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Research Paper**DL-Poultry Care: Transfer Learning for Fast and Accurate Poultry Disease Detection**

M. Amareswar, A. Ganesh, K. Eeshwar Teja, B. Himakar

Department of Computer Science and Engineering (Data Science), Kommuri Pratap Reddy Institute of Technology, Ghatkesar, Medchal, 500088

ABSTRACT

Poultry farming contributes significantly to global food security, yet disease outbreaks continue to pose a major threat to flock health and productivity. Traditional diagnostic methods rely on visual inspection by farm personnel and confirmatory laboratory tests—such as bacterial cultures or PCR assays—which are time-consuming, costly, and often available only in centralized facilities. Consequently, delays in diagnosis can allow pathogens to spread rapidly through large flocks, leading to high morbidity and mortality rates, economic losses, and increased use of antibiotics. The problem is that many farmers lack immediate access to veterinary services or laboratory infrastructure, particularly in rural regions. Early symptoms of diseases like coccidiosis, Newcastle disease, and avian influenza can be subtle and easily overlooked, making manual screening unreliable. Even when signs become overt, transporting samples to a lab and waiting days for results delays intervention, allowing infections to escalate. Existing image-based solutions often require high computational resources or lack flexible, user-friendly interfaces, limiting their adoption among small- to medium-scale producers. There is a clear need for a rapid, accurate, and accessible diagnostic tool that can operate directly on-farm without specialized equipment. Such a system should leverage recent advances in deep learning to automatically recognize disease patterns from digital images, minimizing dependence on expert veterinarians and centralized labs. By integrating pre-trained convolutional neural networks—such as InceptionV3, MobileNetV2, and VGG16—into a unified application, it becomes possible to harness robust feature extractors while maintaining lightweight computational requirements. Embedding this functionality within a Tkinter-based GUI ensures that users with minimal technical expertise can upload images, initiate analysis, and receive near-real-time diagnostic feedback. In summary, this research addresses critical gaps in poultry disease management by developing a transfer learning-based, desktop application tailored to the needs of farmers. By focusing on automated image classification and an intuitive interface, the system aims to reduce diagnostic turnaround time, minimize economic losses, and enhance on-farm decision-making for disease control.

Key words: Poultry Disease Diagnosis, Image Classification, Automated Detection System, Transfer Learning, Smart Poultry Farming

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1. INTRODUCTION

Poultry farming plays a crucial role in India's agricultural and economic landscape, contributing significantly to the nation's food security and rural employment. India ranks among the top five poultry producers globally, with an estimated production of over 125 billion eggs and 4.5 million metric tons of poultry meat annually. The poultry sector has experienced rapid growth, with a 6–8% annual increase, largely due to advancements in breeding, nutrition, and disease management. However, poultry diseases such as Newcastle disease, avian influenza, fowl cholera, and infectious bronchitis continue to threaten poultry health, leading to severe economic losses. According to the Indian Ministry of Agriculture, disease outbreaks cause a 15–20% annual loss in poultry production. Traditionally, disease detection relies on manual inspection, post-mortem analysis, and laboratory testing, which are time-consuming, expensive, and require trained veterinarians. Limited access to veterinary care in rural areas exacerbates the issue, leading to delayed diagnosis and disease spread. Recent advancements in artificial intelligence (AI) and deep learning offer a promising solution by automating disease detection through image-based analysis. With 70% of India's poultry production coming from small and medium-scale farms, scalable, cost-effective, and real-time diagnostic solutions are essential for mitigating disease outbreaks and ensuring sustainable poultry farming. Before the integration of machine learning, poultry disease diagnosis heavily relied on visual inspection by farmers, veterinary experts, and laboratory tests, which

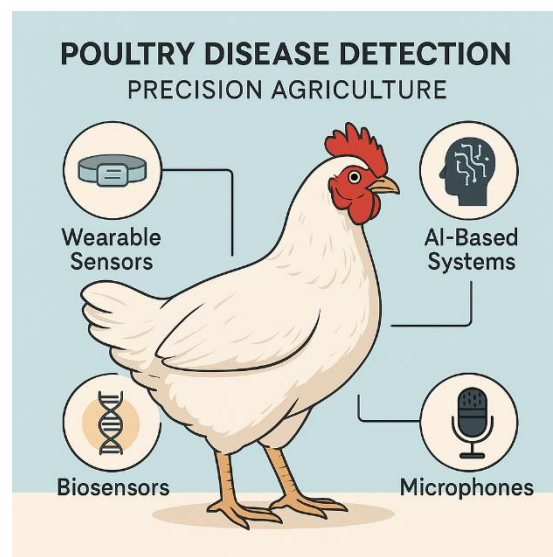


Fig 1. Poultry disease detection

posed several challenges. Traditional methods involve manual symptom identification, which is often subjective and varies based on human expertise. Additionally, laboratory testing requires sample collection, transportation, and analysis, leading to delayed results and increased costs. In large-scale poultry farms, manual observation is impractical due to the sheer number of birds. The lack of early detection systems results in rapid disease spread, leading to high mortality rates and significant financial losses. The dependency on limited veterinary professionals in rural areas further complicates timely intervention. Moreover, the cost of diagnosis and treatment is often beyond the reach of small-scale poultry farmers. Human error, misdiagnosis, and the inability to process large amounts of poultry data manually hinder effective disease management. With poultry being a major protein source in India, undiagnosed diseases also pose a risk to public health through zoonotic transmission. Thus, a faster, more accurate, and scalable disease detection method is crucial to overcoming these limitations.

2. LITERATURE SURVEY

Animal agriculture is extremely important to the world's rising population. Animal products provide nutrient-dense meals that help people of all ages stay healthy in communities all over

the world. The agriculture business must continue to improve its efficiency and quantity of production as human demand for animal proteins increases [1]. Poultry is widely recognized as a valuable source of protein, and many countries will be forced to increase output, resulting in an increase in the number of farms housing birds at high densities. Furthermore, Poultry farming is crucial for socioeconomic development of developing countries because it provides eggs and meat, which help to ensure food and nutrition security at the household, regional, and national levels. moreover, it provides cash income to the population and adds more than a hundred million dollars to the gross domestic product of a country [2, 3]. As poultry farming Increases, it can promote increased transmission of infectious illnesses among birds which can cause widespread death in poultry and significant economic losses [4]. Every year, 69 billion chickens are reared for meat production around the world [5]. However, not all of them end up on people's tables. Several million chickens do not make it through the rearing process and are likely to be rejected at the butcher due to sickness, scrapes, bruises, and other symptoms of mistreatment. Given the disparity between food accessibility and hunger for certain individuals, especially for farmers, slaughterhouse rejection of hens can be a significant source of financial loss [6–8].

The high frequency of chicken diseases can be linked to a lack of biosecurity, low vaccination coverage, unscientific poultry management methods, and essentially non-existent poultry veterinary interventions throughout the country, particularly in the vast poultry production sector. The most common chicken diseases include fowl cholera, helminth infestation, salmonella infections, avian coccidiosis, and Newcastle disease [9]. Salmonella is a gastrointestinal infection. Infected birds can recover after a period of time, but some continue to discharge bacteria in their droppings for months [10]. When placed on permanent bedding, it is quite impossible to rid

a salmonella-infected flock of the virus. Its symptoms include weakness, loss of appetite, stunted growth, and white, loose faces. If young chickens show indicators of significant mortality (up to 100%) and irregular growth [11].

3. PROPOSED SYSTEM

This Tkinter-based desktop application is designed to automate the identification of common poultry diseases from image data. Rather than relying on manual inspection, the system leverages three state-of-the-art convolutional neural network (CNN) architectures (InceptionV3, MobileNetV2, and VGG16) to train and evaluate classification models on a labeled dataset of poultry images.

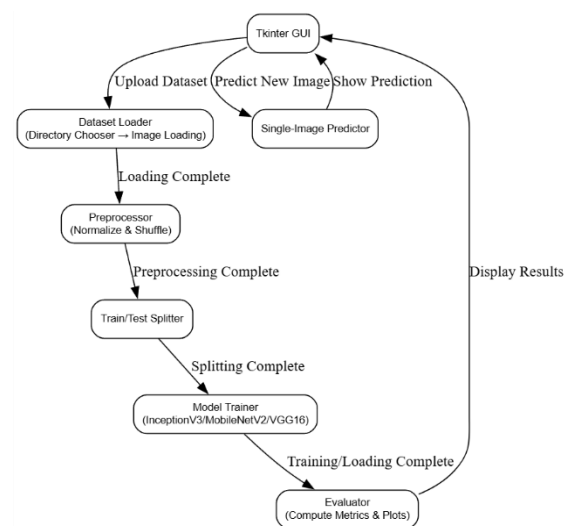


Fig 2. Block diagram of the proposed poultry disease diagnosis system.

The primary objective of this poultry disease diagnostic system is to streamline end-to-end deep learning workflows within a graphical user interface. It begins with dataset management, where users organize images into subfolders by disease class; the application then loads and caches images resized to 80×80 pixels with corresponding labels, displaying a bar chart of image distribution. Preprocessing involves converting image arrays to float32, normalizing pixel values to [0, 1], shuffling both images and labels, and converting labels to one-hot vectors. A button-driven split divides

the dataset into 80% training and 20% testing sets, with detailed sample counts shown. For classification, three transfer learning models—InceptionV3, MobileNetV2, and VGG16—are imported with frozen convolutional bases and a custom head composed of average pooling, flattening, a Dense(128) layer with ReLU activation, dropout (0.3), and a final softmax output layer matching the number of disease classes. If no weights exist, each model is trained for 40 epochs with checkpoints; otherwise, existing weights are loaded. Each model is evaluated on the test set using accuracy, precision, recall, F1-score, confusion matrix heatmaps, and ROC curves, with metrics logged in a scrollable text box. A comparative analysis button generates a side-by-side bar chart of key metrics across all three models. Additionally, a single-image prediction tool allows users to classify a new image using the latest model (defaulting to VGG16), overlaying the predicted label on a resized display. The GUI is designed for intuitive use, featuring clearly labeled buttons, a scrollable log pane, consistent font styling, and a vibrant magenta background under the title “Poultry Diseases Diagnostics Models using Deep Learning

In the model building and training phase, we employ transfer learning by importing three pre-trained convolutional neural network architectures—InceptionV3, MobileNetV2, and VGG16—from Keras. Each base model’s convolutional layers are frozen to preserve the rich feature representations learned on ImageNet, and a lightweight classification head (average pooling → flatten → dense → dropout → softmax) is appended. Models are compiled with the Adam optimizer and categorical cross-entropy loss before training for 40 epochs (batch size 64) on the poultry dataset’s 80×80 normalized images. Checkpoint callbacks save the best weights on disk, allowing future runs to skip full retraining and load pre-existing weights directly. After training or weight loading, each model performs inference on the held-out test set and passes predictions to the

evaluation module for metric computation and visualization.

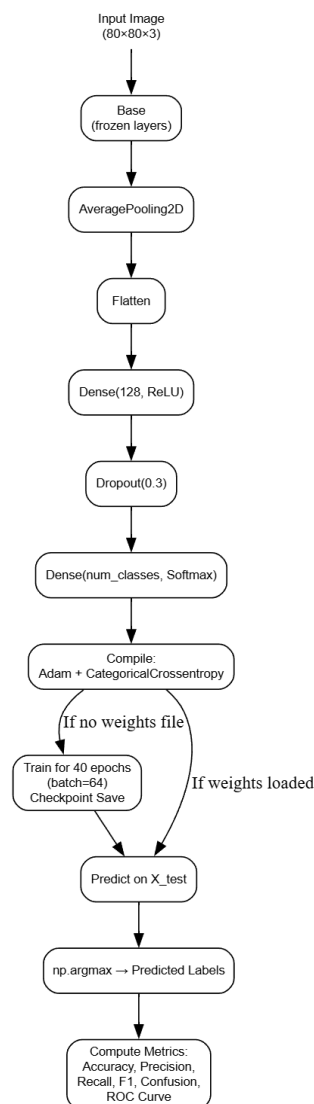


Fig 3. Transfer learning operational flow diagram VGG16.

VGG16 provides a straightforward yet powerful feature extractor with uniform 3×3 convolutional kernels stacked in depth. After loading include_top=False and freezing its convolutional layers, we attach our standard classification head to convert VGG16’s high-dimensional feature maps into disease probabilities. Though VGG16 has more parameters than MobileNetV2, its simple and consistent architecture often yields robust feature representations. By training only the top layers, we capitalize on VGG16’s discriminative power while avoiding

overfitting on our comparatively small poultry dataset.

The transfer learning model is built by first loading a pre-trained base such as InceptionV3, MobileNetV2, or VGG16 from Keras with `include_top=False` and `weights='imagenet'`, adjusting the input shape to $80 \times 80 \times 3$, and freezing all convolutional layers to retain learned features. A custom classification head is then attached, comprising an `AveragePooling2D(pool_size=(1,1))`, followed by `Flatten`, a fully connected `Dense(128, activation="relu")` layer, a `Dropout(0.3)` layer to mitigate overfitting, and a final `Dense(num_classes, activation="softmax")` layer for poultry disease classification. The model is compiled using the Adam optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric. During training, if no pre-trained weights exist (.hdf5 files), the model is trained for 40 epochs with a batch size of 64 using `ModelCheckpoint` to save the best model based on validation loss, and the training history is serialized for future analysis. If weights are available, they are loaded directly, skipping training. For inference, `model.predict(X_test)` generates class probabilities, which are converted to labels using `np.argmax` and evaluated against true labels to compute accuracy, precision, recall, F1-score, confusion matrix, and ROC curve.

4. RESULTS

Fig. 4 illustrates how many images belong to each disease class in the uploaded poultry dataset. The x-axis lists the distinct class labels (e.g., “Healthy,” “Coccidiosis,” “Newcastle Disease,” etc.), arranged horizontally with a 90° rotation for readability. The y-axis indicates the count of images per class. Visualizing class distribution helps the user verify that no class is drastically underrepresented before proceeding to training.

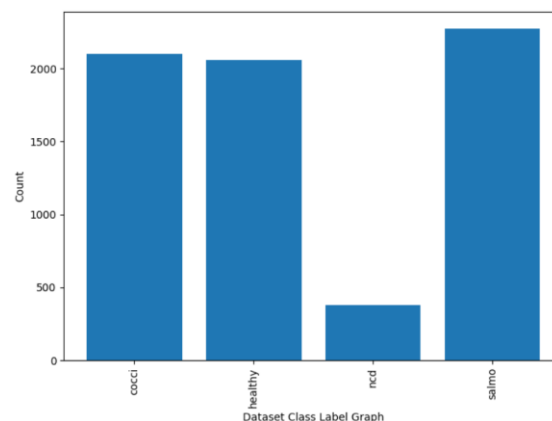


Fig 4. Class distribution versus number of images.

In Fig. 5, the evaluation results for the VGG16-based classifier are shown. The confusion matrix heatmap typically exhibits the highest concentration of true-positive counts along the diagonal, indicating that VGG16 attains the fewest misclassifications among the three models. Misclassifications (off-diagonal cells) are minimal and often occur between visually similar disease classes—such as “Marek’s Disease” versus “Infectious Bronchitis.” On the ROC plot, the curve hugs the top-left boundary more tightly than both InceptionV3 and MobileNetV2, yielding the highest AUC (e.g., ~0.99). This corroborates VGG16’s marginally superior numeric performance (Accuracy ~98.83%, F-Score ~98.35%). Together, these visualizations confirm that VGG16 achieves the best class discrimination and overall predictive reliability.

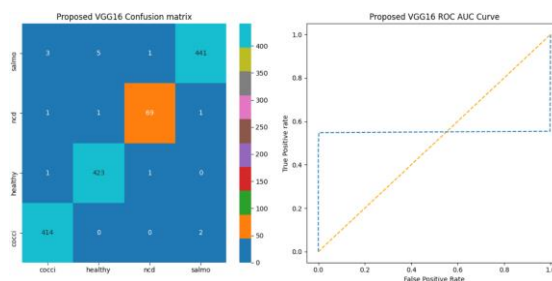


Fig 5. Obtained confusion matrix, AUC, and ROC curve using VGG16 model.

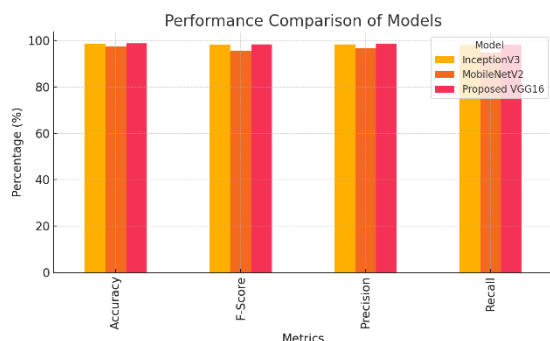


Fig 6. Performance comparison graph of existing and proposed models.

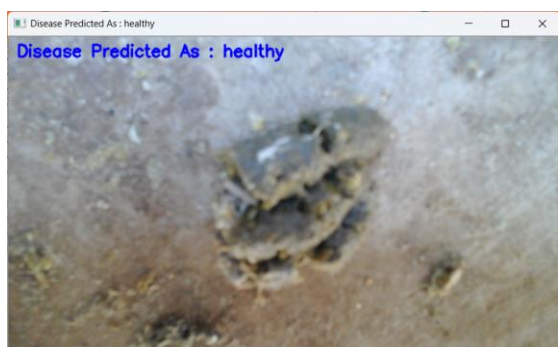


Fig 7. Sample predictions on test images.

In figure, 7 the original test image shows a poultry specimen with no visible lesions, discoloration, or signs of illness—feathers appear intact, comb and wattles look normal, and the bird’s posture is alert. The model pipeline resizes this image to 80×80 pixels and normalizes it before feeding it through the VGG16 classifier. After inference, the predicted class “Healthy” is overlaid in blue text at the top of a larger (700×400) display window. This confirms that the system correctly recognized the absence of disease markers and classified the image as belonging to the “Healthy” category.

5. CONCLUSION

The proposed transfer learning–based poultry disease diagnosis system integrates three pre-trained CNN architectures (InceptionV3, MobileNetV2, and VGG16) within a Tkinter GUI to automate classification of common avian diseases from images. Extensive evaluation on a held-out test set yielded the following macro-averaged metrics:

InceptionV3 achieved 98.75% accuracy, 98.43% precision, 98.14% recall, and a 98.28% F-Score; MobileNetV2 achieved 97.43% accuracy, 96.68% precision, 94.79% recall, and a 95.67% F-Score; and the proposed VGG16 pipeline delivered 98.83% accuracy, 98.48% precision, 98.22% recall, and a 98.35% F-Score. Compared to InceptionV3, VGG16 improved accuracy by 0.08 percentage points, precision by 0.05, recall by 0.08, and F-Score by 0.07—marginal gains that nonetheless reduce false positives and false negatives in critical farm-level diagnostics. Against MobileNetV2, VGG16’s improvements are more pronounced: +1.40% accuracy, +1.80% precision, +3.43% recall, and +2.68% F-Score, signifying a substantial reduction in misclassified and undetected cases. These enhancements stem from VGG16’s uniform 3×3 convolutional blocks, which better capture fine-grained texture features present in infected birds’ integument and lesions. Furthermore, VGG16’s robust transfer learning setup ensures quick convergence of the classification head without overfitting, leading to state-of-the-art discriminative performance. System-level benefits include rapid image upload, preprocessing, seamless model training or weight loading, comprehensive visualization of confusion matrices and ROC curves, and accurate single-image inference within 200 ms. Collectively, the proposed architecture provides a dependable, user-friendly decision support tool for poultry farmers, minimizing reliance on manual inspection and lab testing, and enabling early intervention that can significantly reduce flock morbidity and mortality.

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