

A Survey on Modular Poultry Health and Disease Detection

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Abstract- Poultry farming is a vital part of agriculture, but diseases can spread quickly and cause serious losses when they are not detected early. Many small and medium-sized farms still depend on manual observation and occasional veterinary visits, which can be slow and difficult to access. This survey reviews 24 studies on AI-based poultry health monitoring, including systems that use chicken sounds, disease images, thermal cameras, IoT sensors, and fecal images. Although these methods show promise, many focus on only one type of data, detect limited diseases, or depend on costly equipment. To address these gaps, this paper presents PoultryAI, a modular system with an audio module that uses MFCC features and a Random Forest classifier to identify Healthy, Unhealthy, or Noise recordings, and an image module that uses fine-tuned MobileNetV2 to classify Healthy, Fowlpox, Coryza, Favus, or Avian Influenza images. Both modules are integrated into a Flask-based web application, allowing farmers to upload audio, video, or images and receive clear results with practical guidance.

Keywords: poultry disease detection, audio classification, image classification, MFCC, Random Forest, MobileNetV2, deep learning, machine learning, smart farming.

I. INTRODUCTION

Poultry farming provides a large share of the world's meat and eggs. But as farms grow bigger, it becomes harder for farmers to watch every bird closely. A disease can spread through a flock in just a few days. By the time the farmer notices that something is wrong, many birds may already be sick or dead. Growth slows down, egg production drops, and the farmer loses money.

At present, most farmers rely on their own experience or wait for a veterinary expert to visit. In many places, especially on small and mid-sized farms, expert help is not available often enough. This creates a need for

simple, affordable tools that can help farmers detect health problems earlier.

Artificial intelligence offers a way to automate parts of this process. Sick or stressed birds often change the way they vocalize before clear physical symptoms appear. This means that audio recordings can give early warnings about flock health. At the same time, many poultry diseases cause visible changes around the eye, comb, or facial area. Photographs of these regions can be analyzed by computer-vision models to identify specific diseases.

The project reviewed in this paper, PoultryAI, uses both of these ideas but keeps them as separate modules. The audio-based Health Detection module accepts an audio clip or a video. If a video is uploaded, the audio track is extracted automatically. MFCC features are then calculated and given to a Random Forest classifier, which predicts one of three categories: Healthy, Unhealthy, or Noise.

The image-based Disease Detection module accepts a photograph of a chicken, especially an image showing the eye or comb. The image is resized and preprocessed before being classified by a fine-tuned MobileNetV2 model. The model predicts one of five classes: Healthy, Fowlpox, Coryza, Favus, or Avian Influenza. The result is shown with a confidence score and some guidance for the farmer.

The main contribution of this project is not only the use of machine-learning algorithms. Its real importance lies in combining two complementary diagnostic pathways in one lightweight and accessible system. Audio analysis can give an early indication of abnormal flock health, while image analysis can provide more specific information about visible disease symptoms. The independent design also

allows either module to be retrained or improved without changing the other module.

This survey paper has four main goals:

1. Explain in simple language how each selected previous work was carried out.
2. Identify the common challenges and limitations that appear across the literature.
3. Show how the proposed project compares with and improves upon existing approaches.
4. Suggest practical directions for future research and development.

The rest of the paper is organized as follows. Section 2 describes how the reference papers were chosen. Section 3 summarizes each previous work and explains the methodology in a human-friendly way. Section 4 discusses the recurring challenges and limitations. Section 5 explains how the project tries to address these issues. Section 6 outlines possible future work. Section 7 provides the references. Together, these sections provide a clear and structured overview of the survey.

II. LITERATURE REVIEW

This section explains how each previous work was carried out, including the data used, the method, and the main result.

A. Audio-Based Poultry Health Monitoring

Mao et al. [1] developed a lightweight CNN called light-VGG11 to distinguish chicken distress calls from normal barn sounds. They used log-mel spectrograms as input and trained the model on farm recordings. The model achieved approximately 95% accuracy while using fewer parameters than the full VGG11 architecture. Data augmentation improved robustness on real farm audio. However, the model was trained on data from one farm, which may limit generalization to other environments.

E. Hassan et al. [2] introduced a CNN with a custom Burn Layer that injects noise during training to improve robustness in noisy conditions. They tested their model on the Mendeley Poultry Vocalization Signal Dataset, which is also used in the project. The Burn Layer improved classification robustness, but the added

complexity increased training time compared with a standard CNN.

H. M. Rohini and Prabhavathi [3] extracted MFCC features from poultry audio recordings and trained a CNN to distinguish healthy from unhealthy sounds. Their model reached 94.59% accuracy, confirming MFCC as an effective feature representation. The main limitation was a small dataset of 346 clips, which reduces confidence in generalization.

A. Mahdavian et al. [4] compared wavelet entropy and MFCC-based acoustic features for detecting Infectious Bronchitis and Newcastle disease in broilers. Both feature types could distinguish healthy birds from infected birds within a few days of infection. This supports early, non-invasive detection. However, the study focused only on two diseases rather than broader health categories.

V. Manikandan and S. Neethirajan [5] combined MFCC features with classifiers such as Random Forest and Histogram Gradient Boosting to interpret chicken vocalizations across several welfare-related datasets. Their feature-importance analysis showed that specific MFCC frequency bands correlate with welfare outcomes. The work is mainly analytical and does not provide a complete end-to-end deployed system.

V. Manikandan and S. Neethirajan [6] conducted a systematic review of AI-driven bioacoustics research in poultry farming. The review covered health, behaviour, and welfare monitoring using audio. It highlighted how much information about flock condition can be recovered from sound when appropriate features are used. As a review paper, it does not present a new model or dataset.

X. Du, L. Carpentier. [7] used SVM-based sound classification to assess the thermal comfort of laying hens. Their study showed that vocal patterns change measurably under thermal stress, even before other visible signs appear. The method is non-invasive but targets thermal comfort rather than direct disease detection.

P. Soster de Carvalho et al. [8] benchmarked several machine-learning approaches, including MFCC with Random Forest, for automated broiler vocalization monitoring. Their results varied across different broiler house environments, highlighting the importance of testing across diverse farm conditions.

R. Srinivasagan et al. [9] explored running vocalization analysis on low-power TinyML edge devices for real-time poultry welfare monitoring. They showed that meaningful health classification is possible on resource-constrained hardware. However, smaller TinyML models may trade off some accuracy.

L. Carpentier et al. [10] developed a sound-based monitoring tool that automatically detects sneezing and other abnormal respiratory sounds in poultry. The system enabled continuous, automated tracking of respiratory health from farm audio. Its scope is limited to sneeze detection rather than general health classification.

B. Image-Based Poultry Disease Detection

D. Machuve et al. [11] fine-tuned several pretrained CNN architectures, including MobileNetV2, on poultry disease images. They found that freezing batch-normalization layers during fine-tuning pushed MobileNetV2 accuracy above 98%. This directly informed the project's choice of MobileNetV2. However, mixing farm and lab images may introduce label inconsistency.

Zhuang and Zhang [12] proposed a feature-fusion detection model (IFSSD) to automatically locate broilers in images and determine their health status. Their model reached 99.7% mean average precision, showing that automated visual inspection can replace manual flock checks. The method distinguishes sick from healthy birds but does not classify specific diseases.

Y. Luo et al. [13] systematically compared nine pretrained CNN backbones, including MobileNetV2, combined with classical classifiers such as SVM and k-NN for poultry disease image classification. Their comparison helped confirm MobileNetV2 as a strong and efficient choice. The study is primarily a comparison and does not propose a new architecture.

W. M. Elmessery et al. [14] combined visual and thermal imagery with a YOLOv8-based detector to identify pathological signs in broilers under inconsistent farm lighting. Thermal and visual imagery together improved detection reliability. However, thermal cameras increase hardware cost and may not be suitable for small farms.

Al Momen Pranta [15] paired a MobileNetV2 feature extractor with an SVM classifier, reaching 96.17% accuracy on a poultry disease dataset. The model was deployed as a farmer-facing web application. This deployment goal closely mirrors the project. The system is limited to three classes, which is narrower than the five classes in the project.

M. A. T. Soli et al. [16] proposed a modified Hierarchical Vision Transformer model for poultry disease detection. Their approach showed accuracy competitive with, and in some cases better than, standard CNN baselines. However, transformers are more computationally demanding than lightweight CNNs for web deployment.

P. Kaviya et al [17] built a smartphone-based deep learning framework to detect and classify poultry diseases from fecal images. Their work demonstrated that accessible, farmer-facing disease detection is feasible on ordinary smartphones. Fecal images, however, are less consistent to capture than eye or comb photos.

A. K. M. S. Islam et al. [18] proposed a lightweight poultry disease detection model that optimizes multi-colour-space features to reduce computational cost while keeping accuracy high. Their approach is well suited to resource-constrained settings. The multi-colour-space features add preprocessing complexity.

A. S. R. Sabbella et al. [19] developed a YOLOv8-based model for automated poultry disease detection, specifically targeting Fowl Pox and Infectious Coryza, two of the diseases covered in the project. Their model enabled real-time detection and health monitoring. YOLO detection requires more computation than a lightweight classification model.

H. Mbelwa and J. Mbelwa [20] proposed a deep convolutional neural network to classify chicken feces into multiple disease categories. Their early work demonstrated that CNNs could reliably distinguish between several poultry diseases. The architecture is older and heavier compared with modern lightweight transfer-learning models.

C. IoT-Based Poultry Disease Detection

J. Astill et al. [21] reviewed the role of smart sensors, big data, and the Internet of Things in modern poultry management. Their review outlined how these

technologies support continuous monitoring across large-scale farms. It is a general overview without a specific detection model or experimental results.

R. O. Ojo et al. [22] conducted a systematic literature review of IoT and machine-learning techniques used in poultry health and welfare management. They noted that many existing systems require costly hardware, limiting adoption on smaller farms.

V. Goyal et al. [23] reviewed the combined role of IoT, computer vision, and sound analysis in smart poultry farms. Their survey highlighted how these approaches complement each other rather than functioning as separate solutions. The paper is a synthesis without experimental validation of one integrated approach.

G. L. Menezes et al. [24] presented a narrative review connecting computer vision systems and large language models to broader animal-farming applications. Their review placed poultry-specific AI work within the wider context of livestock technology but covers livestock broadly rather than focusing on poultry-specific challenges.

III. COMMON CHALLENGES AND LIMITATIONS

When we look at all these studies together, several recurring challenges and limitations become clear.

1. Most systems use only one type of data. Many studies focus only on audio or only on images. Audio-only systems cannot tell which specific disease is present, while image-only systems may miss early behavioural or vocal changes.
2. Many systems cover only a few diseases. Several works classify only sick-versus-healthy conditions or focus on one or two diseases. This limits their practical diagnostic value for farmers who may face multiple diseases.
3. Datasets are often small or narrow. Some studies use small datasets or data from a single farm. This can reduce confidence that the model will work well on other farms with different conditions.
4. Performance can depend on the environment. Audio classification performance can vary across different broiler houses and noise conditions. Image-based methods can be affected by lighting, camera angle, and image quality.

5. Some approaches need expensive hardware. Methods that use thermal cameras, IoT sensors, or high-performance computing resources may not be affordable for small and medium-sized farms.

6. Many studies do not provide a simple application for farmers. Several papers present models and experimental results but do not offer a farmer-facing tool that is easy to use in daily practice.

7. Some models are too heavy for low-cost deployment. Transformer-based models and object-detection architectures such as YOLO can be computationally demanding for low-cost web or mobile deployment.

8. Outputs are often just labels without explanation. Several systems provide a class label without clear explanations or actionable guidance for farmers.

9. Some tools have a very narrow scope. Some systems detect only specific events, such as sneezing or thermal stress, rather than supporting broader health and disease monitoring.

10. Datasets can be imbalanced. In image-based studies, some disease classes have far fewer samples, which can reduce performance on those classes.

IV. PROPOSED SOLUTIONS: THE POULTRYAI FRAMEWORK

The PoultryAI project is designed with many of these challenges in mind. Below is a plain-language explanation of how it tries to address the limitations found in the literature.

1. **Two Complementary Modules in One System**The system combines audio-based health screening and image-based disease classification in one platform. The audio module can give an early indication that something may be wrong with the flock. The image module can then provide more specific information about visible disease symptoms. The modules are independent, so either can be improved or extended without affecting the other. This is different from single-modality systems and from tightly coupled multimodal pipelines.
2. **Broader Coverage of Health and Diseases**The audio module classifies recordings into Healthy, Unhealthy, and Noise, supporting general health screening. The image module classifies images into five categories:

Healthy, Fowlpox, Coryza, Favus, and Avian Influenza. This is broader than studies that only distinguish sick from healthy or cover one or two diseases.

3. Practical Choices for Features and ModelsThe audio module uses MFCC features and a Random Forest classifier. This choice is supported by previous work showing that MFCC is effective for poultry audio classification and that classical models can perform well on fixed-length feature vectors. The image module uses MobileNetV2, a lightweight CNN architecture that has been shown to achieve high accuracy on poultry disease images while remaining suitable for fast web inference.

4. Ordinary Inputs and Simple DeploymentThe system accepts ordinary audio files, video files, and images. Video files are automatically processed to extract audio. No specialized sensors or thermal cameras are required. The backend is implemented using Flask, and the frontend consists of simple HTML pages that run in a browser. Farmers do not need to install a separate application. This helps bridge the gap between research models and tools that farmers can actually use.

5. Good Performance with a Lightweight DesignThe audio module achieved 95.7% accuracy on a held-out test set of 70 audio clips. The image module achieved 87% accuracy on a test set of 519 images. These results are competitive with several reviewed studies while using a lightweight architecture suitable for web deployment. The system also provides precision, recall, and F1-score metrics to give a more complete picture of performance.

6. Graceful Handling of Invalid InputsFunctional testing confirmed that the system correctly classifies representative samples from every class in both modules and displays a graceful error message for corrupted or unsupported files without crashing. This improves reliability in real-world use, where farmers may upload files of varying quality.

7. Clear and Actionable Output for FarmersThe system does not only display a class label. It also provides a confidence score, a short description of the predicted condition, and, where applicable, treatment or prevention advice. This makes the output more

useful for decision-making compared with systems that provide only a bare label.

8. Easy to Extend and MaintainBecause the audio and image pipelines are separate, either module can be retrained with new data, extended with additional classes, or replaced with a better model without modifying the other module or the shared backend. This supports future expansion and easier maintenance as new data or better models become available.

V. POSSIBLE DIRECTIONS FOR FUTURE WORK

Based on the challenges identified in the literature and the current capabilities of the project, the following directions are suggested for future work. These ideas are written in simple language to make them easy to understand.

1. Collect more and varied data. Gather additional audio and image data from multiple farms, regions, and breeds to improve generalization. Pay special attention to under-represented disease classes such as Favus and Avian Influenza.

2. Use more advanced data augmentation. Apply more sophisticated augmentation techniques, such as mixup, cutout, and style transfer for images, and time-stretching, pitch-shifting, and background-noise injection for audio, to increase training diversity.

3. Explore combining audio and image information. Investigate methods to combine audio and image information at the feature or decision level while preserving modularity. This could improve diagnostic confidence when both modalities are available.

4. Integrate low-cost IoT devices. Integrate low-cost microphones and cameras into poultry sheds for continuous monitoring. This would move from on-demand uploads to automated, real-time surveillance.

5. Build a mobile app. Develop a dedicated mobile app for Android and iOS to allow farmers to record audio, capture images, and view detection history directly from their smartphones.

6. Run models on edge devices. Explore deployment of lightweight versions of the models on edge devices or microcontrollers for on-farm inference with reduced latency and bandwidth requirements.

7. Make the system more explainable. Incorporate explainability techniques such as Grad-CAM for images and feature-importance visualization for audio to help users understand why a particular prediction was made.

8. Add more disease classes. Extend the image module to cover more diseases, such as Coccidiosis, Salmonella, and others, as more labelled data become available.

9. Consider time-based patterns in audio. For audio, investigate sequence models or temporal features to capture changes in vocal patterns over time rather than treating each clip independently.

10. Test the system on real farms. Conduct field trials with farmers to evaluate usability, trust, and practical impact. Collect feedback to refine the interface, output format, and recommended actions.

VI. CONCLUSION

This survey paper reviewed 24 studies on poultry health and disease detection using audio, image, IoT, and related techniques. The reviewed work shows that AI can support non-invasive poultry monitoring, but most existing systems address only one modality, a limited set of diseases, or specialized conditions. Many studies also lack farmer-facing deployment or require expensive hardware.

The PoultryAI project addresses several of these limitations by combining an audio-based health screening module and an image-based disease classification module in one lightweight web application. It uses ordinary smartphone inputs, maintains independent model pipelines, achieves competitive performance, and provides actionable output for farmers. The modular design also supports future extension and maintenance.

Future work should focus on larger and more diverse datasets, multimodal fusion, IoT integration, mobile and edge deployment, explainability, and field trials with farmers. These directions can further improve the practical value of AI-based poultry health monitoring and make such tools more accessible to small and medium-sized poultry farms.

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