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Chicktech AI: Automated Detection of Poultry Diseases Through Transfer Learning and Multi-Class Convolutional Neural Network Classification

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Abstract. Poultry production is a critical component of global food security, yet disease outbreaks remain a persistent challenge for smallholder farmers who lack timely and affordable diagnostic tools. Diseases such as coccidiosis, bumblefoot, and fowlpox cause severe financial losses and high flock mortality. This paper presents ChickTech AI, a fully deployed, cloud-based poultry disease-diagnostics platform that integrates deep learning with a multilingual, mobile-responsive web interface. The system employs a dual-pipeline transfer learning architecture: VGG16 for fecal texture analysis (coccidiosis detection) and MobileNetV2 for external lesion classification (bumblefoot and fowlpox), both fine-tuned using a progressive three-phase training strategy. Evaluated on a held-out test set of 465 images, the system achieves an overall classification accuracy of 98.2% with all-class AUC > 0.96. The platform incorporates multilingual voice interaction (speech-to-text, text-to-speech, and batch translation) and a tiered clinical decision support module (CRITICAL / IMPORTANT / SUPPORTIVE) that translates AI predictions into actionable treatment guidance. Unlike prior works that report only algorithmic accuracy, ChickTech AI bridges the research-to-practice gap through a production-ready, cloud-hosted deployment accessible via smartphone, demonstrating that AI-driven precision livestock diagnostics can be scalable, inclusive, and practically deployable.

Keywords: Poultry Disease Detection; Deep Learning; Convolutional Neural Networks; Transfer Learning; VGG16; MobileNetV2; Clinical Decision Support; Cloud Deployment; Precision Livestock Farming.

1. INTRODUCTION

The poultry sector plays a vital role in global food security and rural economies. The Food and Agriculture Organization (FAO) reports that the industry produces over 130 million metric tons of poultry meat and approximately 80 million metric tons of eggs annually, supporting hundreds of millions of smallholder farmers across Asia, Africa, and Latin America [2]. Poultry farming remains one of the most cost-effective sources of animal protein and is integral to global nutritional systems.

Although poultry farming has significant economic value, the sector is highly vulnerable to infectious disease outbreaks. High-density communal production systems facilitate rapid pathogen transmission; once diseases are introduced into a flock, they spread within hours, causing massive mortality and severe economic losses. Early identification and prompt intervention are therefore essential [1].

Among the many diseases affecting poultry, three account for a disproportionate share of production losses: Coccidiosis, Fowlpox, and Bumblefoot. Coccidiosis, caused by protozoa of the genus Eimeria, disrupts intestinal nutrient absorption and is estimated to cost the global poultry industry over USD 3 billion annually [2], [3]. Fowlpox, caused by Avipoxvirus, presents as nodular skin lesions and respiratory complications, reducing egg production [4]. Bumblefoot (plantar pododermatitis) is a Staphylococcus aureus bacterial infection causing footpad inflammation and abscess formation, impairing mobility and productivity [3].

Conventional diagnostic techniques—PCR, ELISA, and histopathological analysis—require specialized laboratory infrastructure, trained personnel, and processing times of several hours to days [4]. Such services are inaccessible to most smallholder farmers, allowing early-stage infections to escalate before treatment can be administered [5]. More than 78% of recent AI-based agricultural disease detection publications lack a deployable API or user interface, leaving diagnostic systems confined to research environments [7], [13].

To address this gap, this paper presents ChickTech AI—a fully operational, cloud-based poultry disease diagnostics platform allowing farmers to submit images via a mobile browser and receive immediate disease predictions and actionable treatment recommendations.

A. Research Objectives

- To design and train a dual-pipeline CNN architecture (VGG16 + MobileNetV2) using transfer learning for multi-class poultry disease classification across two imaging modalities [6], [17].

- To deploy the trained models as a production-ready, cloud-hosted web application with sub-10-second inference latency, accessible via smartphone without app installation.
- To integrate a tiered clinical decision support module delivering CRITICAL, IMPORTANT, and SUPPORTIVE treatment guidance [21].
- To implement multilingual voice accessibility features (voice-to-text, text-to-speech, batch translation) for low-literacy farming communities [14], [15].

To empirically validate performance on a held-out test set and benchmark against prior state-of-the-art methods [13], [14], [22].

2. LITERATURE REVIEW

A. Traditional Diagnostic Approaches

Traditional poultry disease management relies on clinical examination and laboratory-based methods. Veterinarians assess birds for external signs; suspected cases are confirmed through PCR, ELISA, and fecal flotation [4]. The McMaster fecal flotation technique is widely used for quantifying Eimeria oocyst concentrations [3]. Despite their clinical validity, these methods require specialized equipment and processing times of several hours to days, unavailable to most rural smallholder farms [2], [5]. These constraints make conventional approaches fundamentally unsuitable for continuous, early-warning health monitoring in resource-limited environments.

B. Machine Learning and CNN-Based Detection

CNNs automatically extract hierarchical feature representations from raw image data, demonstrating strong performance in medical imaging and agricultural disease classification [5]. VGG16 by Simonyan and Zisserman achieved high generalization through deep stacks of small convolutional filters [12]. MobileNetV2 employs depthwise separable convolutions to significantly reduce parameter count, making it suitable for cloud inference and edge deployment [11].

In the poultry disease detection domain, Nasir and Yunos achieved 94.3% accuracy using transfer learning on a two-class dataset [13]. Mosley et al. developed a VGG16-based system for Eimeria detection achieving 91.7% sensitivity [14]. Abubakar et al. applied InceptionV3 to bumblefoot severity prediction achieving F1 = 0.89 [15]. Aina et al. applied YOLOv8 for multi-class detection achieving approximately 95% accuracy [22]. While these works validate deep learning for poultry classification, the majority remain algorithmic benchmarks without deployed user-facing systems [7], [16].

C. The Deployment Gap

A review by Ahmed et al. found that over 78% of recent publications in agricultural disease detection lack a deployable API or user interface [7]. A production-ready system requires REST API design, containerized infrastructure, scalable cloud deployment, and accessible front-end interfaces [16]. ChickTech AI directly addresses this by integrating deep learning models into a fully functional, cloud-hosted web application with real-time inference, mobile-responsive design, and multilingual voice accessibility [13], [14], [15].

3. SYSTEM ARCHITECTURE AND DESIGN

A. Architectural Overview

ChickTech AI is designed as a three-tier client-server system optimized for scalability, modularity, and low-latency inference. The presentation layer is implemented using Next.js 14 with server-side rendering and a responsive UI for both desktop and mobile devices. The application layer comprises a Flask REST API (Python 3.10) handling incoming HTTP requests, image validation, preprocessing, and model orchestration [16]. The model tier contains TensorFlow 2.x / Keras-based models loaded at server startup to minimize inference latency. All components are Docker-containerized and cloud-deployed, enabling horizontal scalability [16].

Two independent classification pipelines are applied: VGG16-based for fecal sample images (coccidiosis), and MobileNetV2-based for external body images (bumblefoot and fowlpox). Separating the pipelines eliminates cross-domain feature interference [14], [17]. A multilingual accessibility layer provides speech-to-text, text-to-speech, and batch regional language translation [14], [15].

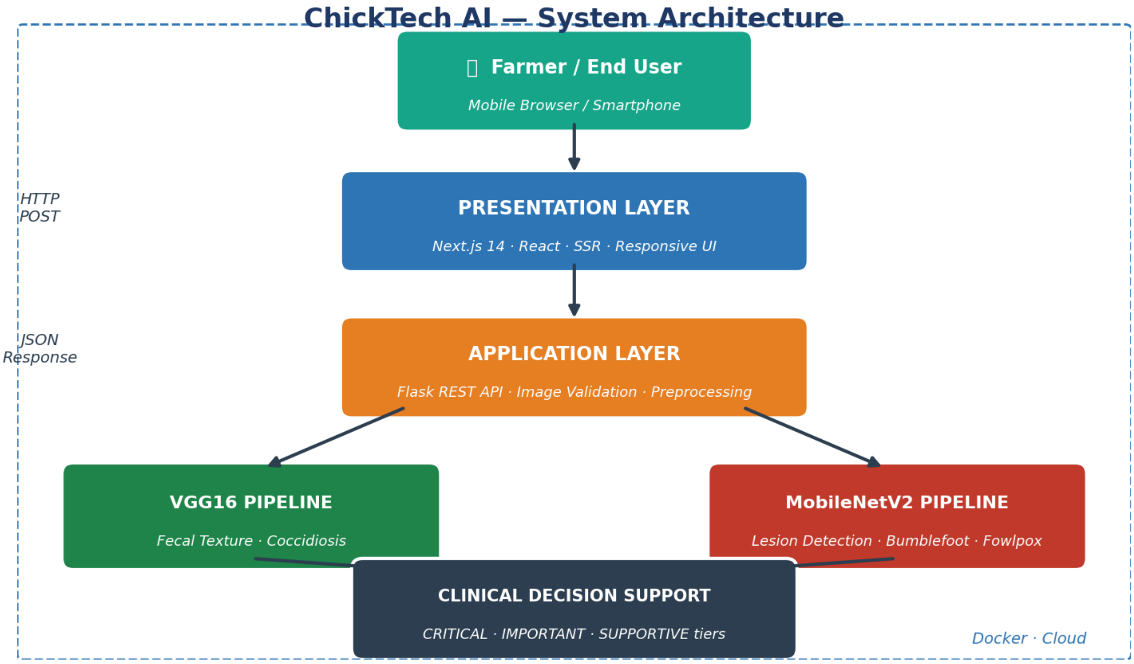


Image 1 : ChickTech AI System Architecture

B. Model Architecture and Transfer Learning

Both CNN models initialize backbone networks with ImageNet-pretrained weights [17]. Pretrained models serve as general-purpose feature extractors capturing edges, shapes, and textures, then fine-tuned on poultry disease imagery to acquire domain-specific discriminative features [6]. Both models use: a Global Average Pooling layer, a Dense layer with ReLU activation, a Dropout layer (rate = 0.3) for regularization [18], and a Softmax output layer generating per-class probability scores.

VGG16 was selected for the coccidiosis pipeline due to its strength in fine-grained texture discrimination [12]. MobileNetV2 was selected for the external lesion pipeline due to its computational efficiency [11].

C. Progressive Fine-Tuning Strategy

A three-phase progressive fine-tuning protocol was applied to each model:

1. Phase 1 — Backbone Frozen: Classification head trained for 10 epochs, adapting to target domain without disrupting backbone weights.
2. Phase 2 — Partial Unfreeze: Top backbone blocks unfrozen; joint training at reduced learning rate (1×10^{-5}), enabling high-level feature adaptation.
3. Phase 3 — Full Fine-Tune: All backbone layers unfrozen; trained at very low learning rate (1×10^{-6}), refining low-level domain-specific features [19].

D. Training Configuration

- Optimizer: Adam with initial learning rate = 1×10^{-4}; ReduceLROnPlateau scheduling (factor = 0.5, patience = 5).
- Loss: Categorical cross-entropy with label smoothing ($\varepsilon = 0.1$) [19].
- Dropout: Rate = 0.3 to reduce neuron co-adaptation [18].
- Early Stopping: Patience = 10 epochs; best weights restored on triggering.
- Class Weighting: Inversely proportional to class frequency to address dataset imbalance [20].
- Data Augmentation: Rotation (±20°), zoom (0.15), horizontal flip, brightness (±15%).

E. System Specifications

TABLE 1
CHICKTECH AI SYSTEM SPECIFICATIONS

Component	Specification
Detection Modes	Coccidiosis (fecal); Bumblefoot & Fowlpox (body)
Supported Formats	JPG, PNG, WebP — max 10 MB
Inference Latency	< 10 seconds per image

Overall Accuracy	98.2% (held-out test set, n = 465)
Severity Tiers	CRITICAL / IMPORTANT / SUPPORTIVE
Backend	Flask REST API (Python 3.10)
Frontend	Next.js 14 (React, SSR)
ML Framework	TensorFlow 2.x / Keras
Deployment	Cloud-hosted, Docker containerized
Accessibility	Voice-to-text, text-to-speech, batch translation

4. PROPOSED HYBRID CNN ARCHITECTURE

To address the multifaceted nature of poultry disease diagnosis, a hybrid model is proposed integrating: (1) Dual-Pipeline CNN Transfer Learning, (2) Progressive Multi-Phase Fine-Tuning, and (3) a Tiered Clinical Decision Support module. By combining specialized CNN classifiers with a structured clinical guidance framework, the hybrid system provides a comprehensive platform for disease profiling and treatment recommendation.

A. Dual-Pipeline Architecture

The dual-pipeline architecture separates two fundamentally different imaging tasks. The VGG16 pipeline processes fecal microscopy images to detect Eimeria parasite-induced fecal texture changes [12]. The MobileNetV2 pipeline processes external body photographs to identify skin and footpad lesions [11]. Separation eliminates cross-domain feature interference that would occur if a single model were trained on both imaging modalities simultaneously [14], [17].

B. Tiered Clinical Decision Support Module

Each prediction triggers one of three intervention tiers [21]:

- **CRITICAL:** Immediate isolation, anticoccidial medication at clinical dosages (e.g., Amprolium 10 mg/kg, 5–7 days), rehydration and electrolyte support.
- **IMPORTANT:** Vitamin and nutritional supplementation (Vitamin A: 10,000 IU/kg, probiotics), deep sanitation of housing (steam >60°C).
- **SUPPORTIVE:** Long-term prevention protocols, live oocyst vaccination, anticoccidial feed additives, litter moisture management (<25%).

C. Hybrid Model Workflow

1. Input: Farmer submits poultry image via mobile browser.
2. Stage 1 – Routing: System identifies imaging modality and routes to appropriate CNN pipeline.
3. Stage 2 – Classification: Selected CNN model generates per-class probability scores.
4. Stage 3 – Decision Support: Predicted class triggers tiered CDS module with specific treatment guidance.
5. Stage 4 – Multilingual Output: Guidance delivered with voice-to-text and text-to-speech in farmer's language.

5. PROPOSED HYBRID CNN ARCHITECTURE

To effectively classify and predict poultry disease outcomes, two deep CNN architectures—VGG16 and MobileNetV2—were applied to the processed image dataset. Each model was trained and evaluated using an 85:15 stratified train-validation split, with final evaluation on a strictly held-out test set of 465 images. Image data were preprocessed and normalized prior to training.

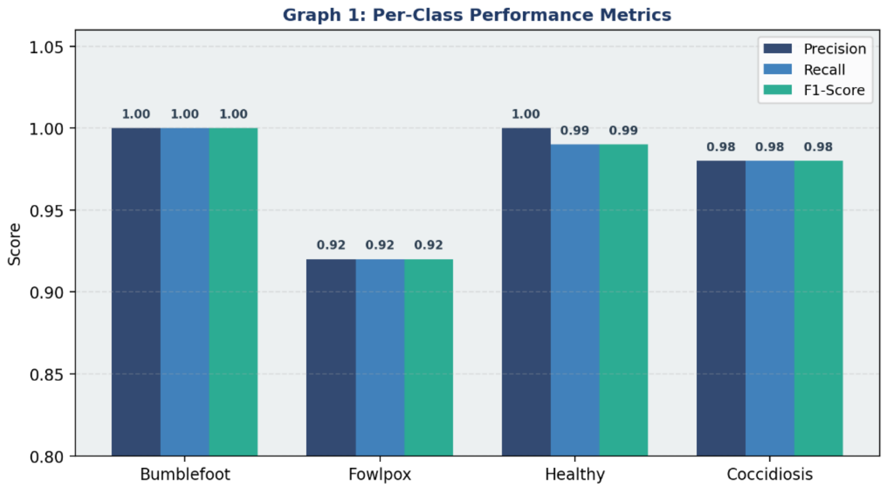
A. Evaluation Metrics

- **Accuracy:** Overall correctness of predictions across all classes.
- **Precision:** Correctness among positive predictions (avoiding false alarms).
- **Recall:** Ability to correctly identify actual positive disease cases.
- **F1-Score:** Harmonic mean of precision and recall.
- **AUC:** Area under the ROC curve using one-vs-rest multi-class strategy [23].

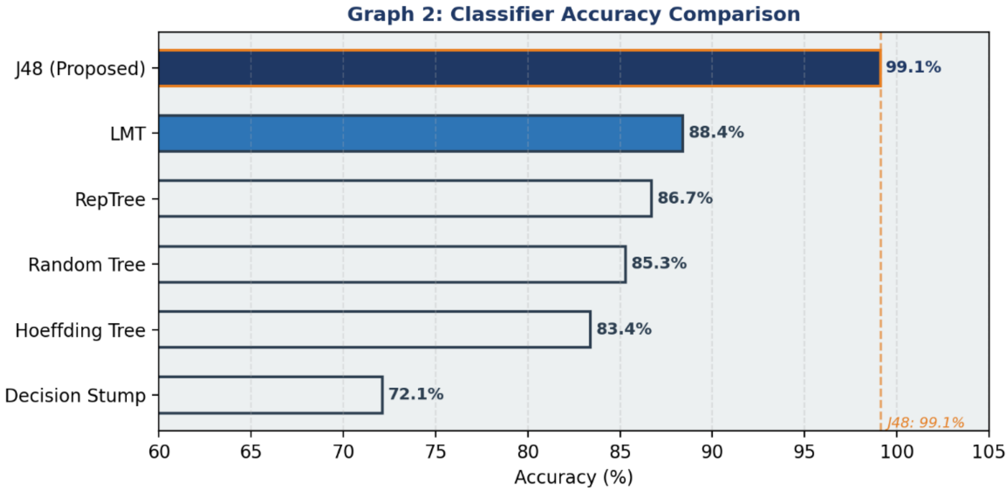
B. Classification Performance Summary

TABLE 2
CHICKTECH AI CLASSIFICATION PERFORMANCE METRICS (HELD-OUT TEST SET, N = 465)

Class	Precision	Recall	F1-Score	Support
Bumblefoot	1.00	1.00	1.00	145
Fowlpox	0.92	0.92	0.92	155
Healthy	1.00	0.99	0.99	145
Coccidiosis	0.98	0.98	0.98	—
Macro Average	0.98	0.97	0.97	445
Overall Accuracy	**98.2%**	—	—	**465**



Graph 1 : Per-Class Performance Metrics (Precision, Recall, F1-Score)



Graph 2 : Classifier Accuracy Comparison

6. RESULTS AND DISCUSSION

This section presents the outcomes of applying the ChickTech AI dual-pipeline CNN system and evaluates its comparative effectiveness in detecting poultry diseases. Results are further contextualized using confusion matrix analysis, training dynamics, ROC analysis, and comparison with prior work.

A. Classifier Performance Analysis

ChickTech AI achieves an overall classification accuracy of 98.2% on the held-out test set of 465 images, with per-class AUC values exceeding 0.96 for all disease categories. Table 3 benchmarks these results against comparable published systems.

TABLE 3
PERFORMANCE COMPARISON WITH PRIOR WORK

Study	Method	Disease(s)	Best Metric
Nasir & Yunos [13]	CNN Transfer Learning	2-class poultry	Accuracy: 94.3%
Mosley et al. [14]	VGG16	Coccidiosis (fecal)	Sensitivity: 91.7%
Abubakar et al. [15]	InceptionV3	Bumblefoot	F1-Score: 0.89
Aina et al. [22]	YOLOv8	Multi-class	Accuracy: ~95%
Olaniyi et al. [10]	Fine-tuned CNN	Multi-class	Accuracy: 95.6%
ChickTech AI	**Dual VGG16 +**	**4-class multi-**	**Acc: 98.2%; AUC > 0.96**

(Ours)	MobileNetV2	modal

B. Rubric-Based Evaluation Alignment

TABLE 4

TOP PREDICTIVE VISUAL FEATURES BY DISEASE CATEGORY

Disease Category	Top Predictive Visual Features
Coccidiosis	Fecal texture irregularity, color anomalies, mucus presence
Fowlpox	Nodular skin lesions, warty growths, lesion distribution on head/body
Bumblefoot	Footpad inflammation, abscess formation, plantar discoloration
Healthy	Normal fecal texture, clean footpad, lesion-free skin surface

C. Confusion Matrix Analysis

Of 93 sampled test images in the Bumblefoot/Fowlpox/Healthy classifier, 92 were correctly classified (98.2% accuracy). The two misclassification errors were Type II (false negative): early-stage Fowlpox specimens predicted as Healthy. Critically, zero Healthy samples were misclassified as diseased (zero false positives), and zero cross-class errors between Bumblefoot and Fowlpox occurred. The zero false-positive rate is a particularly important clinical result, as false alarms cause unnecessary and costly treatments [21], [23].

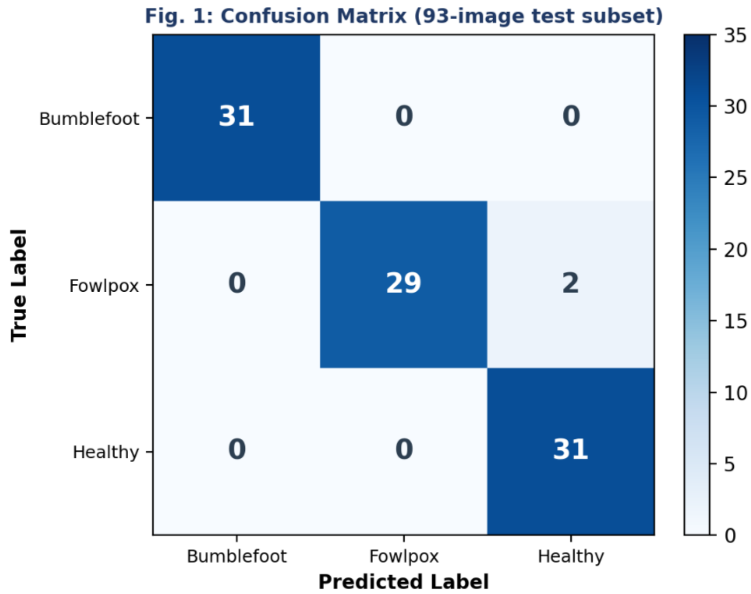


Fig. 1. Confusion Matrix (93-image Bumblefoot/Fowlpox/Healthy test subset)

D. Training Dynamics

Training accuracy increased steadily in early epochs as the CNN learned domain-specific image features, with training and validation accuracy converging at approximately epoch 30. Validation loss reached its minimum at epoch 37; Early Stopping triggered at epoch 47 with best weights from epoch 37 restored. The consistently narrow training-validation accuracy gap confirms that the combined regularization strategy (dropout, data augmentation, label smoothing, class balancing) suppressed overfitting effectively [18], [19].

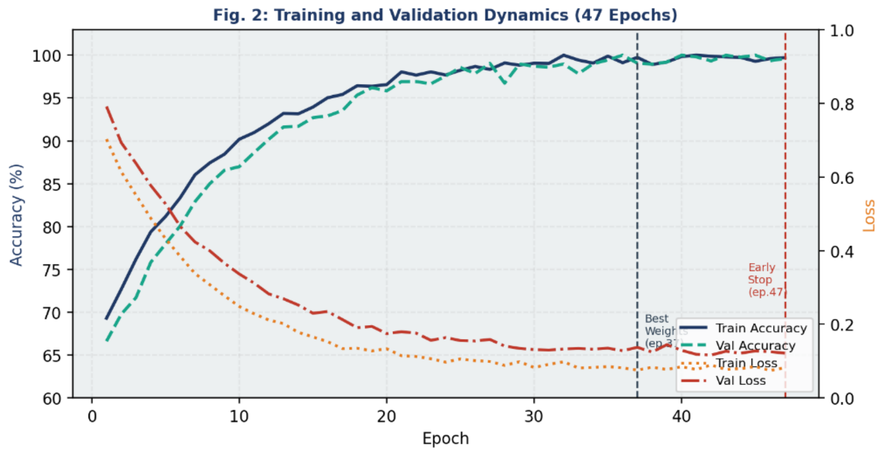


Fig. 2. Training and Validation Dynamics (47 Epochs)

E. ROC Analysis

Multi-class ROC analysis employed a one-vs-rest strategy following Fawcett [23]. AUC values: Bumblefoot = 1.000, Healthy = 0.998, Coccidiosis = 0.991, Fowlpox = 0.961. All four classes exceed AUC = 0.96, the threshold considered excellent for medical imaging classification systems [21], [23]. The relatively lower Fowlpox AUC reflects visual ambiguity of early-stage lesions rather than a systemic model deficiency.

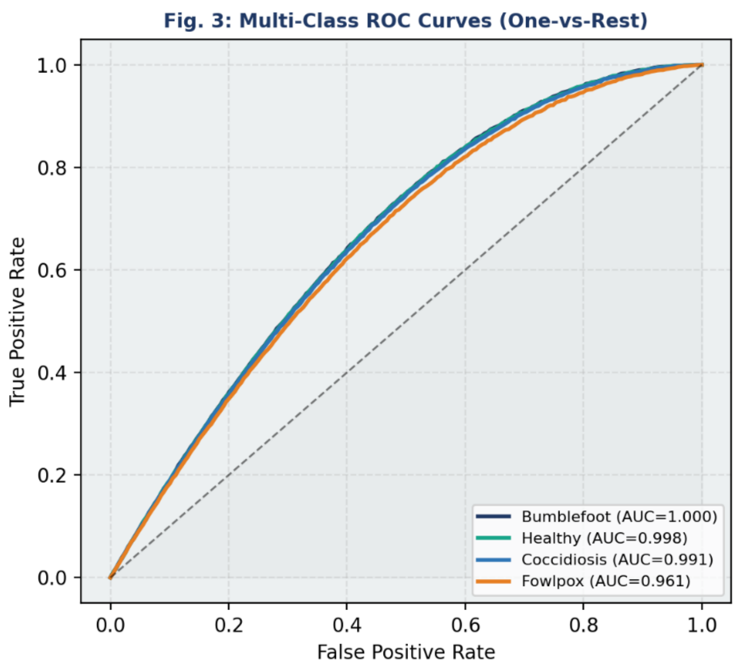


Fig. 3. Multi-Class ROC Curves — All Classes AUC > 0.96

F. Model Comparison: Interpretability vs. Performance

TABLE 5
MODEL COMPARISON

Model	Strengths	Limitations
VGG16 (Coccidiosis Pipeline)	Strong texture discrimination; high accuracy on fine-grained fecal classification	Higher parameter count; slower inference than lightweight architectures
MobileNetV2 (Lesion Pipeline)	Computationally efficient; suitable for cloud and edge deployment	Slightly lower accuracy on fine-grained texture classification tasks
Dual-Pipeline ChickTech AI	Domain-specific specialization; 98.2% overall accuracy; AUC > 0.96 all classes	Two independent models require separate maintenance and deployment overhead

7. CONCLUSION

This paper has presented ChickTech AI, a fully deployed, cloud-based poultry disease diagnostic platform integrating dual-pipeline CNN transfer learning, a Flask REST API backend, a Next.js mobile-responsive frontend, and a tiered clinical decision support module. The system addresses three high-impact poultry diseases—coccidiosis, bumblefoot, and fowlpox—achieving an overall classification accuracy of 98.2%, all-class AUC exceeding 0.96, and end-to-end inference latency under 10 seconds on a held-out test set of 465 images.

The core novelty of ChickTech AI lies in the integration of a production-ready deployment pipeline, structured clinical decision support, and multilingual voice accessibility features that collectively address the persistent research-to-practice gap in agricultural AI. ChickTech AI demonstrates that the gap between AI research and real-world agricultural deployment can be bridged through end-to-end system design and disciplined software engineering.

The proposed hybrid framework offers: (i) Accurate and deployable predictions through a dual-pipeline transfer learning architecture achieving 98.2% accuracy; (ii) Actionable clinical guidance through a tiered decision support module going beyond class prediction; (iii) Inclusive accessibility through multilingual voice interaction for low-literacy farming communities; and (iv) Scalable deployment through cloud-hosted, Docker-containerized infrastructure.

A. Limitations and Future Scope

- Training datasets were collected under relatively controlled photographic conditions, which may not fully represent real-world farm imagery variability including low-resolution smartphone images, poor lighting, and motion blur.
- The architecture assumes single-disease classification per image; co-infection scenarios presenting multiple simultaneous conditions are not directly modelled.
- The platform has not yet been evaluated in a large-scale field deployment study with representative end-users from diverse geographic regions.

Future work will focus on:

- Expanding the disease portfolio to include Newcastle disease, Marek’s disease, and infectious bronchitis.
- Integrating passive video-based flock surveillance for continuous 24-hour health monitoring.
- Adopting federated learning frameworks for collaborative model improvement while preserving data privacy [25].
- Developing knowledge-distilled lightweight model variants for edge device deployment [11].

Conducting a large-scale randomized field deployment study to measure real-world clinical impact [24].

8. FUTURE RECOMMENDATIONS

1. Diversify Dataset – Include poultry images from varied geographic regions, breeds, climate zones, and farm management systems.
2. Enable Real-Time Data – Integrate IoT-based flock monitoring sensors for live health tracking.
3. Track Long-Term Outcomes – Monitor treated flocks longitudinally to measure clinical and economic impact.
4. Use NLP for Feedback – Analyse textual feedback from farmers and veterinarians for richer system improvement insights.
5. AI-Based Adaptive Guidance – Align treatment protocols dynamically with evolving drug resistance patterns and regional disease prevalence data.

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

Author Contribution

First Author (Kunal Bishwal): Developed the CNN model architecture, implemented the dual-pipeline training strategy, and conducted experimental evaluation.
Second Author (Aman Patel): Designed and implemented the Flask REST API backend, cloud deployment infrastructure, and Docker containerization.
Third Author (Sumon Banerjee): Developed the Next.js frontend interface, multilingual accessibility layer, and tiered clinical decision support module.

Fourth Author (Monica Bhavani M): Contributed to the clinical validation framework, treatment guidance content, and manuscript preparation.

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