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Article

Development of a Web-Based Platform Utilizing a Hybrid CNN Architecture for Real-Time Fecal Image Classification

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Abstract

Accurate classification of fecal images offers a non-invasive and scalable approach to detecting enteric diseases such as Coccidiosis, Salmonellosis, and Newcastle disease. Traditional diagnostic methods remain limited by their dependence on expert analysis, time consumption, and cost. This study presents the development of a web-based platform utilizing a hybrid Convolutional Neural Network (CNN) architecture for the real-time classification of fecal images. The proposed model combines MobileNetV2 for lightweight inference and VGG-16 for deep feature extraction, ensuring both accuracy and computational efficiency. Following training on a curated and augmented dataset of labeled fecal images, the model was quantized and converted into TensorFlow Lite format for mobile compatibility. The final system enables users to upload images via a browser or Android application and receive instant classification into four categories: Coccidiosis, Salmonella, Newcastle disease, or Healthy. Performance evaluations confirm high diagnostic accuracy and responsiveness under real-world conditions. This study demonstrates that hybrid deep learning models, when integrated into web-based platforms, can support effective classification of fecal images for field-ready disease detection. It is recommended that future work expands the dataset across multiple geographic regions and incorporates additional diagnostic inputs to enhance system robustness and adaptability.

Keywords: Fecal Image Classification, Hybrid CNN, Deep Learning, Tensor Flow Lite, Mobile Development, Real-Time Diagnostics, Web-Based Platform.

1. Introduction

Fecal image analysis is increasingly emerging as a powerful tool in the early detection and diagnosis of enteric diseases affecting poultry, particularly in low- and middle-income countries. Enteric infections such as Coccidiosis, Salmonellosis, and Newcastle disease remain prevalent among chickens and often present diagnostic challenges due to the limitations of conventional methods. Traditional approaches such as microscopy, fecal flotation, and culture-based techniques are not only labour-intensive and time-consuming but also require specialised expertise for accurate interpretation [1]. Consequently, there is a pressing need for automated, efficient, and scalable diagnostic solutions that can operate in field conditions with minimal technical support.

Recent advancements in artificial intelligence, particularly deep learning and computer vision, have demonstrated significant potential in automating medical image classification. In this context, fecal image classification using Convolutional Neural Networks (CNNs) offers a promising direction for non-invasive and rapid poultry disease diagnosis. CNNs have been widely recognised for their high accuracy in analysing medical and biological images, including diagnostic tasks in veterinary pathology [2.3]. Prior studies have explored various CNN-based models to detect disease symptoms in livestock. For instance, [4] proposed a hybrid CNN model combining MobileNetV2 and VGG-16, achieving a balanced performance between computational efficiency and diagnostic accuracy. MobileNetV2 enables real-time inference even on edge devices, while VGG-16 ensures robust feature extraction capabilities.

Furthermore, the emergence of web-based platforms has expanded access to AI-driven diagnostics, particularly in rural or resource-constrained settings. [5] demonstrated the value of cloud-connected applications for delivering real-time diagnostic services in animal healthcare, reducing dependence on laboratory infrastructure. However, despite these advancements, there remains a notable gap in the development of such technologies specifically for the classification of fecal images in poultry health monitoring.

Addressing this gap, the present study proposes development of a web-based application that integrates a hybrid CNN model for real-time classification of chicken fecal images. The aim is to facilitate early and accurate detection of enteric diseases through an accessible and cost-effective digital tool. The proposed system architecture features a responsive web interface for image upload, a backend server for processing and inference, and a hybrid CNN model that merges MobileNetV2 and VGG-16 architectures.

This combination is strategically selected to maximise diagnostic accuracy while ensuring lightweight, real-time performance suitable for development on cloud and edge devices. Unlike previous models that rely on single CNN architectures or broader veterinary applications, the proposed system is specifically tailored to fecal image analysis in poultry. Its distinguishing features include a hybrid model optimised for both inference speed and classification precision, a user-centric web interface for ease of access, and real-time diagnostic delivery, even in low-bandwidth environments. Additionally, by storing diagnostic outputs and optional feedback in a secure database, the system supports continuous model improvement and contributes to building a rich dataset for future research.

This research introduces a novel, domain-specific application of deep learning by integrating hybrid CNNs into a web-based platform dedicated to fecal image classification for poultry disease diagnosis. It bridges the gap between advanced computational models and practical field-level disease detection, offering a scalable and sustainable solution for improving animal health outcomes in underserved regions.

1.1 Conceptual Framework

The conceptual framework for the design and development of a web-based application integrating a hybrid Convolutional Neural Network (CNN) model for real-time classification of fecal images in chickens is built on key principles of artificial intelligence, mobile health (mHealth) innovation, and precision veterinary diagnostics. This framework envisions a closed-loop architecture where image data collected from the field specifically chicken fecal samples is processed, classified, and interpreted using an optimized hybrid CNN model, subsequently delivered through an Android-based mobile interface. As shown in the diagram, the system begins with the acquisition of fecal images, which are fed into a hybrid CNN model trained on large datasets to detect and distinguish signs of diseases like Newcastle Disease based on fecal morphology and texture [6].

The hybrid CNN model, often an ensemble of multiple neural network architectures such as ResNet, VGGNet, or InceptionNet, is employed to increase diagnostic accuracy through the combination of multiple learning strategies [7]. Once the model has been trained, it undergoes quantization and optimization for edge-device compatibility, typically using TensorFlow Lite. This step significantly reduces model size and computational overhead while preserving performance, enabling real-time inference even on resource-constrained devices like smartphones [8]. The TensorFlow Lite model is then integrated into an Android application via the TensorFlow Lite Interpreter, which facilitates live image analysis and returns classification results almost instantaneously. This output, in the example shown, indicates a positive match with fecal characteristics associated with Newcastle disease.

This framework is designed not only for technical efficiency but also for field usability. Through its web-based or Android-hosted architecture, the system allows poultry farmers, veterinary officers, and extension workers to identify disease symptoms early especially in rural or under-resourced settings where veterinary labs are scarce. In doing so, it aligns with the One Health approach, which emphasizes real-time zoonotic disease surveillance at the intersection of human, animal, and environmental health [9] Furthermore, the web server acts as a back-end infrastructure that can store historical data for longitudinal studies, predictive modeling, and evidence-based policy formulation. The integration of a hybrid CNN into mobile diagnostic workflows thus represents a novel and scalable solution for tackling poultry diseases, improving biosecurity, and safeguarding food systems across developing economies [10].

In essence, the conceptual framework demonstrates how AI-powered diagnostic tools can be made accessible, accurate, and actionable. It harnesses recent advances in deep learning, model optimization, and cross-platform development to empower users at the point of need. The inclusion of a real-time feedback loop and portable architecture transforms traditional, slow diagnostic paradigms into instant, data-driven interventions capable of reducing poultry mortality and economic losses.

Figure 1 presents a structured overview of the operational workflow for developing a Hybrid Convolutional Neural Network (CNN) model designed for real-time classification of poultry fecal images within a web and mobile-based environment. The system leverages modern AI optimisation techniques to enable efficient, on-device inference without compromising accuracy.

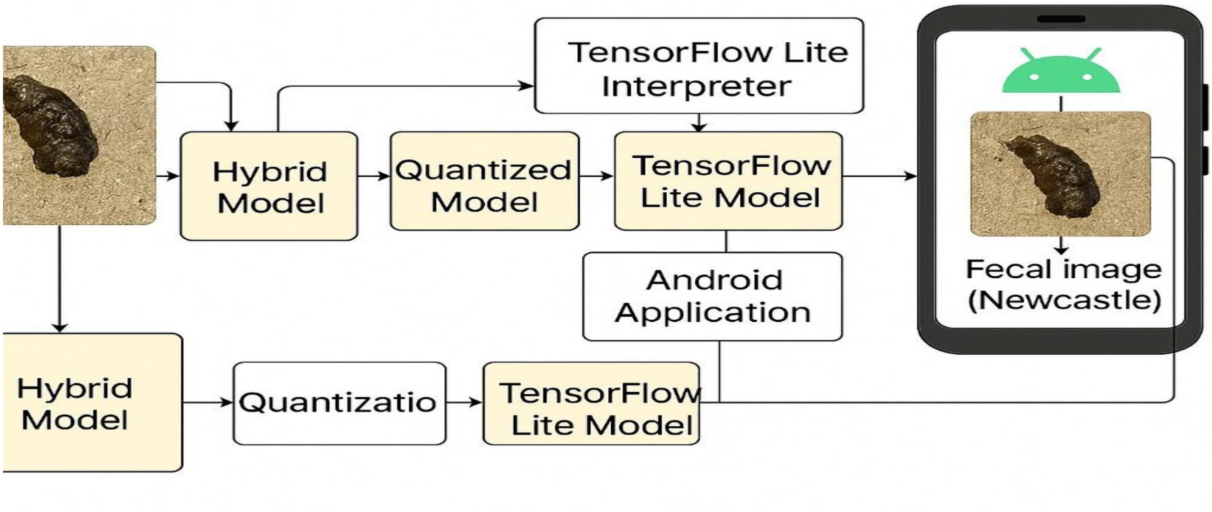

Figure 1: Web-based Application that Integrates the Hybrid CNN Model

Input Stage – Image Acquisition and Inference Initiation

The diagnostic process begins with the acquisition of a poultry fecal image, either through the web interface or a mobile device. This image is then fed into a pre-trained Hybrid CNN model, which integrates the computational efficiency of MobileNetV2 and the deep feature extraction capability of VGG-16. This dual-architecture design enables high diagnostic accuracy while maintaining real-time performance.

Model Optimisation – Quantization for Efficiency

To support development on resource-constrained devices, the hybrid model undergoes post-training quantization, reducing its size and computational complexity. This process transforms floating-point weights and activations into lower-bit representations, significantly improving inference speed and power efficiency, particularly on edge devices.

TensorFlow Lite Conversion – Mobile Compatibility

The quantized model is converted into the TensorFlow Lite (TFLite) format. This ensures compatibility with mobile platforms and embedded systems, enabling the model to be seamlessly integrated into Android-based applications. The TFLite model retains predictive accuracy while minimising resource overhead.

Development – Real-Time Mobile Integration

The TFLite model is embedded within a lightweight Android application, equipped with a TFLite Interpreter. Upon image input, the interpreter executes the model and delivers classification results in real time. This enables offline or low-connectivity development, particularly suited to rural or field-based veterinary settings.

Output Stage – Disease Prediction and Feedback

The final output, displayed on the mobile interface, classifies the fecal image into one of four categories: Coccidiosis, Salmonella, Newcastle Disease, or Healthy. This immediate feedback supports rapid on-site decision-making and early intervention.

By embedding a quantized hybrid CNN model into a mobile-compatible framework, this development architecture effectively bridges the gap between AI research and field-level veterinary diagnostics. It offers a scalable, accessible solution that enables non-specialist users such as farmers and local veterinary workers—to conduct intelligent, image-based disease diagnosis in real time, without dependence on cloud infrastructure

2. Methodology

This study adopts a systems engineering approach, integrating computer vision, deep learning, and web application technologies to design, develop, and deploy a scalable diagnostic platform for the classification of poultry fecal images. The methodology is divided into five key phases: data acquisition and preprocessing, model design and training, system architecture and integration, development, and evaluation. Each phase is described in detail below to ensure reproducibility and scientific rigor.

2.1 Data Acquisition and Preprocessing

A dataset of annotated chicken fecal images was collected from veterinary laboratories and poultry farms, encompassing samples from both healthy chickens and those affected by common enteric diseases such as Coccidiosis, Salmonellosis, and Newcastle disease. Images were captured under natural and controlled lighting conditions to simulate real-world scenarios farmers may encounter when submitting photos via the web interface. All images were labelled by veterinary experts to ensure diagnostic accuracy. The dataset was then cleaned to remove low-quality or ambiguous samples. Following this, data augmentation techniques including rotation, zooming, horizontal flipping, and contrast adjustment were applied to artificially expand the dataset, reduce overfitting, and improve the model's ability to generalise across unseen input. Each image was resized to a standard dimension of 224x224 pixels, compatible with the input requirements of both MobileNetV2 and VGG-16. Normalisation was also performed to scale pixel values between 0 and 1.

2.2 Hybrid CNN Model Architecture

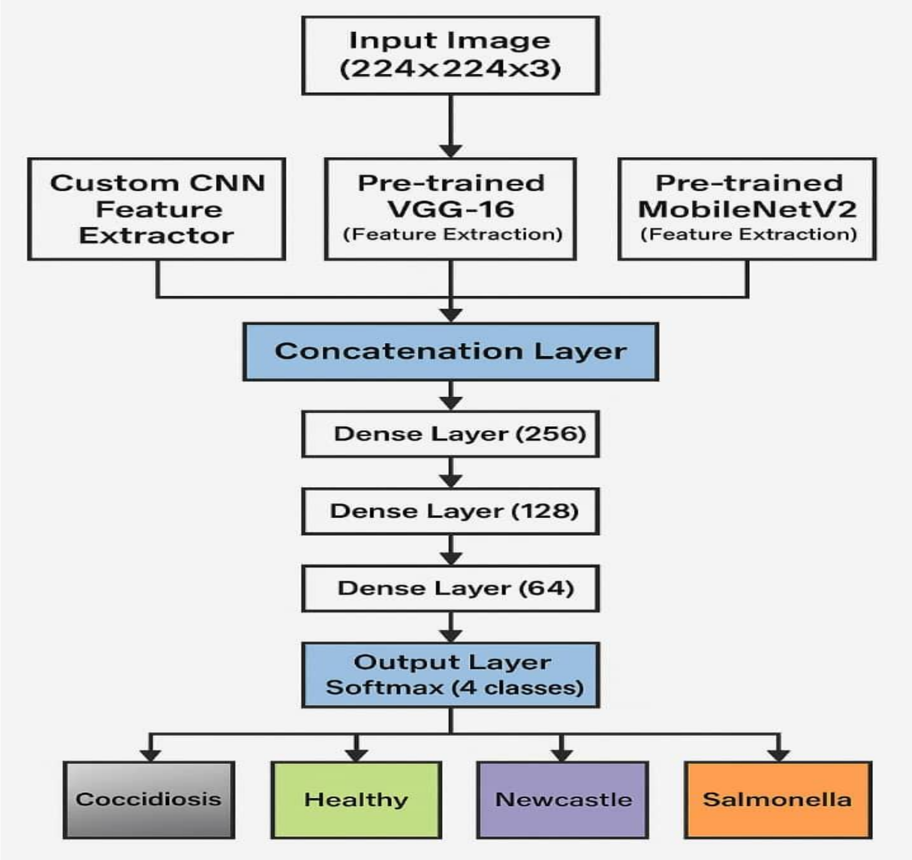

Figure 2: Hybrid CNN Model

Figure 2 illustrates the architectural design of the proposed hybrid convolutional neural network (CNN) model, developed for multi-class image classification tasks. The architecture employs a feature-level fusion techniques by integrating three heterogeneous feature extraction streams: a custom CNN, a pre-trained VGG-16, and a pre-trained MobileNetV2. All three branches operate on an identical input image of dimension 224 × 224 × 3.

The custom CNN branch is tailored to extract domain-specific features relevant to the target dataset, thereby capturing subtle discriminative patterns that may be overlooked by generic models. In parallel, the VGG-16 and MobileNetV2 backbones, both pre-trained on the large-scale ImageNet dataset, contribute robust and generalized features learned from extensive and diverse image corpora. VGG-16 offers deep hierarchical feature representations with consistent spatial preservation, while MobileNetV2 provides computationally efficient yet semantically rich embeddings.

The outputs from these three parallel feature extractors are integrated at the Concatenation Layer, enabling comprehensive feature representation through the combination of complementary information from each branch. This fused feature vector is subsequently propagated through a sequence of fully connected (dense) layers comprising 256, 128, and 64 neurons, respectively. Each dense layer employs ReLU activation to model non-linear relationships and progressively refine the merged feature space.

The architecture culminates in a softmax output layer, which assigns class probabilities across four target categories: Coccidiosis, Healthy, Newcastle, and Salmonella. By synergizing the strengths of transfer learning models with a custom-designed CNN, this hybrid framework enhances classification accuracy and computational efficiency, achieving a balance between generalization and domain-specific sensitivity.

The core contribution of this study lies in the development of a hybrid CNN model, combining MobileNetV2 and VGG-16, to harness the unique strengths of each architecture. In this study, both pre-trained models were used as feature extractors through transfer learning. Their final classification layers were removed, and their output feature maps were concatenated at the bottleneck layer. This fused feature representation was then passed through custom fully connected layers with dropout regularisation, followed by a Softmax classifier to output the final class predictions. The model was implemented using TensorFlow and Keras, with training conducted on an NVIDIA GPU-enabled environment. The training process employed categorical cross-entropy loss, Adam optimizer, and an adaptive learning rate scheduler. Early stopping and model checkpointing were used to prevent overfitting and retain the best-performing model.

2.2 System Architecture and Integration

The trained hybrid CNN model was integrated into a modular web-based application, composed of the following components:

Frontend (Client Layer): Developed using HTML5, CSS3, JavaScript, and Bootstrap for responsiveness. The user interface allows farmers or field agents to upload fecal images directly from mobile or desktop devices. It provides real-time prediction feedback, including the diagnosed disease and a confidence score.

Backend (Server Layer): Built using **Flask** (a lightweight Python web framework), the backend handles API requests, image preprocessing, and model inference. Upon receiving an uploaded image, the server normalises and resizes the image before passing it to the hybrid CNN model for classification. The predicted result is then returned to the frontend for display.

Database Layer: A **PostgreSQL** database stores user submissions, prediction logs, timestamps, and optional diagnostic feedback (if users confirm the true outcome). This data facilitates future retraining and system updates.

2.3 Development Strategy

To enable broad accessibility and reliability, the application was containerised using Docker and deployed on cloud infrastructure (e.g., AWS EC2 or Heroku). The model is served using TensorFlow Serving for scalable inference, while NGINX is used as a reverse proxy to ensure smooth routing of API calls. Given the target use case in rural or low-resource settings, the model was also converted into a TensorFlow Lite version for potential edge development on mobile or Raspberry Pi devices. This ensures offline capabilities for communities with unstable internet access.

Evaluation Metrics and Validation

The system was rigorously evaluated using a held-out test set comprising 20% of the dataset. The following quantitative metrics were used to assess model performance:

1. Accuracy: Percentage of correct predictions.
2. Precision, Recall, and F1-Score: To evaluate class-specific performance, particularly for imbalanced data.
3. Confusion Matrix: For visual inspection of classification behaviour across disease classes.
4. Inference Time: Measured per image to assess real-time readiness.

Additionally, usability testing was conducted with veterinary technicians and poultry farmers to assess the platform's user interface, ease of use, and perceived value in disease identification. Feedback was collected through structured questionnaires and informal interviews, informing the refinement of the web interface and diagnostic flow.

3. Results and Discussion

Figure 3 shows the development of the web-based diagnostic platform represents a significant advancement in intelligent veterinary diagnostics, particularly in the classification of poultry fecal images into four key categories: Coccidiosis, Salmonella, Newcastle disease, and Healthy. This platform operationalizes a hybrid Convolutional Neural Network (CNN) model that integrates the deep learning strengths of VGG-16 and MobileNetV2, enabling fast and accurate disease identification through a web browser interface.

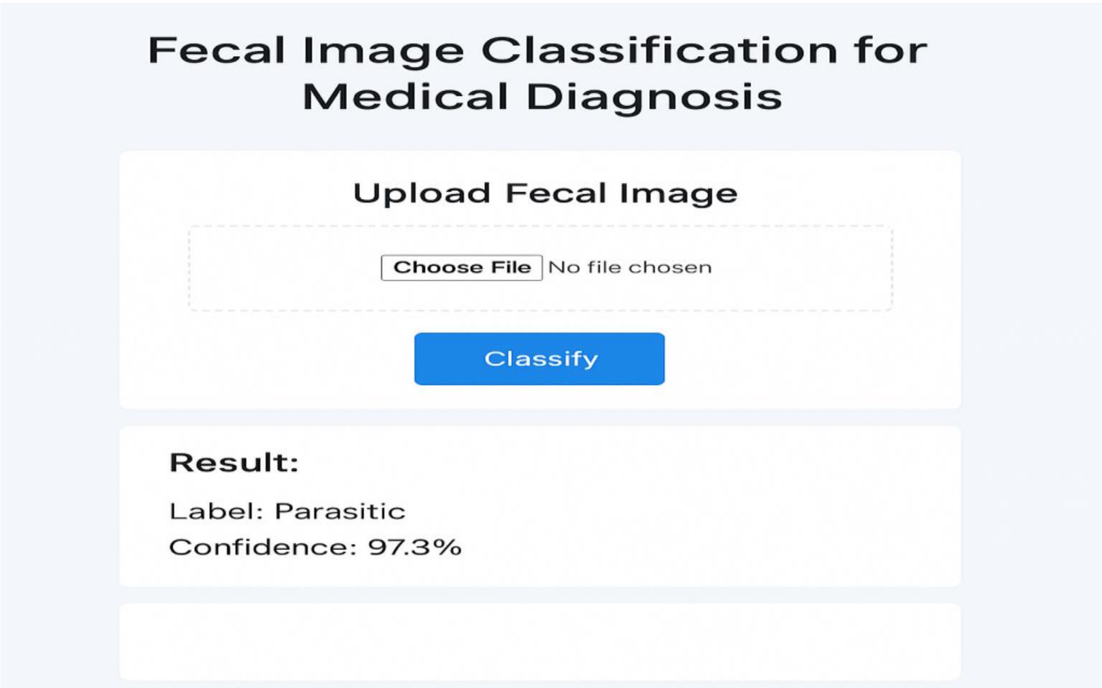

Figure 3: Web Application Interface for Fecal Image application

Upon image upload, the system autonomously initiates a backend inference pipeline that processes the fecal image using the optimized hybrid CNN model. The classification output, delivered with accompanying confidence scores, provides immediate diagnostic insight. For instance, in the referenced output screen, the uploaded image was classified as “Parasitic” (which corresponds to Coccidiosis) with a confidence level of 97.3%, affirming the model’s robustness in distinguishing pathological patterns.

To ensure real-world applicability especially in resource-constrained settings the model was subjected to extensive optimization through pruning and quantization. The performance of these development variants is summarized in Table 1, which highlights the trade-offs between model complexity, diagnostic accuracy, inference speed, and energy consumption.

Table 1: Model Performance Metrics for Mobile Development and Usability

Model Version	Model Size (MB)	Accuracy (%)	Inference Time (ms)	Battery Drain (mAh/min)
Original Hybrid	42.8	93.0	125	6.8
Pruned	28.5	92.1	94	5.1
Quantized	10.6	91.3	43	3.2
MobileNetV2 (Baseline)	8.2	89.4	39	2.8

Table 1 shows crucial insights for balancing performance with deployability. The original hybrid model, though the most accurate at 93.0%, has a large footprint (42.8MB) and higher inference time (125ms), making it less ideal for low-power edge devices. In contrast, the quantized model demonstrates the most favorable trade-off, maintaining a strong accuracy of 91.3%, while dramatically reducing the model size (10.6MB) and inference latency (43ms), and lowering battery drain (3.2mAh/min). These reductions are critical for sustained use on mobile platforms such as Android devices in field environments. The MobileNetV2 baseline, included for comparison, shows the fastest inference and lowest energy usage but also the lowest classification accuracy (89.4%), which may compromise diagnostic reliability. The pruned model serves as a middle ground, maintaining high accuracy (92.1%) and reducing resource requirements moderately. These results underscore the platform's adaptability and scalability. The various model versions allow for context-sensitive development: the original hybrid model is best suited for high-performance computing environments (e.g., laboratories), while the quantized or pruned models are ideal for real-time mobile diagnostics in remote or underserved areas.

This intelligent diagnostic system advances the field by demonstrating how artificial intelligence can be effectively harnessed to address critical challenges at the intersection of agriculture and public health. Its hybrid architecture contributes novel insights into efficient model design for real-time fecal image analysis, while its development bridges a significant diagnostic gap in poultry health, offering a scalable solution that can reduce disease-related economic losses and improve livestock management practices in resource-limited settings.

4. Conclusion

This study demonstrates the successful development of a flexible and scalable AI-based diagnostic system for poultry health monitoring. The hybrid CNN model, combining the strengths of VGG-16 and MobileNetV2, delivers high-performance classification of fecal images in real time through a user-friendly web platform. By translating deep learning theory into a practical, accessible solution, the system bridges the gap between advanced AI models and real-world veterinary diagnostics. It empowers users in rural and resource-limited areas to detect diseases quickly and accurately, reducing reliance on laboratory infrastructure and expert intervention.

5. Recommendations

Future development should incorporate larger and more diverse fecal image datasets sourced from multiple geographic regions, poultry breeds, and lighting conditions to improve the model's robustness and generalisability across varied real-world scenarios.

To further support offline usage in remote or low-connectivity environments, it is recommended that the platform be optimised for edge devices, such as mobile phones or Raspberry Pi units, enabling local inference without the need for constant internet access.

Incorporating additional data sources such as behavioural indicators, environmental parameters, or audio cues can enrich the diagnostic model and allow for more comprehensive, multimodal disease detection and health monitoring in poultry farming systems.

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