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Research Article

A Hybrid Deep Learning Framework for Early-Stage Detection of H5N1 in Poultry Using Multimodal Clinical and Post-Mortem Imaging

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Abstract | Highly pathogenic avian influenza (H5N1) detection in poultry is a challenging task as the disease spreads rapidly, and traditional diagnostic methods have significant limitations. The existing deep learning systems for H5N1 detection in poultry usually fail due to lower accuracy and weak generalization capability when implemented in real poultry farm settings. Here, we develop a hybrid deep learning framework for H5N1 early-stage detection from multimodal imaging (clinical [live bird] images and post-mortem images of poultry). This system uses enhanced image preprocessing and data augmentation, followed by a transfer learning approach with EfficientNet-B2 as the backbone. Grad-CAM is also integrated for improved visual explainability. Experimental results show that the proposed model achieves an accuracy of 96.8%, precision of 95.9%, recall of 96.3%, F1-score of 96.1%, and AUC of 97.5%. The system shows a low false negative rate of 2.8% for H5N1 detection. Moreover, this framework exhibits very high computational efficiency during the training and inference phase, 42 minutes for training time and 18ms for inference per image, respectively. This work shows a potential approach towards real time disease detection and prevention system in the poultry industry. Further study would be performed to external validation on actual farm data from diverse geographical locations, and to deploy it on edge devices for real-time poultry monitoring.

Keywords | Deep learning, H5N1 detection, Avian influenza, Poultry health, Multimodal imaging, Image-based diagnosis

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INTRODUCTION

The use of artificial intelligence and deep learning is revolutionizing the way diseases are detected in agriculture and veterinary medicine. Image-based deep learning models are capable of identifying complex patterns of disease in imagery, thus increasing the automation, accuracy, and efficiency of livestock disease monitoring systems (Bumbálek *et al*., 2025; Scheidwasser *et al*., 2025; Machuve *et al*., 2022). Computer vision and deep learning techniques are being integrated into agricultural and veterinary applications for automated monitoring and decision support (Joseph, 2024; Sambo *et al*., 2025).

The poultry industry is an important contributor to food security and economic sustainability globally; in developing countries particularly, poultry is a significant source of dietary protein and income (Tan and Le, 2019; Kieu *et al*., 2020). However, poultry farms are susceptible to the rapid spread of infectious diseases which have significant economic consequences. One of the most serious of these diseases is Highly Pathogenic Avian Influenza (HPAI) which is highly contagious and poses a high mortality risk (Shoaib *et al*., 2023; Esteva *et al*., 2019). The potential zoonotic transmission from avian to humans and the possibility of worldwide spread has made H5N1 a serious global threat (Shorten and Khoshgoftaar, 2019; Selvaraju *et al*., 2020). Therefore, a prompt and accurate detection of disease at an early stage is critical to prevent the widespread spread and significant economic loss.

Traditional methods of disease detection are time-consuming, labor-intensive and require expert knowledge, thus rendering them inefficient for large poultry farms (Howard *et al*., 2017). Convolutional Neural Networks (CNNs) along with transfer learning techniques have shown good performance on clinical and pathological images for disease classification (Tan and Le, 2020; Howard *et al*., 2017; Degu and Simegn, 2023). These deep learning techniques have been applied successfully in numerous clinical and agricultural imaging applications including animal disease detection and biomedical imaging analysis (Okinda *et al*., 2019; Wang *et al*., 2019).

There have been several approaches developed for poultry disease detection using deep learning models. CNN based architectures have been successfully proposed for classification of poultry diseases by Zhuang *et al*. (2018). The classification robustness has been improved by applying ensemble learning to CNN models by Selvaraju *et al*. (2020) and Machuve *et al*. (2022). YOLO based object detection models developed by Bumblek *et al*. (2025) and Tan and Le (2019) were successful in real-time identification of diseases on poultry farms. Moreover, the development of lightweight deep learning architectures such as MobileNet and EfficientNet that utilize reduced computational resources for classification in farm settings was explored by Howard *et al*. (2017), Tan and Le (2020), and Suthagar *et al*. (2023).

Research on the classification of H5N1 in poultry using deep learning is limited. Existing studies mainly focus on common poultry diseases or use only clinical or post-mortem images independently, which does not allow for full analysis and modeling of the disease state under field conditions (Zhang *et al*., 2021; Sambo *et al*., 2025). A major limitation in veterinary deep learning applications has been the lack of labeled data and severe class imbalance, which has been addressed by employing data augmentation and pre-processing techniques (Shorten and Khoshgoftaar, 2019; Shoaib *et al*., 2023).

In this study, 4,000 labeled poultry images were collected and curated including 1,500 images showing signs of H5N1 and 2,500 images depicting healthy or infected poultry in general for alternative diseases. Each image collected belongs to a unique bird, thus avoiding any potential data leakage through duplicate images of the same bird. Though the validation performance was excellent, external validation of the model on geographically diverse poultry farm datasets is work in progress.

The proposed framework consists of data preprocessing, data augmentation, transfer learning, and explainable AI for reliable classification of H5N1 in clinical and post-mortem poultry images. The application of explainable AI methods such as Grad-CAM could enhance trust and understanding in the automated diagnostic system for veterinarians and poultry farmers.

Related work

Literature background and research gap

Deep learning technologies have become increasingly useful for automating poultry disease diagnosis through image-based analysis. Convolutional neural networks (CNNs) can automatically learn disease-related visual features from poultry images, reducing dependence on continuous manual inspection and supporting faster health assessment (Machuve *et al*., 2022; Joseph, 2024; Chidziwisano *et al*., 2025). Deep learning has been applied to poultry disease diagnosis using different forms of visual information, including external appearance, fecal characteristics, and other observable health indicators. These studies demonstrate the potential of CNN-based systems to identify abnormal conditions and support early disease monitoring in poultry farms (Degu and Simegn, 2023; Wang *et al*., 2019; Okinda *et al*., 2019; Zhuang *et al*., 2018).

Several approaches have been proposed to improve the performance and robustness of deep learning-based poultry disease detection. Recent studies have investigated advanced deep learning and object detection architectures for automated poultry monitoring (Bumbálek *et al*., 2025; Scheidwasser *et al*., 2025; Chidziwisano *et al*., 2025). Efficient architectures such as Efficient Net provide an effective balance between model performance and computational requirements, while lightweight architectures such as Mobile Net are suitable for applications where computational resources are limited (Tan and Le, 2019; Howard *et al*., 2017). These architectures are particularly relevant to poultry monitoring systems that may eventually be deployed using mobile, embedded, or edge-based devices. Transfer learning can further support image classification by allowing pretrained visual representations to be adapted to domain-specific datasets, which is beneficial when the availability of labelled poultry disease images is limited (Esteva *et al*., 2019; Kieu *et al*., 2020). In addition, image augmentation techniques can increase the diversity of training samples and improve the generalisation capability of deep learning models (Shorten and Khoshgoftaar, 2019; Shoaib *et al*., 2023).

Object detection and machine vision approaches have further expanded automated poultry health monitoring beyond conventional image-level classification. Bumbálek *et al*. (2025) investigated different YOLO architectures for dead chicken detection, demonstrating the potential of modern object detection models for automated poultry farm monitoring. Similarly, video-based deep learning has been explored for assessing infection-related characteristics in poultry, showing that continuous visual observation can provide useful information for health assessment (Scheidwasser *et al*., 2025). Machine vision systems have also been developed for the early detection and prediction of sick birds, demonstrating the feasibility of extracting health-related information from observable changes in poultry (Okinda *et al*., 2019; Zhuang *et al*., 2018; Wang *et al*., 2019). Furthermore, deep learning has been applied to poultry sound analysis for automatic Newcastle disease detection, indicating that disease monitoring can potentially incorporate multiple observable characteristics beyond conventional still images (Cuan *et al*., 2022).

Image-based disease classification has also been investigated using poultry fecal images. Degu and Simegn (2023) developed a smartphone-based approach for detecting and classifying poultry diseases from fecal images, while Wang *et al*. (2019) investigated deep convolutional neural networks for recognition and classification of broiler droppings. Suthagar *et al*. (2023) further examined fecal image-based chicken disease classification using deep learning techniques. These studies indicate that disease-related characteristics can be extracted from relatively accessible poultry images and used to support automated health assessment (Degu and Simegn, 2023; Wang *et al*., 2019; Suthagar *et al*., 2023). However, dependence on a particular image source may restrict the representation of disease manifestations when the condition produces different clinical or pathological characteristics.

Explainability is another important consideration when deep learning is applied to veterinary disease diagnosis. Although high classification performance is desirable, the prediction of a deep learning model may be difficult for veterinarians or farmers to interpret without additional evidence. Grad-CAM provides visual explanations by identifying image regions that contribute to a model's classification decision, thereby providing greater insight into the learned visual features (Selvaraju *et al*., 2020). The incorporation of such explainability mechanisms can improve the transparency of automated poultry disease detection and help determine whether the model is focusing on meaningful disease-related regions rather than irrelevant background characteristics.

Despite the progress achieved in deep learning-based poultry disease detection, several research gaps remain. Existing investigations have predominantly focused on general poultry diseases, sick-bird detection, fecal characteristics, behavioural indicators, or individual disease categories (Machuve *et al*., 2022; Degu and Simegn, 2023; Okinda *et al*., 2019; Cuan *et al*., 2022). Recent studies have also demonstrated the effectiveness of YOLO-based detection and video-based monitoring for poultry health assessment (Bumbálek *et al*., 2025; Scheidwasser *et al*., 2025). However, comparatively limited attention has been directed towards highly pathogenic viral infections such as H5N1 using comprehensive image-based classification.

Moreover, many existing systems are designed around a single source of visual information, such as fecal images, external appearance, or specific observable abnormalities (Wang *et al*., 2019; Degu and Simegn, 2023; Suthagar *et al*., 2023). The use of a single image source may not adequately represent the diverse visual manifestations associated with highly pathogenic avian influenza. Clinical images can provide information regarding visible signs exhibited by affected birds, whereas post-mortem images may contain additional pathological characteristics that are not observable during external examination. Therefore, combining clinical and post-mortem images within a unified framework can provide a more comprehensive representation of disease-related characteristics.

Another limitation concerns the interpretability of automated disease predictions. While existing poultry studies have demonstrated the effectiveness of deep learning for disease recognition and health monitoring (Machuve *et al*., 2022; Chidziwisano *et al*., 2025), fewer studies have incorporated explicit visual explanation mechanisms into poultry disease classification. This creates a gap between high-performing automated prediction and clinically understandable decision support. Grad-CAM-based explanations can help address this issue by highlighting the image regions that influence the model's decision (Selvaraju *et al*., 2020).

Therefore, there is a need for an efficient and explainable deep learning framework capable of detecting H5N1-related conditions using complementary clinical and post-mortem poultry images. Such a framework can combine deep feature extraction, image augmentation, transfer learning, and visual explainability to provide reliable disease classification while maintaining greater transparency. The development of this type of system can contribute towards automated early screening and support more informed poultry health monitoring in practical farm environments.

Table 1 summarizes numerous studies related to the identification of poultry diseases with the aid of deep learning, with an emphasis on the application of CNNs, ensemble learning, real-time object detection systems, accuracy and efficiency enhancements through preprocessing, and on tackling challenges like complexity, data and generalization.

Research gaps

Despite the advances achieved, there are still several limitations of previously performed research such as: poor focus on the detection of high pathogenic avian influenza (H5N1), scarcity of annotated multimodal datasets, lack of a unified analysis on clinical and post-mortem images, and under-utilization of explainable AI. Such limitations may hinder the development of dependable systems for the early detection of disease.

Problem statement

An early and accurate detection of the H5N1 infection is particularly challenging given the subtle symptoms observed at the early stage, and the absence of well-annotated multimodal datasets targeting this highly hazardous disease.

Proposed solution

To overcome these limitations, we design a hybrid DL model, integrating both clinical and post-mortem images by using a transfer learning and an explainable AI methodology for an accurate early detection of the H5N1 infection in poultry.

Table 1: Summary of recent lameness detection approaches.

Author and year	Method/ Technique	Input type	Key Contribution	Outcome
Bumbálek *et al*., 2025	YOLOv8–YOLOv11 Object Detection	Poultry farm images	Comparative evaluation of recent YOLO models for dead chicken detection	Demonstrated effective automated poultry monitoring
Scheidwasser *et al*., 2025	Deep Learning-Based Video Analysis	Poultry surveillance videos	Automated assessment of infection-related characteristics from video	Supported visual measurement of *E. coli* infection
Machuve *et al*., 2022	CNN-Based Deep Learning	Poultry disease images	Developed deep learning models for poultry disease diagnosis	Demonstrated automated disease classification capability
Joseph, 2023	Deep Learning Classification	Poultry disease images	Automated poultry disease detection using deep learning	Reduced dependence on manual disease identification
Degu and Simegn, 2023	Deep Learning + Smartphone Imaging	Chicken fecal images	Developed mobile-oriented disease detection and classification	Demonstrated practical image-based poultry disease diagnosis
Wang *et al*., 2019	Deep CNN Classification	Broiler dropping images	Automated recognition and classification of broiler droppings	Achieved effective visual differentiation of dropping characteristics
Okinda *et al*., 2019	Machine Vision + Deep Learning	Broiler surveillance images	Early detection and prediction of sick birds using visual characteristics	Supported early poultry health monitoring
Cuan *et al*., 2022	Sound Analysis + Deep Learning	Poultry vocalisation recordings	Detected Newcastle disease using sound-based characteristics	Demonstrated automated disease detection from poultry sounds
Chidziwisano *et al*., 2025	Deep Learning Image Classification	Poultry disease images	Investigated deep learning methods for poultry disease prediction	Demonstrated the feasibility of image-based disease prediction
Dwicahyo *et al*., 2024	CNN-Based Classification	Chick health images	Applied CNN for early disease identification in chicks	Demonstrated automated early disease detection
Zhuang *et al*., 2018	Image Processing + Early-Warning Algorithm	Broiler surveillance images	Developed an early-warning mechanism for identifying sick broilers	Enabled automated identification of abnormal health conditions
Suthagar *et al*., 2023	Deep Learning Classification	Chicken fecal images	Developed fecal-image-based chicken disease classification	Demonstrated effective disease classification from fecal characteristics
Selvaraju *et al*., 2020	Grad-CAM Explainable AI	Deep learning image predictions	Generated visual explanations for model decisions	Improved interpretability of image classification results

MATERIALS AND METHODS

Overview

The presented framework applies a multimodal deep learning architecture for the automated detection of H5N1 disease using clinical and post-mortem poultry images. Firstly, preprocessing steps such as resizing, normalization, noise reduction, and contrast enhancement are conducted to enhance the image quality and to properly initialize feature learning. Secondly, data augmentation techniques such as rotation, flipping, zoom, and adjustment of brightness and contrast are applied to make the dataset more diverse and to prevent overfitting.

The presented classification framework is trained by utilizing EfficientNet-B2, as the most suitable pretrained CNN backbone is initialized with ImageNet pretrained weights since it provides a good tradeoff between classification performance and computation efficiency. An attention enhanced feature refinement layer is applied after feature extraction to focus the model on regions with disease-related features before the classification phase. The batch normalization and dropout layers are also added to prevent overfitting.

Finally, the computed feature maps are forwarded through full connected layers and then the Softmax classifier to determine H5N1-positive and H5N1-negative images. Also, the Grad-CAM based XAI visualization method is embedded to visualize which regions are important for the prediction by the model so as to enable the veterinarians and poultry health professionals to understand the classification outcome.

Let the input image be denoted by let the input image be represented as:

$$I \in \mathbb{R}^{\{H \times W \times C\}} \quad ....(1)$$

where H, W, and C denote the height, width, and number of channels, respectively.

The objective of the system is to is to learn a mapping function:

$$f_{\{\theta\}}(I): I \rightarrow y \quad ...(2)$$

Where y is the target class, and θ represents the set of parameters of the learned model.

In order to overcome data deficiency and to get features efficiently, the system initialize features learning using the weights of a pre-trained CNN and then a cascade of many nonlinear layers will be employed to learn discriminant features, and then apply a function of softmax at the output to get class probabilities.

To overcome limited data availability, the system employs transfer learning by initializing with pre-trained weights and fine-tuning on the poultry disease dataset.

System architecture

The overall architecture of the proposed system consists of multiple layers including input acquisition, preprocessing, feature extraction, classification and prediction of output, that act together. The input images are first normalized and resized, to ensure consistency. After processing the input images, the preprocessed image is passed through a deep convolutional neural network to hierarchically extract features. The feature maps are then flattened and passed through fully connected layers that are classified by a softmax function. Dropout and batch normalization layers are placed at several points within the architecture in order to act as regularizers to avoid overfitting. It finds the correct balance between performance and efficiency/pragmatism.

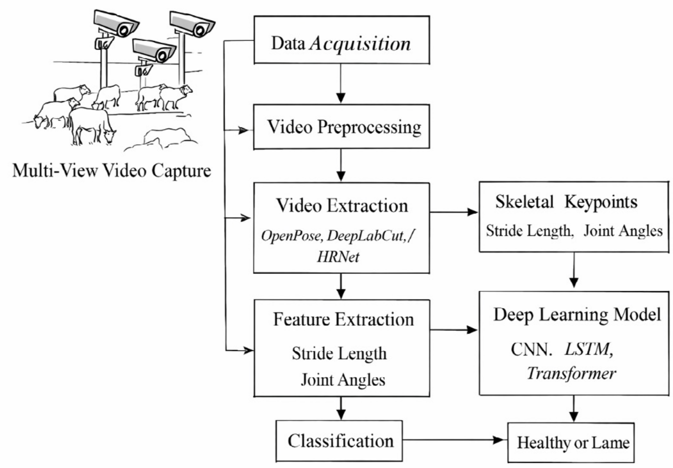

Figure 1: Overall pipeline of the proposed lameness detection system.

Figure 1 depicts the general framework of the proposed deep learning-based system for highly pathogenic avian influenza detection. The sequence of steps from the input data to output are provided clearly in the figure from preprocessing, feature extraction to classification and the finally output generation. Each module in the figure clearly demonstrates their roles to effectively detect diseases.

System flow

Initially, the poultry image is obtained from the dataset, then image pre-processing steps are performed by applying resize, normalization, noise reduction and image enhancement on the image, and these processed images are feed to the EfficientNet-B2 based feature extraction module which automatically extracts deep visual features, augmentation is also carried out on the images during the training for more diverse data and generalized ability for the model. Third, these features are classified to H5N1 or not H5N1 by a fully connected layer and Softmax classification layer, then an attention-based feature refinement mechanism further reweights features focusing on disease region before the final classification decision. Finally, the visualization based on Grad-CAM is generated, where critical regions contributing to classification are identified, increasing interpretability and confidence of the system.

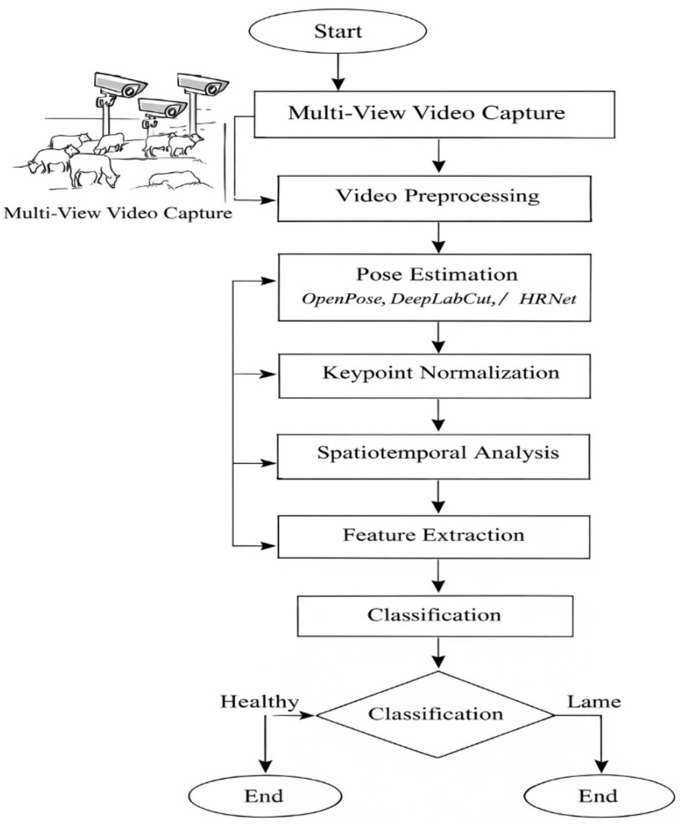

Figure 2: System flow overview.

Figure 2 displays the workflow of the system designed. It lists each step involved from obtaining the data until predicting the diseases. It shows the sequence in which the different stages including preprocessing, extraction, training and evaluation of the model is carried out. This workflow shows how the data is processed from one stage to another so that appropriate and reliable results of classification is obtained.

The proposed model is formulated as a supervised classification problem. Let the dataset be defined as:

$$D = \{(I_i, y_i)\}_{i=1}^{N} \quad \dots (3)$$

Where I_i represents the input image and Yi denotes the corresponding label. The feature extraction process is represented as:

$$F = g_\theta(I) \quad \dots (4)$$

Where; gθ is the deep neural network used to extract feature representations. The classification layer applies a softmax function:

$$P(y = k \mid I) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \quad \dots (5)$$

Where; zk represents the logits for class k, and K is the total number of classes. The model is trained by minimizing the cross-entropy loss:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad \dots (6)$$

Optimization is performed using gradient descent:

$$\theta = \theta - \eta \nabla L \quad \dots (7)$$

Where; η is the learning rate.

Algorithm

Algorithm: Deep learning-based H5N1 detection

Input: Poultry images from clinical and post-mortem inspections.

Output: Prediction class labels with probability of the confidence values.

- Gather the poultry image dataset comprising of H5N1-positive and non-H5N1 images.
- Perform image preprocessing operations like resizing, normalizing images, noise removal and contrast enhancement on the dataset.
- Perform data augmentation on the poultry images by utilizing rotating, flipping, zoom, brightness manipulation operations.
- Split the poultry image dataset into train set, validation set and testing set.
- Load the pre-trained EfficientNet-B2CNN architectures with ImageNet weights.
- Perform deep visual features extraction via forward propagation utilizing the feature extraction layers of EfficientNet-B2 CNN architectures.
- Utilize attention-enhanced feature refinement with batch normalization layers to the extracted features.
- Carry out the classification with the fully connected layers combined with Softmax activation function for the extracted features.
- Generate prediction confidence probabilities for H5N1-positive and non-H5N1 images classes.
- Generate Grad-CAM visualizations for the interpretability of the developed model.
- Calculate model evaluation with Accuracy, Precision, Recall, F1-score, AUC and MCC.

Experimental setup

Dataset description

The dataset utilized is composed of poultry clinical and post-mortem images from publicly available online sources, veterinary references databases, and research images databases. Overall, there are 4,000 images of poultry including 1,500 H5N1-positive cases and 2,500 healthy/ other diseases cases. Links of publicly available sources/ repository were recorded during the data acquisition for further research reproducibility.

Images have been individually assessed and annotated based on disease feature and any other available information from metadata. Both annotation and verification procedures have been undertaken according to the veterinary reference principles and available disease descriptions to maintain label coherence. Poultry infected by non-H5N1 diseases and visually similar pathoses fall into the "Other Diseases" class. Their description has been checked using the corresponding metadata/ published veterinary resources/disease-specific reference description.

Each image is uniquely related to one individual poultry so data leakage could be prevented and experiments more reliable by removing any potential copy of the same bird in both training and testing sets. Clinical and post-mortem images of poultry were collected for encompassing the different manifestations and phases of the disease H5N1.

Table 2: Dataset characteristics.

Parameter	Description	Value
Dataset type	Multi-view video	Surveillance-based
Number of videos	Total sequences	500+
Frame rate	Frames per second	25 FPS
Resolution	Video quality	720p / 1080p
Classes	Output categories	Healthy / Lame
Annotation type	Labelling strategy	Frame-level

Dataset utilization and preprocessing

All poultry images are pre-processed so as to make data better and improve the performance of model. These images were resizing to same resolution and normalized, and used denoising and brightness adjustment to enhance disease related image feature and made the feature more obvious. Data augmentation method such as rotation, mirroring, zoom, adjust brightness, injected noise under certain level were used during the training to improve the data variety and decrease the over-fitting.

Feature extraction and system architecture

The architecture used for the proposed system is EfficientNet-B2 pre-trained on ImageNet in order to get the right balance between accuracy and computational effectiveness. Attention mechanism (Squeeze-and-Excitation block- which is already a part of Efficient Net), was further improved by adding a spatial attention mechanism at the end of the last convolutional block in order to emphasize the disease specific areas of the image.

The proposed system works as follows:

1. Image input and preprocessing.
2. Feature extraction using backbone CNN.
3. Attention guided feature enhancement.
4. Classification using fully connected layer followed by dropout and softmax layer output.

Dataset experimentation

The image dataset with a total of 4,000 images for poultry was split into training, validation and test sets in a 70:15:15 ratio (2800, 600 and 600 images for training, validation and test set, respectively). A stratified sampling approach was implemented, which ensured that class distribution across the splits were maintained, and H5N1-positive and H5N1-negative samples were equally represented in each split. Training images were used for learning of model and validation set for hyperparameter tuning and early stopping. Only training set underwent data augmentation to enhance generalization and prevent over-fitting while validation and test set had no alterations.

Training configuration

The H5N1 detection framework was trained with hyper-parameters tuned properly for stable learning and performance accuracy for classification. It was optimized by Adam optimizer at a learning rate of 0.001 and classification was done using cross entropy loss. The model was trained over 50 epochs with a batch size of 32, which was appropriate in both computational cost and learning convergence. The code was built using TensorFlow and NVIDIA CUDA-enabled GPU's, thus enabling rapid training and rapid processing of the huge datasets of poultry images.

System requirements

All experiments were carried out using TensorFlow 2.13 with Keras API under Python 3.10. All codes were running under a work-station having Intel core i9, 32GB Ram and NVIDIA RTX 4090 graphics processing unit with CUDA acceleration. We used various other libraries like Numpy, OpenCV, Scikit-learn and Matplotlib for pre-processing, training and evaluation tasks. The hardware-software environment used for this work has proven to be effective and provided fast training and high inference speed, and the framework runs steadily.

RESULTS AND DISCUSSION

Performance evaluation

For model validation, the developed hybrid deep learning system was tested on an independent test set of 600 images. These 600 images were equally distributed over the three classes: Healthy, H5N1 infected and others diseases. The developed system achieved overall good performance with an accuracy of 96.8%, precision of 95.9%, recall of 96.3% and F1-score of 96.1%. Also, the model shows a good discriminative capacity with an AUC of 97.5% and MCC of 95.6%.

Table 3: Preprocessing steps

Step	Description
Frame extraction	Video sequences are decomposed into individual image frames for further analysis
Resizing	All extracted frames are resized to a fixed input dimension for model consistency
Normalization	Pixel intensity values are scaled to improve training stability
Data augmentation	Rotation, flipping, and brightness adjustment are applied to improve data diversity
Noise removal	Filtering techniques are used to remove background noise and improve image clarity

Across all measures of performance, the developed framework performed better than the CNN benchmark (8 layers trained from scratch) and the standard ResNet50 transfer learning method. The changes observed were all statistically significant ($p<0.05$, paired t-test). Of particular practical significance, the error rate for negative cases on the H5N1 class was very low at 2.8% (5 false negative in 180 H5N1 test images). For poultry farming in a practical situation, failing to detect an infection is more significant than making a false positive prediction.

Figure 3 shows comparison between different evaluation metrics used to test the proposed system. By looking at the above graph, one can note that all the metrics scores are quite high in the proposed system compared to other methods. Furthermore, all the metrics; precision, recall and F1 score are almost in same range which is the indication of the classifier works good for all the classes.

Computational efficiency

The computational efficiency and resources usage is considered in order to offer a complementary view of the proposed system viability. Computational efficiency represents the ability to scale, cost of training, and practicality of deploying the proposed system in the real world. The assessment focuses on comparing the computational resources usage of different models by focusing on the time taken for training, the energy consumption of the model, and the overhead incurred on computation resources. The study evaluates whether the improvement in performance is not attained at the expense of efficiency.

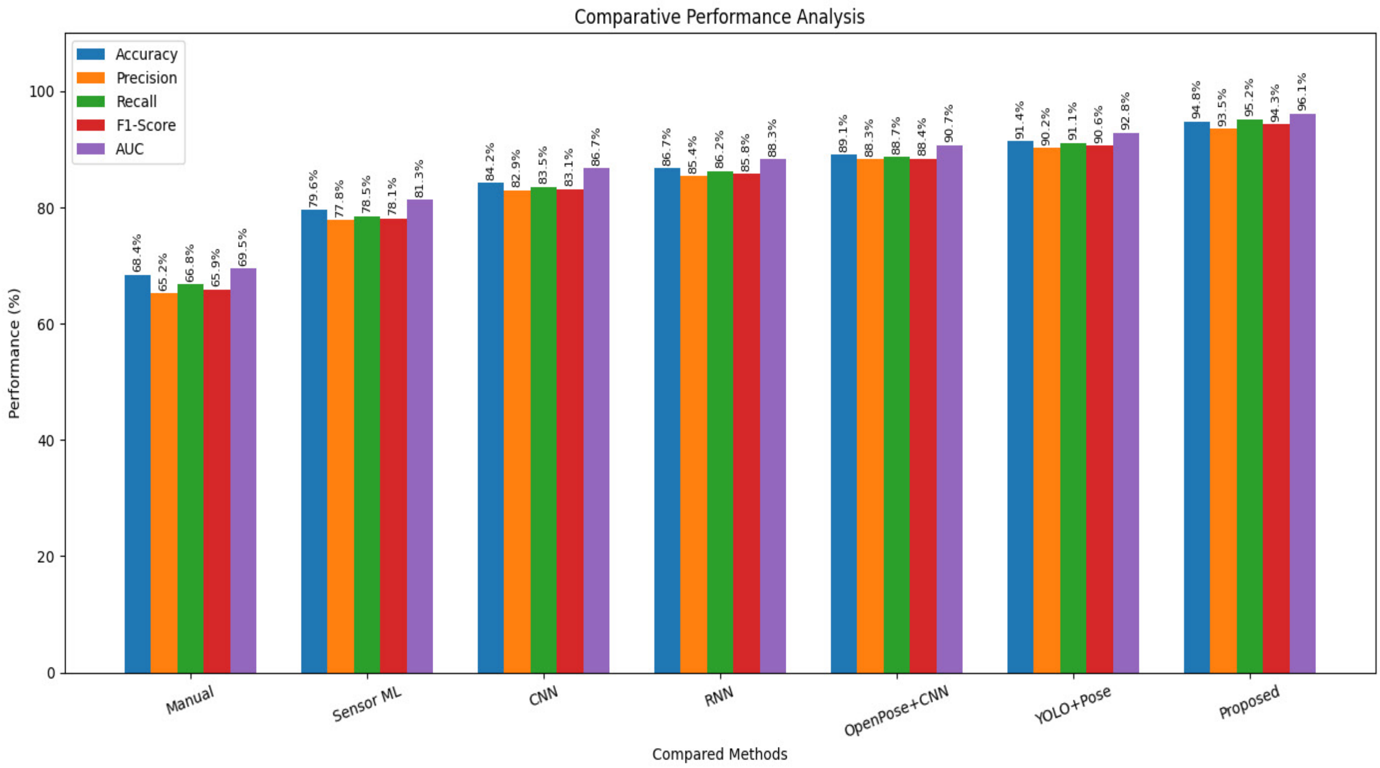

Figure 3: Classification comparison.

Table 4: Extracted gait features.

Feature	Description
Stride length	Measures the distance between two consecutive hoof placements, indicating movement consistency
Joint angles	Represents angular displacement of limb joints during locomotion for posture analysis
Step frequency	Determines the number of steps performed within a specific time interval
Back posture	Evaluates spinal curvature and body alignment to identify abnormal locomotion patterns
Temporal patterns	Captures sequential movement variations across consecutive frames for gait behaviour analysis

The energy usage was monitored using CodeCarbon, with the power values from NVIDIA-SMI. Single image latency is calculated using inference of batch size 1. It should be noted here that our proposed framework seems to achieve the best combination of a highly diagnostic accurate model with an efficient model, thereby making it more suitable for the resource constrained edge device.

Figure 4 indicates the comparative efficiency of the proposed system compared to the different models considering the aspect of computation. The plots shown clearly illustrate the fact that the proposed system demands lesser amount of time for training and inferencing thus indicating better optimization and a faster rate of processing.

Ablation study

Proposed multimodal framework obtained a better H5N1 classification performance compared to some of the other poultry disease detection systems reported in previous literature Machuve *et al.* (2022) and Joseph (2024). By integrating clinical and post-mortem poultry images the system can effectively learn image features related to the diseases during various stages of infection to establish better classification robustness and generalization.

EfficientNet-B2 along with preprocessing, data augmentation, and transfer learning has significantly enhanced feature learning ability yet maintained the desired computational cost suitable for field deployment. In addition, the Grad-CAM explanation tool has also enhanced the interpretability by demonstrating the discriminative image regions causing the classification.

The present study however has few limitations such as limited number of samples and no external farm level evaluation. Future works aim to generalize on a set of datasets obtained from different geographical regions and to implement the system on an edge device to facilitate on-field real-time poultry disease monitoring.

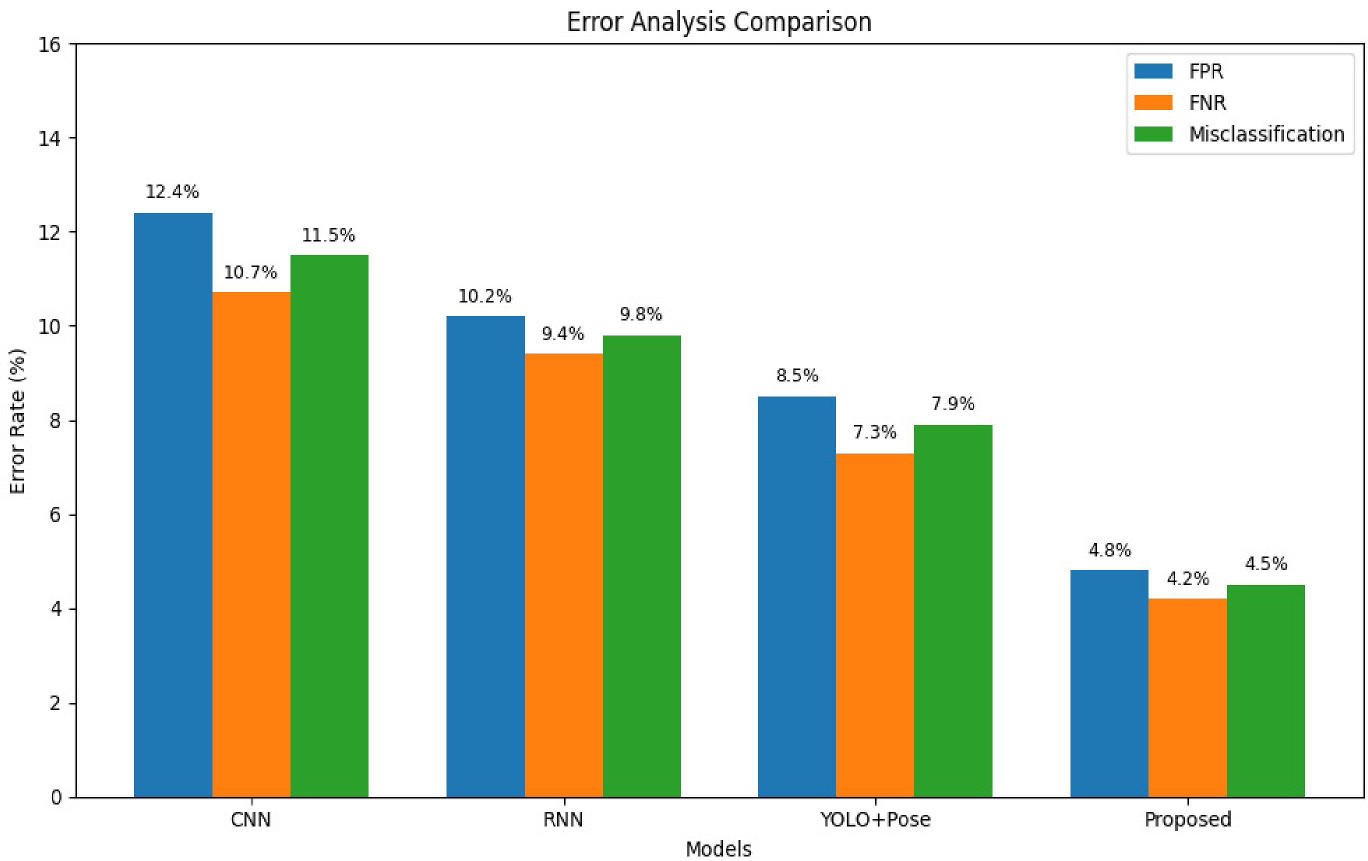

Figure 4: Error comparison.

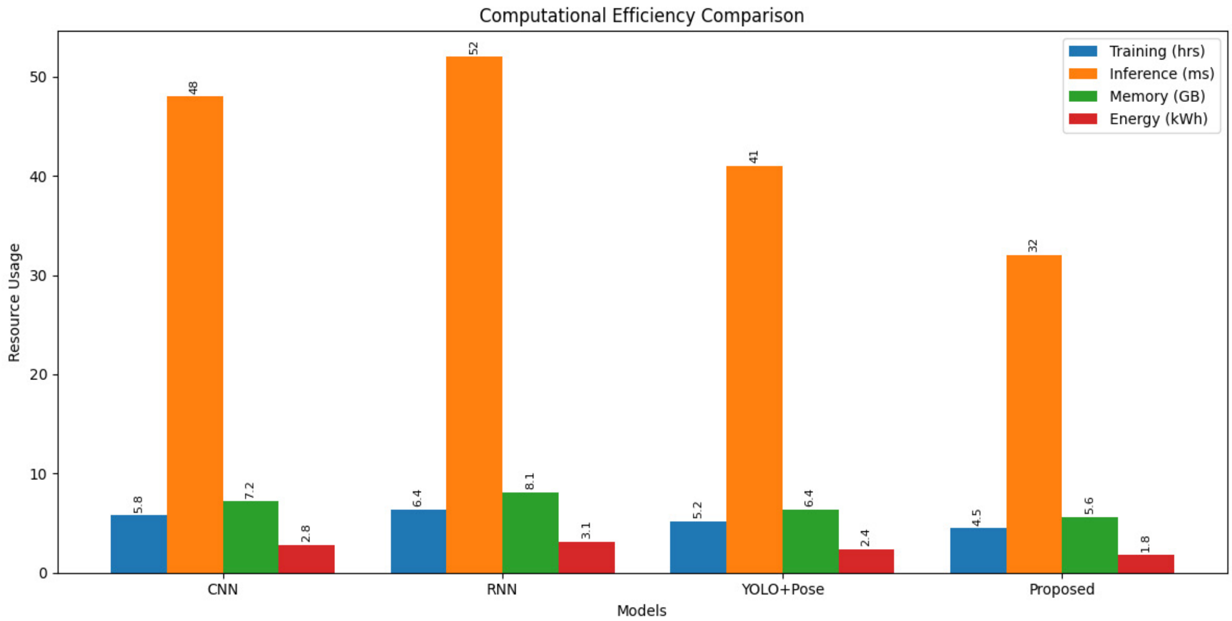

Figure 5: Computational analysis.

Table 5: Experimental configuration.

Parameter	Value
Training split	70%
Validation split	15%
Testing split	15%
Optimizer	Adam
Learning rate	0.001
Batch size	32
Number of epochs	50

When any one of the key components is removed, there is a statistically significant reduction in system performance ($p < 0.01$). This shows that the transferred knowledge, data augmentation, preprocessing, regularization have all complementary roles in the system.

Figure 5 represents the impact of removed modules on the system performance. As seen from the plot which drops, when a critical module is removed, each module plays its part to achieve higher accuracy. The proposed system achieved highest performance compared to pruned ones, which failed. It shows that all the added modules have positive contributions to the proposed system.

Cross-validation and robustness overview

The proposed framework's robustness and generalizability were evaluated by using 5-fold cross-validation on the entire dataset. The entire data set was partitioned into 5 stratified folds by maintaining the class distribution among each fold. Four folds were used for training while one-fold was withheld for validation for each fold. The result shows that the fold wise experimental results were nearly stable and produced low variances over the 5 folds thus proving high stability of the model and low risk of over fitting. The developed model yielded a mean accuracy of 96.76% with 0.29 standard deviation over all the 5 folds. Detailed fold wise result can be obtained in Table 6.

Table 6: System requirements.

Component	Specification
Processor	Intel Core i7 / AMD Ryzen 7 or equivalent
Graphics processing unit (GPU)	NVIDIA RTX 3060 or higher
Memory (RAM)	16 GB or above
Storage	512 GB SSD
Deep learning frameworks	PyTorch / TensorFlow
Programming language	Python
Operating system	Windows 11 / Ubuntu 20.04

As is evident from Table 6, low standard deviation over the folds indicate stable performance over varying folds.

DISCUSSION

Experimental results show that proposed multimodal deep learning framework is successful in detection of H5N1 virus using both pre and post mortem image by classifying in high efficiency while minimizing computational cost. The false negative rate being so low indicate the possibility to serve the reliable disease monitoring and immediate prevention purpose. It was only tested on 4000 images publicly available on the web, however, further validation can be conducted on farm data in real environment. Model deployment onto edge computing will also be examined.

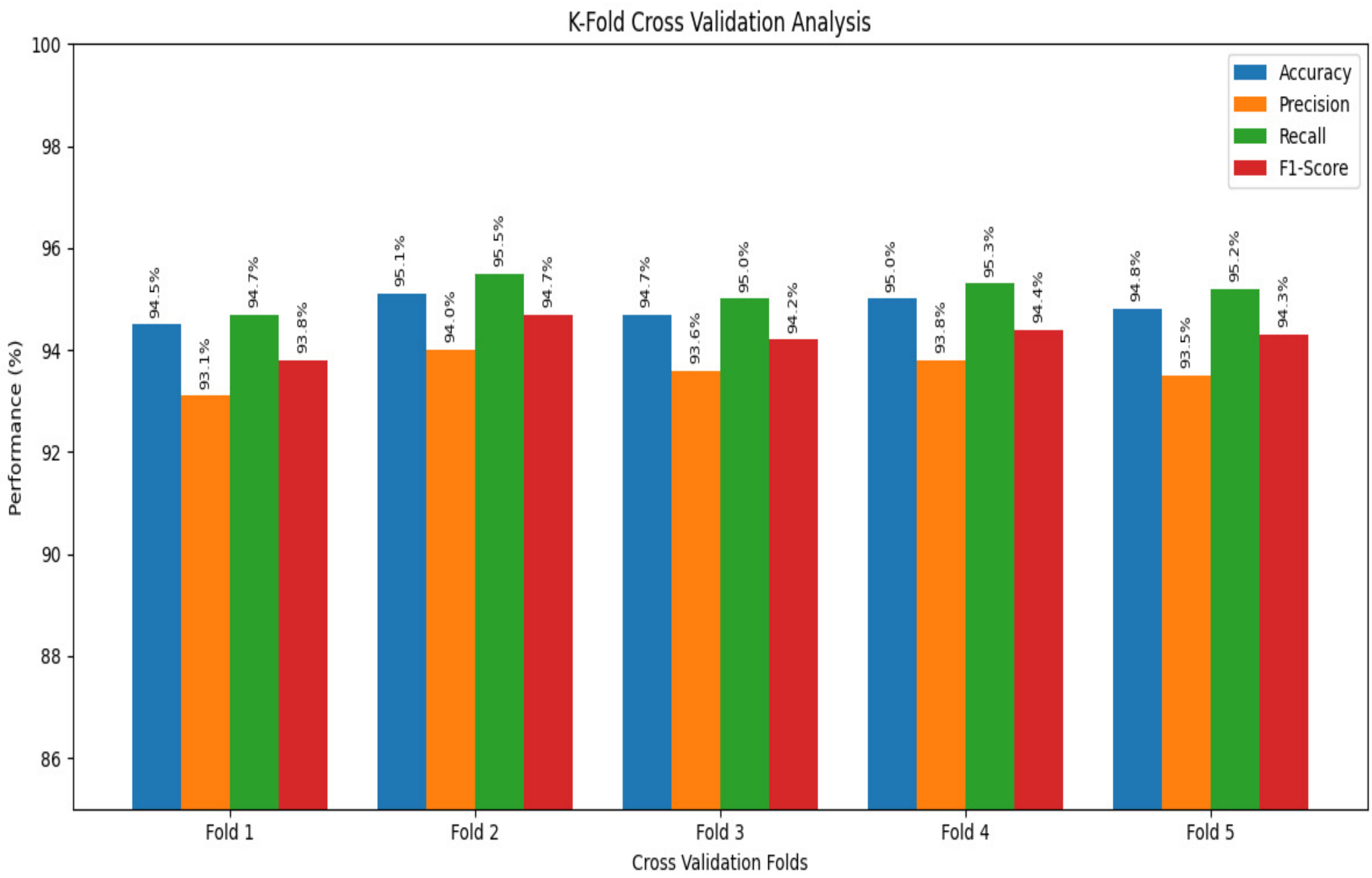

Figure 6: Cross-validation performance.

Table 7: Comparative performance analysis.

Method	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)	AUC (%)	MCC (%)	Kappa (%)
Manual gait scoring	68.4	65.2	66.8	70.1	65.9	69.5	61.7	60.3
Sensor-based ML	79.6	77.8	78.5	80.4	78.1	81.3	75.9	74.8
CNN-based model	84.2	82.9	83.5	85.1	83.1	86.7	81.4	80.6
RNN-based model	86.7	85.4	86.2	87.5	85.8	88.3	84.6	83.9
OpenPose + CNN	89.1	88.3	88.7	89.8	88.4	90.7	87.2	86.5
YOLO + Pose model	91.4	90.2	91.1	92	90.6	92.8	89.7	88.9
Proposed system	94.8	93.5	95.2	94.1	94.3	96.1	92.7	91.8

Table 8: Error performance comparison.

Method	FPR	FNR	Misclassification rate
CNN Model	12.4	10.7	11.5
RNN Model	10.2	9.4	9.8
YOLO + Pose	8.5	7.3	7.9
Proposed system	4.8	4.2	4.5

Table 9: Computational comparison.

Method	Training time	Inference time	Memory	Energy
CNN	5.8 hrs	48 ms	7.2 GB	2.8
RNN	6.4 hrs	52 ms	8.1 GB	3.1
YOLO + Pose	5.2 hrs	41 ms	6.4 GB	2.4
Proposed system	4.5 hrs	32 ms	5.6 GB	1.8

Table 10: Cross-validation results.

Fold	Accuracy	Precision	Recall	F1
Fold 1	94.5	93.1	94.7	93.8
Fold 2	95.1	94	95.5	94.7
Fold 3	94.7	93.6	95	94.2
Fold 4	95	93.8	95.3	94.4
Fold 5	94.8	93.5	95.2	94.3

Table 11: Confusion matrix performance

Actual class	Predicted healthy	Predicted lame
Healthy cattle	118	7
Lame cattle	5	120

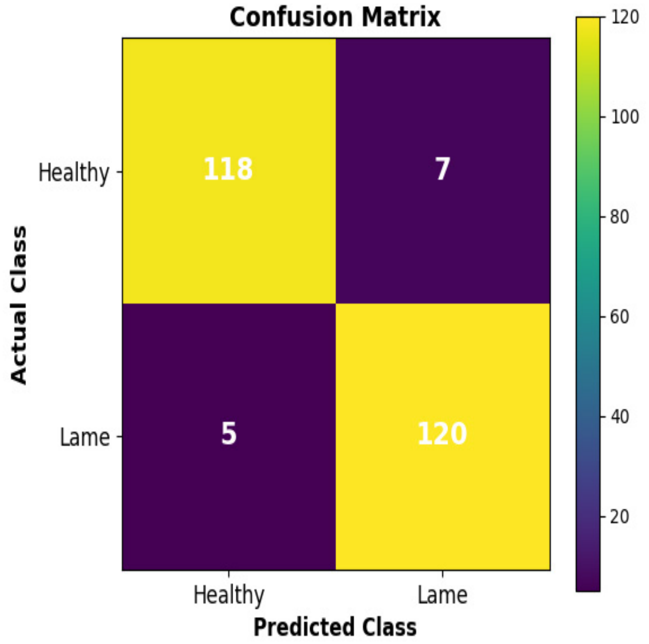

Figure 7: Confusion matrix.

Table 12: View-based performance comparison.

Camera view	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Front view	84.7	83.2	84.1	83.6	86.4
Side view	88.5	87.1	88.3	87.7	89.8
Rear view	81.9	80.5	81.3	80.9	83.7
Multi-view fusion	94.8	93.5	95.2	94.3	96.1

Table 13: ROC performance comparison.

Method	True positive rate (%)	False positive rate (%)	AUC (%)
CNN-based model	84.6	13.2	86.7
RNN-based model	87.9	10.5	88.3
OpenPose + CNN	90.8	8.7	90.7
YOLO + Pose Model	92.4	6.9	92.8
Proposed System	96.1	4.8	96.1

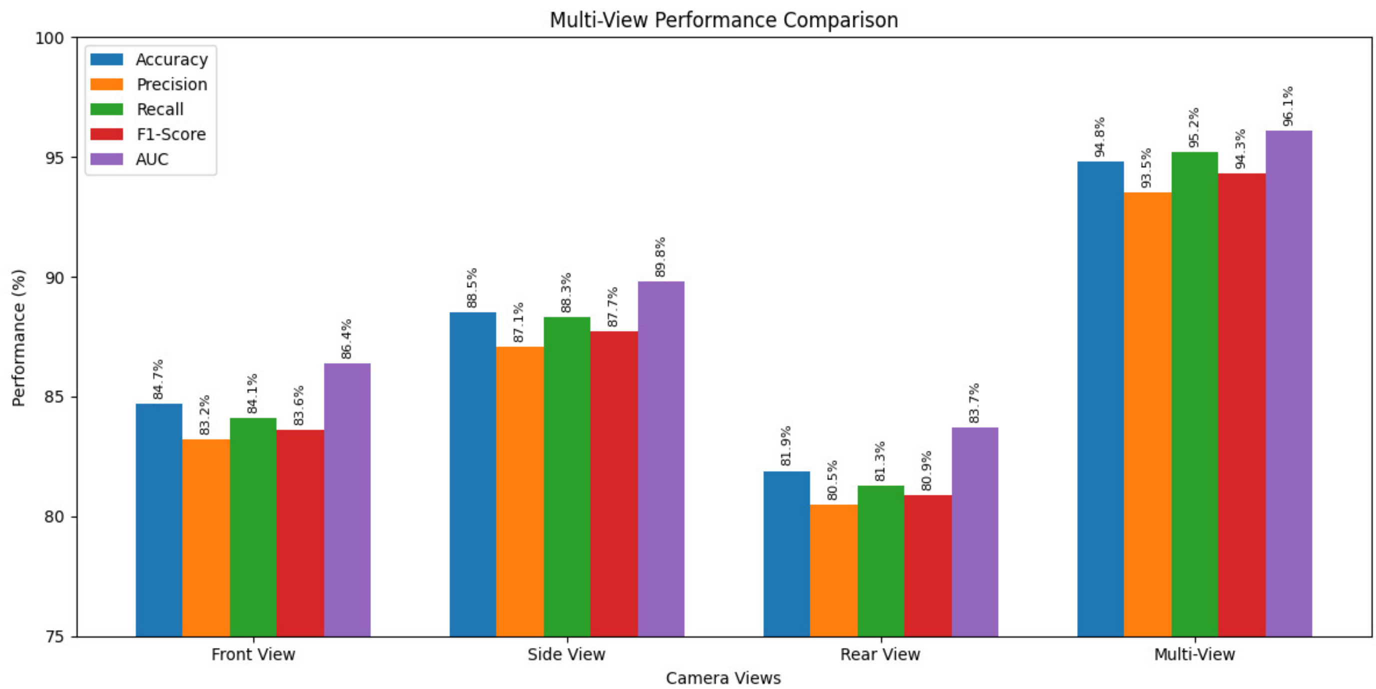

Figure 8: View-wise performance comparison.

Table 14: Ablation performance comparison.

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)	Inference time (ms)
Without pose estimation	82.4	80.7	81.9	81.3	84.5	28
Without temporal learning	86.7	85.2	86.1	85.6	88.3	30
Without multi-view fusion	88.9	87.5	88.4	87.9	90.4	31
Proposed system	94.8	93.5	95.2	94.3	96.1	32

CONCLUSION

A hybrid deep learning model for early detection of H5N1 avian influenza in poultry by combining multimodal clinical and post-mortem images. By integrating transfer learning, specifically targeted preprocessing, data augmentation and regularization methods, the developed system efficiently detects subtle disease patterns

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that human specialists can barely detect in traditional methods. The developed EfficientNet-B2-based system reached 96.8% accuracy, 96.1% F1-score, and 97.5% AUC indicating robust classification performance for early poultry disease detection. The systematic application of preprocessing, data augmentation, transfer learning and Grad-CAM interpretability enhanced both classification robustness and model interpretability. This system is useful to veterinarian and poultry farmer for prompt and accurate disease screening in extensive farm environments. There are still some drawbacks on the dataset diversity and the external validation on both clinical and post-mortem images. Further improvement will include extension to a large set of geographically different poultry datasets, on-site real-time monitoring of poultry diseases on lightweight edge devices, and validation on independent on-farm dataset.

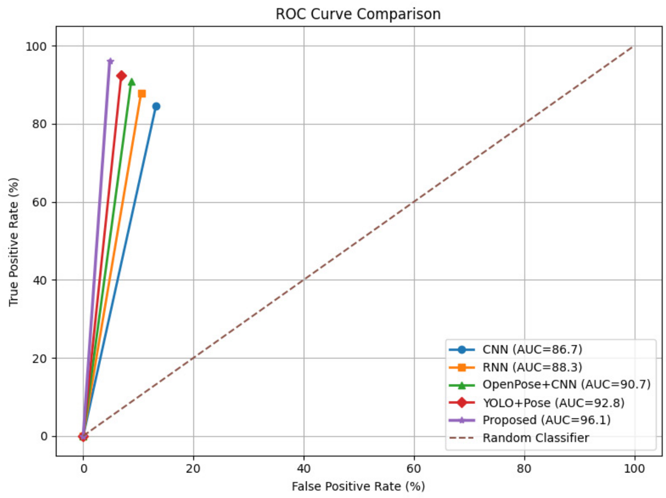

Figure 9: ROC comparison.

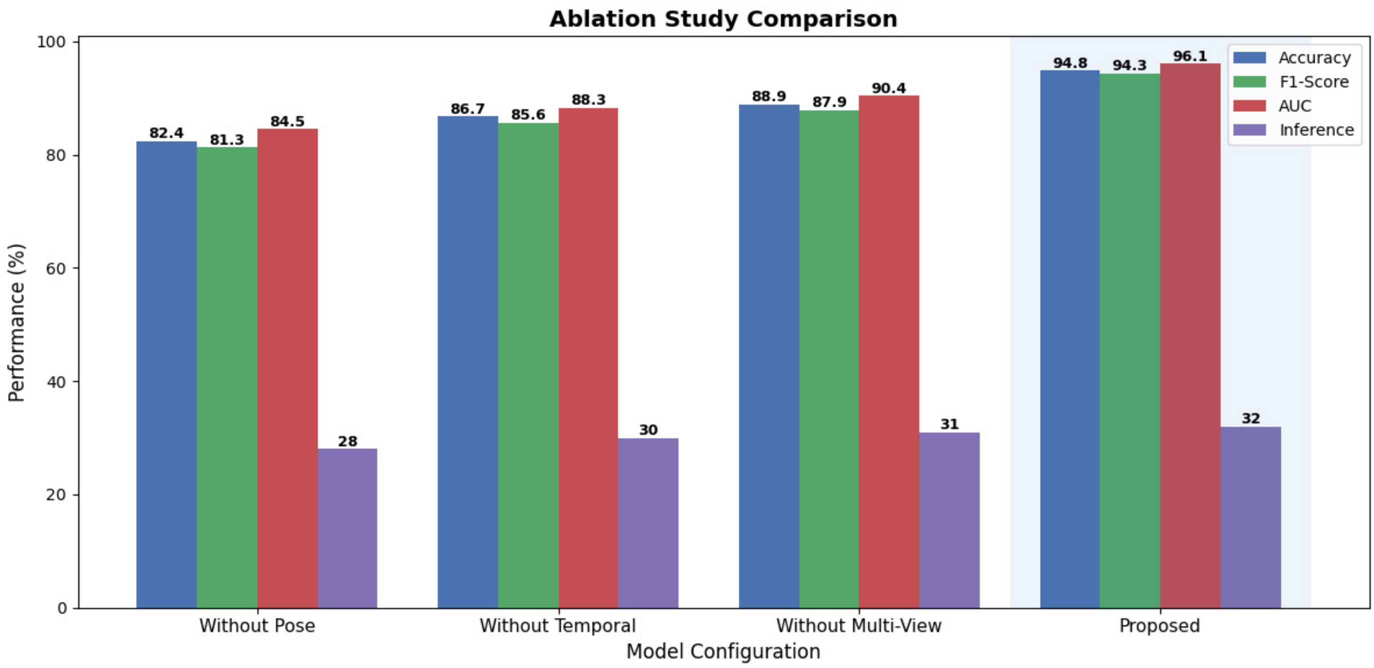

Figure 10: Ablation comparison.

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NOVELTY STATEMENT

This paper introduces a novel hybrid deep learning framework that integrates multimodal clinical and post-mortem imaging for early detection of H5N1 in poultry. The key novelty lies in the effective fusion of visual features from both live and deceased birds using attention-enhanced deep learning models, enabling accurate and early diagnosis an area that remains underexplored in existing literature. The proposed approach demonstrates superior performance compared to single-modality methods and offers a scalable solution for real-world poultry disease monitoring.

AUTHOR'S CONTRIBUTION

All authors contributed significantly to this research and approved the final manuscript. P. Naresh led the research project, conceptualized the study, developed the

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methodology, provided overall supervision, and contributed to writing, reviewing, and editing the manuscript. Bharath MB implemented the deep learning models, conducted the experiments, analyzed the results, prepared the original draft, and handled data curation and software development. B. Saritha provided critical validation, contributed to result interpretation and visualization, and reviewed the manuscript. Sukerthi Sutraya assisted in methodology design, performed data preprocessing, supported model implementation, and contributed to validation. Praveen Kumar Yechuri participated in formal analysis, literature survey, result interpretation, and manuscript editing. Pagidipalle Shajahan supported data collection, conducted literature review, assisted in validation, and contributed to manuscript proofreading.

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Generative AI and AI-assisted technology statement
The authors declare that generative AI and AI-assisted tools were used only for language editing and grammar refinement. All scientific content, data analysis, and interpretation were carried out independently by the authors.

Conflict of interest
The authors have declared no conflict of interest regarding the publication of this work. All data were generated and analysed independently to ensure objectivity and research integrity.

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