section 5 outlines the contribution of this study to the body of knowledge, emphasizing both practical and research domain impacts. Finally, Section 6 concludes the paper by summarizing the findings and discussing future research directions, including improvements in model generalization and real-time deployment.

## 2. Existing Work

For the purpose of enhancing classification accuracy, several studies have utilized machine learning and deep learning techniques like support vector machines (SVM), convolutional neural networks (CNNs), and transfer learning approaches. This section separates the methodologies, scope, and evolution of recent research on chicken breed classification and overall general applications of deep learning for animal classification.

### 2.1 Work Related to Chicken Breed Identification

One study utilized hyperspectral imaging coupled with chemometrics in identifying four breeds of chicken: Guangdong (Qingyuan chicken), Guangxi (Tuxiang chicken), Jiangxi (Black bone chicken), and Beijing (Butter chicken) [3]. Scientists acquired hyperspectral data from chicken breasts in the wavelength range of 400–900 nm and utilized five preprocessing methods to enhance the quality of signals. It benchmarked classification models such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Partial Least Squares Discriminant Analysis (PLS-DA), with SVM having the best accuracy of 96.25% [3]. Although this research showed the potential of hyperspectral imaging, it was restricted to pure breeds and excluded crossbreeds.

One more experiment was done on chicken population identification with the help of machine learning models depending on a small number of single nucleotide polymorphisms (SNPs) [4]. With a total of 47,303 SNPs, AdaBoost, Random Forest, and Decision Tree models were attempted. Among them, AdaBoost was the most successful with 36 SNPs alone, thereby establishing the effectiveness of machine learning in breed identification based on genes [4]. However, this method was based solely on genetic markers and not on phenotypic characteristics, restricting its practical use for visual breed identification.

Another study utilized machine learning algorithms for gender and breed identification of Indian native chickens [5]. K-means clustering, Gray-Level Co-occurrence Matrix (GLCM), Principal Component Analysis (PCA), and Boosted Tree (BT) classifiers were employed with high accuracy in the study [5]. The research was limited to Indian breeds and did not employ deep learning methods, which can bring enhanced accuracy and scalability to bigger datasets.

A comparative analysis compared MobileNet, DenseNet, and a conventional CNN for the classification of bird species, confirming MobileNet to be more accurate [6]. Though, the research was not dedicated to the classification of chicken breeds, nor the utilization of SVM as a classifier was in the scope. The research accentuates the effectiveness of deep learning models for species classification but leaves a gap for exploration in the domain of breed classification using hybrid strategies.

In the same way, a deep learning system based on the YOLOv3 model was used by researchers to detect dead broiler chickens [7]. Although the research focused on automating health inspection in commercial chicken production, breed classification was not addressed. Although sophisticated methods such as mosaic augmentation and spatial pyramid pooling were applied, the research did not touch on breed classification, meaning that there is scope to apply similar deep learning methods in distinguishing between chicken breeds.

### 2.2 Work Related to Other Animal Classification

Research created a CNN model for the identification of bird species with a dataset constructed through Microsoft's Bing Image Search API [8]. The VGG Net-like architecture-based model was identified with 93.19% accuracy on the training dataset and 84.91% on the test dataset, showing the efficiency of CNNs in species identification [8]. Though applied to wild birds, the method can be employed for poultry breed identification.

Another experiment investigated the breed identification of dogs and cats with improved pre-trained models like ResNet-152 v2, Inception-ResNet v2, and Xception [9]. Xception achieved the best accuracy of 99.49% in training, 99.21% in validation, and 91.24% in testing [9]. This work illustrated the success of transfer learning in breed identification and is thus applicable to poultry.

Furthermore, a study explored the recognition of dog breeds with CNNs, employing the VGG-19 model, with 93.3% accuracy on 120 breeds of dogs [10]. The research also built a software system with a mobile app and a web server in between for classifying breeds [10]. These results confirm the success of CNNs on fine-grained classification, backing their use in chicken breed recognition.

## 3. Methodology

This study aims to develop a novel poultry breed classification mechanism by integrating transfer-learning-based Convolutional Neural Networks (CNNs) with a Support Vector Machine (SVM) classifier [11],[12]. The hybrid approach leverages the strengths of deep learning and classical machine learning to enhance classification accuracy and efficiency. By utilizing a pre-trained CNN for feature extraction and SVM for robust classification, the system provides a scalable and effective solution for applications in agriculture and conservation. This section outlines the key implementation steps, including data collection, preprocessing, feature extraction, classification, and model optimization[13][14].

### 3.1 Data Collection

Approximately 2,000 images were gathered in a dataset for this research from websites such as Kaggle and Roboflow [15],[16]. For the correct standardization, the gathered images were processed through formatting, annotation, and verification. For the correct training of a classification model, this combined dataset, which had breed-specific labels, was later used for testing, validation, and training.

### 3.2 Data Augmentation

Augmentation techniques such as rotation, zoom, and adjustment of brightness are applied in order to introduce additional variability in the initial data. This aims at assisting in generalizing abilities among different cases in classes represented by large images. Additional preprocessing normalizes sizes of images and converts them to predefined sizes for submitting clean, standard input to the model.

### 3.3 Data Splitting

Data is split into training, validation, and test sets. 80% training, 10% validation, and the remaining for testing. Thus, the model gets trained on an astronomical amount of data, validated in training so as not to overfit, and tested eventually on unseen data for actual performance.

### 3.4 Feature Extraction

The meaningful visual features from every chicken image are pulled out by the pre-trained InceptionV3 model. Any given breed's unique features caused by color and pattern of the feathers, which are responsible for breed identification, are extracted in the process. The classifier utilizes these extracted features for identification [11]. The model architecture is showcased in Figure 1.[17]

### 3.5 Incorporating Weights and Callbacks

First, weights are applied to address class imbalance so that less frequent classes have more importance. Second, ReduceLROnPlateau and Early Stopping callbacks during training prevent overfitting by monitoring performance, saving the best model and halting the training at maximum accuracy.

### 3.6 Grid Search and SVM Classification

The features learned are classified using an SVM model; grid search is used in determining the optimal hyperparameters that yield maximum accuracy. As SVM easily deals with high-dimensional data, this classifier will ensure that every breed will exactly fall into the class it belongs to when learning the features [18][19].

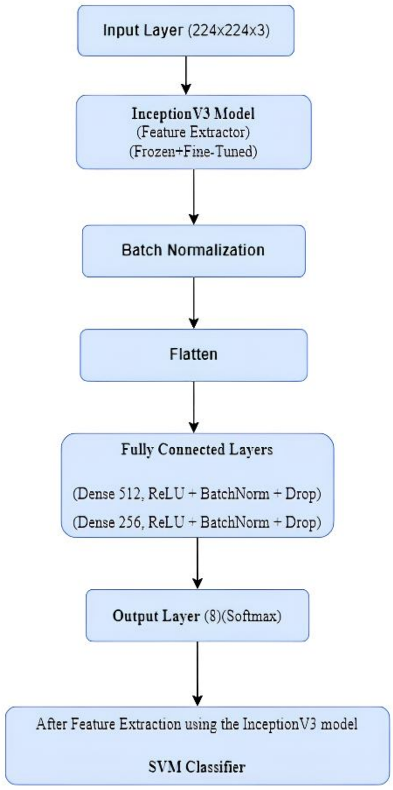


Fig 1: Model Architecture.

## 4. Accuracy and Evaluation

The Chicken Breed Identification Model was tested on a dataset of around 2000 images, across 8 chicken breeds, comprising 4 pure breeds and 4 crossbreeds. It had a validation accuracy of 96% and test accuracy of 86%. This is not bad performance, but more testing must be done in order to have a well-rounded idea as to how it performs across breeds.

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### 4.1 Classification Report

The classification report (Figure 2) , discloses in detail about eight chicken breed model performance. The overall accuracy is 95.91%, a high proportion of correct prediction.

- The positive prediction accuracy is measured in terms of Precision (average: 96%). Lohman and Plymouth Rock have perfect precision with no cases of incorrect positive prediction.
- Recall (average: 96%) shows recall of all actual positive cases.
- The recall of most classes is high, with relatively low recall (86%) in Wyandotte and therefore possibly having missed a few cases.
- The F1-Score (average: 96%) shows a balancing act between recall and precision, with strong and consistent performance in all classes.

The macro average and weighted average both confirm that the model performs consistently regardless of class size. The report discloses that most of the breeds have correct classification, but with minor improvements, individual breeds such as Wyandotte could have recall increased even further.

```
Overall Accuracy: 0.9591

Classification Report:
                   precision    recall  f1-score   support

        Australorp      0.95      0.95      0.95        19
        Black star      0.91      1.00      0.95        10
Blue Plymouth Rock      0.93      1.00      0.96        13
            Brahma      0.90      0.96      0.93        27
           Leghorn      0.96      1.00      0.98        27
            Lohman      1.00      0.97      0.98        29
      PlymouthRock      1.00      0.96      0.98        25
         Wyandotte      1.00      0.86      0.92        21

          accuracy                          0.96       171
         macro avg      0.96      0.96      0.96       171
      weighted avg      0.96      0.96      0.96       171
```

Fig 3: Confusion Matrix

### 4.2 Confusion Matrix

Model accuracy in predicting various chicken breeds can be observed from the confusion matrix, depicted in Figure 3. Rows represent the true classes, and columns represent the predicted classes. The diagonal values represent the correctly classified samples, while the off-diagonal values represent incorrectly classified samples. High accuracy in classification is represented when the majority of the predictions were on the diagonal. A few of the classes are mislabeled, i.e., Wyandotte mixed up with Brahma three times. Visually similar breeds are likely explanations for these mistakes. The majority of breeds are correctly identified, indicating the model is performing well overall on classification.

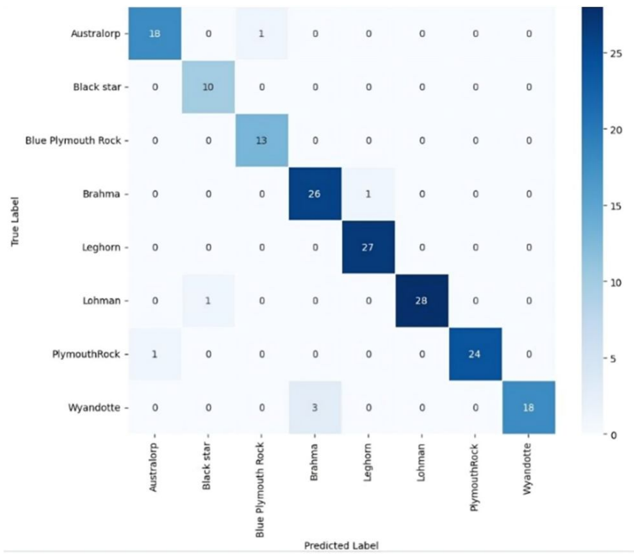


Fig 3: Confusion Matrix

### 4.3 Training vs Validation vs Test Accuracy Graph

The plot (depicted in Figure 4) shows the model's performance becoming ever more precise through a series of epochs, blue for training accuracy and red for validation accuracy; both measures demonstrate a consistent upward trend with a plateau at 90–95%. The sudden increase in the two measures initially indicates successful learning, and there is not much overfitting observed with both curves displaying a high degree of correlation between them. The accuracy on the test, plotted in a green dash, slightly ahead of the validation accuracy, indicates successful generalization. The model exhibits complete training and stable performance when executed on new, unseen data, and this is evident with the uniform convergence of all three accuracy measures.

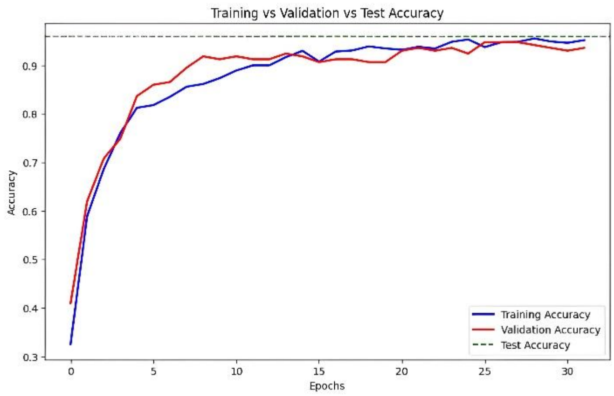


Fig 4: Training vs Validation vs Test Accuracy Graph

### 4.4 Benchmarking

The system in consideration is evaluated using a range of transfer learning approaches, namely, MobileNetV2, VGG16, and InceptionV3, in an attempt to determine the most accurate model for chicken breed identification. The Table 1 summarizes performance metrics, including accuracy, F1, precision, and recall for each model under consideration. Comparison of such metrics helps in selecting a model that yields best performance for the desired application.

Table 1: Benchmarking Summary (Transfer Learning Approaches)

| Transfer Learning Technique | Accuracy | F1-Score | Recall | Precisions |
|---|---|---|---|---|
| VGG16 + SVM | 0.75 | 0.72 | 0.72 | 0.75 |
| MobileNetV2 + SVM | 0.84 | 0.82 | 0.83 | 0.82 |
| InceptionV3 + SVM | 0.96 | 0.96 | 0.96 | 0.96 |

In addition, proposed work is contrasted with current work in the field. It is important to note that no studies have utilized a combination of transfer learning and machine learning approaches for chicken breed identification in the past. However, in order to set some meaningful benchmark, techniques from the literature reviewed were applied on a simplified model which was tested with the current study dataset. Results are presented in the Table 2.

Table 2: Benchmarking Summary (Existing Work)

| Reference | Original Method(s) | Reported Accuracy (%) | Accuracy on Our Dataset (%) |
|---|---|---|---|
| Subramani, Jeganathan and Balasubramanian, 2023 | K-means, GLCM, PCA, BT | 99 | 40 |
| Reddy et al., 2023 | MobileNet, DenseNet, CNN | 94 | 74 |
| Seo et al., 2021 | AdaBoost, RF, Decision Tree (SNP-based) | 99 | 78 |
| **Our proposed approach** | **InceptionV3 +SVM** | **96** | **96** |

The results, summarized in Table 2, clearly show that while existing models perform well on their original datasets, their performance tends to drop when applied to this study's dataset. This highlights the generalization challenge and emphasizes the strength of the proposed hybrid approach, which maintains high accuracy by leveraging both transfer learning and machine learning techniques.

## 5. Contribution to the Body of Knowledge

This study resolves some real-world problems of the poultry and agriculture sector by creating a centralized system to make information on different breeds of chicken more accessible. It aids in agricultural research, breeding programs, and conservation by enabling precise identification of breeds. The system provides coverage of classification to pure and crossbred chickens and therefore is even more useful for a range of farm environments.

From a research point of view, a neatly structured dataset was developed exclusively for this research work by merging two pre-existing data repositories [20]-[22]. The research work further suggests a hybrid model by fusing transfer learning-based CNNs and SVM classifiers to enhance classification effectiveness and precision. Data augmentation techniques were also used to enhance data sparsity and make the model more generalizable. In addition, benchmarking analysis using MobileNetV2, VGG16, and InceptionV3 architectures was carried out to compare their performance, presenting new knowledge in the literature related to the usability of models for poultry classification issues.

## 6. Conclusion

The Chicken Breed Identification Model demonstrated the effectiveness of combining transfer-learning-based CNNs with traditional SVM classifiers for accurate breed classification. The model achieved an average training accuracy of 86% and a validation and test accuracy of 96%, highlighting its potential for real-world applications in poultry farming and conservation. It successfully classified eight chicken breeds—four purebred and four crossbreeds—though distinguishing between visually similar breeds remained a challenge. Confusion matrix and training-validation graphs provided valuable insights into model performance and areas for improvement.

While the current model performs well, several areas warrant further development. Enhancing data augmentation techniques or utilizing higher-quality, region-specific datasets could improve model generalization, particularly for underrepresented breeds. Hyperparameter tuning and exploring deeper networks or hybrid architectures may further enhance accuracy. Additionally, integrating external data sources—such as behavioral or environmental factors—could improve breed identification. Finally, optimizing the model for real-time and on-device deployment would increase accessibility and practicality for agricultural applications.

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