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Smart Poultry Farm: IoT Monitoring, Automation and AI-Based Bird Health Analysis

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Abstract: *Poultry farming requires continuous monitoring of temperature, humidity, harmful gases, water availability, lighting, feed, bird activity and health. Manual inspection can make it difficult to identify abnormal conditions quickly, especially in large farms or when monitoring is required throughout the day. This literature paper reviews four recent studies on IoT-based poultry monitoring, farm automation, artificial intelligence and computer vision [1]–[4], and uses the findings to define an integrated Smart Poultry Farm system. The proposed system combines environmental sensing, automated control, AI-based bird/activity monitoring, remote alerts and a centralized dashboard. The methodology includes data collection, sensor validation, controller processing, database management, AI analysis, decision making, actuator control, notification generation and system testing. The literature shows strong results from EfficientNet-B0 (99.19% test accuracy), YOLOv5s (about 96% mAP) and edge-AI approaches (up to 98% AP50), but also identifies limitations such as limited real-world datasets, bird occlusion, changing lighting, camera dependence and separation between AI analysis and farm-control functions. The proposed system aims to provide a low-cost, modular and farmer-friendly platform that supports continuous monitoring and safer farm decisions.*

Keywords: Smart Poultry Farm; Internet of Things; Artificial Intelligence; Computer Vision; Deep Learning; ESP32; Sensors; Farm Automation; Remote Monitoring; Bird Health Monitoring.

I. INTRODUCTION

Poultry farming requires continuous attention to environmental conditions, feed, water, lighting, ventilation, safety and bird health. Temperature and humidity directly affect bird comfort, while inadequate water, poor ventilation and harmful gases can create unhealthy farm conditions. Traditional monitoring depends heavily on workers who repeatedly inspect the poultry house and identify abnormal conditions. This approach becomes difficult when the farm is large, when monitoring is required continuously, or when abnormal conditions develop between manual inspections.

Smart poultry farming attempts to address these problems by connecting sensors, controllers, cameras and software into a coordinated monitoring system. IoT devices can collect environmental and equipment information continuously. Artificial intelligence can analyse collected data and support prediction or classification. Computer vision can analyse camera images or video to detect, count and track birds and identify visible abnormalities. Automated actuators can respond to selected conditions, while dashboards and notifications can inform the farm owner remotely.

The reviewed literature represents complementary approaches. Sakib et al. [1] combine IoT automation with deep-learning-based chicken health detection. Depuru, Putsala and Mishra [2] focus on real-time detection and tracking of broiler chickens. Chigwada et al. [3] demonstrate low-cost remote poultry management using IoT. Cakic et al. [4] investigate edge-AI computer vision for detection and segmentation. These studies provide a strong basis for designing an integrated Smart Poultry Farm platform.

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II. LITERATURE SURVEY

Existing literature indicates that smart poultry farming is moving from manual observation toward connected sensing, automation and AI-supported decision making. The four studies reviewed here can be grouped into complementary directions: IoT environmental monitoring and automation [1], [3]; individual bird detection and tracking [2]; AI-based health analysis [1], [2]; and edge-AI computer vision [4]. Each study is summarised below, followed by a synthesis of what the studies together show.

A. Sakib et al. (2026) — IoT-Enabled Smart Poultry Farming with Deep Learning for Chicken Health Detection [1]

Sakib et al. developed an end-to-end smart poultry farm that integrates IoT-based automation with deep-learning-based disease detection. An ESP32 microcontroller reads a DHT22 (temperature and humidity), an MQ135 (harmful gas), an ultrasonic sensor (feed level), a water-level sensor and a flame sensor (fire). Predefined thresholds drive actuators in a closed loop: a fan and heating bulb for temperature, a servo motor for feed release, a water pump for refilling and a buzzer for gas or fire warnings. In parallel, an ESP32-CAM captures images of poultry droppings and sends them over Wi-Fi to a FastAPI backend, where an EfficientNet-B0 classifier labels each image as healthy, coccidiosis, Newcastle disease or salmonella. Results and sensor data are stored in an SQLite database and shown on a web dashboard that works on desktop and mobile.

Seven architectures (including ResNet50, MobileNetV3-Large, DenseNet121, ConvNeXt-Tiny, EfficientNet-V2-S and ViT-B/16) were benchmarked and EfficientNet-B0 (about 5.3 million parameters) was selected for its accuracy-to-complexity ratio. On a held-out test set of a public Kaggle fecal-image dataset it reached 99.19% accuracy and a macro F1-score of 0.9956. Because the Newcastle disease class was under-represented (301 training images), the authors used offline augmentation, a weighted sampler and class-weighted loss. On a separate real-world dataset of 137 images from local commercial farms (verified by a veterinary surgeon and used only for testing), accuracy fell to 95.62%, which the authors attribute to domain shift. Actuator response times were below 2 seconds (1.35–1.87 s across conditions), and the prototype hardware cost about 4,640 BDT.

Limitations noted: the real-world dataset is small (only two Newcastle disease images); the economic payback (about 2 months in the realistic scenario) comes from a literature-based scenario model rather than a long-term field trial; health detection depends on fecal images only; and the paper reports different fan-activation temperatures in different sections (30, 32 and 35 °C), which supports the point that thresholds must be configured and verified for each farm rather than assumed.

B. Depuru, Putsala and Mishra (2024) — Real-Time Detection and Tracking of Broiler Chickens [2]

Depuru et al. built a computer-vision system to detect and track individual broiler chickens for health monitoring. Following the CRISP-ML(Q) process, images of broilers aged one to four weeks were collected by web scraping, resized to 416×416 and annotated in four classes by age (1WOC to 4WOC, where WOC means “week of chicken”). Roboflow augmentation expanded the original 850 images to about 25,000. Several detectors were tried, and YOLOv5s — a small YOLOv5 variant with around 7.2 million parameters (CSPDarknet53 backbone, PANet neck, YOLO head) that also runs on a CPU — gave the best result with about 96% mAP.

The trained model was converted to ONNX, and a Centroid Tracker (computing bounding-box centroids and matching them across frames by Euclidean distance) assigns each bird a persistent ID. OpenCV is used for video handling, a Streamlit application provides a webcam-based interface on a local machine, and output is stored in a MySQL database. The authors suggest that the same pipeline could later support monitoring of temperature, weight, flock behaviour and similar indicators.

Limitations noted: centroid trackers are simple but can fail with occlusion, object deformation and camera motion; the images were web-scraped and the dataset is not publicly available (provided on request); classes are age groups, so the system supports age-based monitoring rather than direct disease diagnosis; and there is no environmental sensing or actuator control. The authors also mention high start-up cost and limited technical skills as adoption obstacles.

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C. Chigwada et al. (2022) — Remote Poultry Management Using IoT [3]

Chigwada et al. present a low-cost IoT system for small to medium-scale producers. It is built around the WiFi-enabled ESP8266 NodeMCU and monitors and regulates temperature, humidity, water level, ammonia gas and lighting. A PIR sensor provides security. The system supports light scheduling, automatic switching and remote monitoring through a web-based portal, with control of fans, water pumps and lights. The stated aim is to reduce manual effort, save time and improve poultry-farm management.

Limitations noted: as described in the available record of the paper, the system concentrates on environmental monitoring and control; it does not describe camera-based or AI-based bird-level analysis or disease detection.

D. Cakic et al. (2023) — Edge-AI Computer Vision for Smart Poultry Farms [4]

Cakic, Popovic, Krco, Nedic, Babic and Jovovic used high-performance computing (HPC) and deep learning to create prediction models for chicken object detection and instance segmentation, deployed on edge-AI devices in poultry farms. The proposed smart-camera functions include chicken counting, dead-chicken detection, weight assessment and uneven-growth detection. Experiments focused on Faster R-CNN architectures and AutoML. Reported results were AP = 85%, AP50 = 98% and AP75 = 96% for object detection, and AP = 90%, AP50 = 98% and AP75 = 96% for instance segmentation. The models were evaluated on actual poultry farms.

Limitations noted: the work is mainly an AI-vision component without environmental sensing or actuator control, and the authors identify further dataset and model improvements as future work. Its main value for this project is that processing close to the camera can reduce dependence on continuous video transmission and allow faster local analysis.

E. Synthesis of the Reviewed Studies

Together, these studies demonstrate that no single technology is sufficient for complete poultry-farm management. IoT is useful for environmental conditions and automation, while computer vision provides bird-level information. AI can analyse complex patterns, and dashboards can convert technical outputs into understandable information for farm owners. Table I summarises which capabilities each study covers; a dash means the capability is not reported in the source material used for this review.

TABLE I: CAPABILITIES COVERED BY EACH REVIEWED STUDY

Capability	Sakib et al. [1]	Depuru et al. [2]	Chigwada et al. [3]	Cakic et al. [4]
Environmental sensing	Yes (5 sensor types)	—	Yes (temp., humidity, water, ammonia, light)	—
Automatic actuator control	Yes (fan, heater, pump, servo, buzzer)	—	Yes (fans, pumps, lights)	—
Web dashboard / portal	Yes (FastAPI + web)	Streamlit interface (local)	Yes (web portal)	—
Bird detection / tracking	—	Yes (YOLOv5s + Centroid Tracker)	—	Yes (detection + segmentation)
Health-related analysis	Fecal-image disease classification	Age-group classification	—	Dead-chicken, weight, uneven growth
Edge / local processing	Cloud/server inference; ESP32-CAM captures only	Local machine deployment	—	Yes (edge AI)
Cost analysis	Yes (≈4,640 BDT)	—	“Low-cost” (stated)	—

III. COMPARATIVE LITERATURE MATRIX

Table II compares the reviewed papers by main focus, technology, important result and main limitation.

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TABLE II: COMPARATIVE SUMMARY OF THE REVIEWED PAPERS

Paper	Main Focus	Technology	Important Result	Main Limitation
Sakib et al. (2026) [1]	Farm automation + fecal-image health detection	ESP32, ESP32-CAM, IoT sensors, EfficientNet-B0, FastAPI	99.19% (public dataset); 95.62% (real-world dataset); actuator response < 2 s	Small real-world dataset (137 images); scenario-based economics
Depuru et al. (2024) [2]	Individual broiler detection and tracking	YOLOv5s, Centroid Tracker, ONNX, OpenCV, Streamlit, MySQL	≈96% mAP; 850 images augmented to ≈25,000	Occlusion/camera movement; age-based classes; no farm automation
Chigwada et al. (2022) [3]	Remote farm management	ESP8266 NodeMCU, environmental sensors, PIR, web portal	Remote monitoring with automatic control of fans, pumps and lights	No advanced AI bird analysis
Cakic et al. (2023) [4]	Edge-AI computer vision	Deep learning, Faster R-CNN, AutoML, HPC, edge AI	Detection AP50 98%; segmentation AP 90%, AP50 98%	Mainly AI vision component; wider integration needed

IV. RESEARCH GAP

The reviewed studies provide important foundations, but there remains scope for a lightweight, integrated and farmer-oriented system that connects environmental sensing, automatic control, bird-level AI analysis and remote alerts in one platform.

The major gaps identified are: (1) limited real-world and diverse datasets; (2) bird overlap and occlusion during computer-vision tracking; (3) dependence on camera position, lighting and image quality; (4) limited health or disease coverage in individual systems; (5) separation between AI analysis and physical farm-control functions; (6) network interruptions and sensor-maintenance requirements; and (7) the need to convert multiple technical outputs into simple alerts that a farm owner can understand.

Therefore, the proposed research focuses on integrating sensor monitoring, safe automatic control, AI-based bird/activity analysis, remote notifications and a centralized dashboard. The system is intended as a practical prototype rather than a claim of a completely new AI algorithm.

V. OBJECTIVES OF THE PROPOSED SYSTEM

The major objectives of the Smart Poultry Farm system are:

1) To continuously monitor temperature, humidity, harmful gases, water level, lighting and selected farm conditions.
2) To collect sensor and equipment data through a low-cost microcontroller such as ESP32 or ESP8266.
3) To automate selected farm operations such as fan, pump, heater and lighting control using predefined safe conditions.
4) To use computer vision and deep learning for bird detection, counting, activity monitoring and selected health-related observations.
5) To provide remote monitoring through a web dashboard.
6) To generate understandable alerts when abnormal environmental or bird conditions are detected.
7) To maintain historical records for trend analysis and system evaluation.
8) To provide appropriate human approval for critical actions such as medicine-related operations.
9) To develop a modular architecture that can be expanded with larger datasets, predictive analytics and edge AI.

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VI. PROPOSED METHODOLOGY

The proposed Smart Poultry Farm methodology follows a structured process for sensing farm conditions, validating information, analysing data, controlling selected devices, monitoring birds and generating alerts. The system is designed as an integrated platform containing a sensing layer, controller/communication layer, database layer, AI/computer-vision layer, decision layer, actuator layer, notification module and dashboard. The main purpose is to reduce continuous manual effort, improve visibility of farm conditions and support faster responses to abnormal situations. The system does not replace responsible human supervision; rather, it provides measurements, analysis, reminders and controlled automation.

A. System Architecture

The proposed architecture consists of Users, Sensor Layer, ESP32/ESP8266 Controller, Communication Network, Backend/Application Server, Database, AI/Computer Vision Engine, Decision Layer, Actuators, Alert and Notification Module, Dashboard and Optional External Services (Fig. 1).

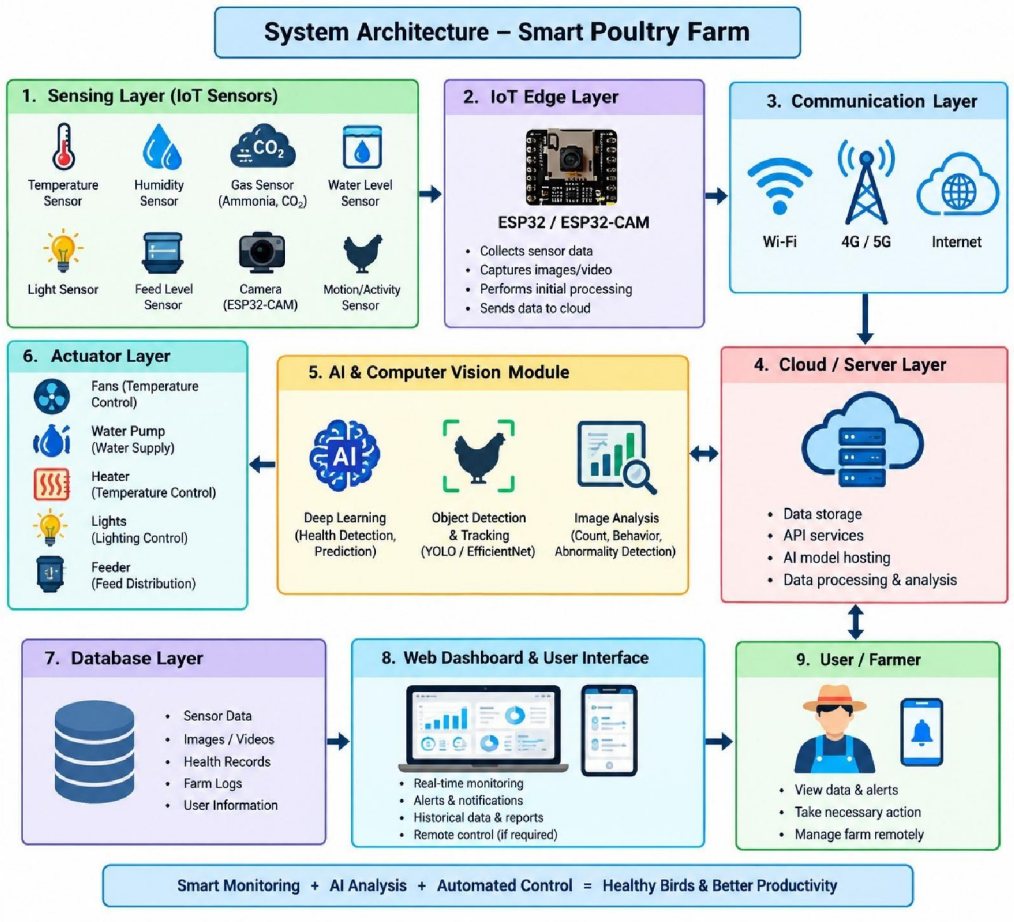


Fig. 1. Proposed system architecture of the Smart Poultry Farm

The overall workflow is: Farm Environment → Sensors/Cameras → Controller → Validation & Data Processing → Database/AI Analysis → Decision Layer → Actuator/Alert → Dashboard/Notification. The sensing layer measures temperature, humidity, gas level, water level and other selected parameters. The controller reads these values and communicates them to the processing layer. Camera images or video are passed to the AI/computer-vision component.

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The decision layer combines sensor rules and AI outputs. Safe predefined actions can activate actuators, while actions requiring human judgement can request owner approval.

B. Data Collection

The first step is collecting environmental, equipment and bird-related information. Sensor records may include timestamp, temperature, humidity, gas concentration, water level, light status, fan status, pump status and other selected parameters. Camera records may include image/video identifiers, detected bird count, activity information, bounding boxes, confidence scores and selected health observations.

The system can collect data periodically rather than continuously where appropriate to reduce communication and storage requirements. Historical data should be retained so that trends and abnormal patterns can be analysed. For AI training, representative images from different lighting conditions, bird ages, breeds, densities and camera positions are important because model performance can change across farm environments.

C. Input Validation

Before data are stored or used for decisions, the application should validate sensor and user inputs. Validation can check whether values are present, within reasonable ranges, correctly formatted and associated with a valid timestamp. Sensor failures, disconnected devices and impossible readings should be identified.

For image data, the system should verify that images are readable and that model outputs contain valid confidence values. Validation is important because incorrect sensor readings or poor-quality images can produce incorrect alerts or unnecessary actuator operations.

D. Database Management

The database can contain logical sections such as Sensor Readings, Bird Monitoring, Device Status, Alerts, User Data and Activity Logs. Sensor Readings stores timestamped temperature, humidity, gas, water-level and lighting information. Bird Monitoring stores image/video references, detected counts, activity observations and AI results. Device Status stores fan, pump, heater, light and controller states. Alerts stores alert type, time, severity, status and acknowledgement. User Data stores authentication and role information. Logs and History maintain important system activities.

Persistent storage enables historical trend analysis and supports reports about environmental conditions, device activity and bird-monitoring events.

E. Backend/Application Processing

The backend is the central processing layer. It receives sensor data, user requests and AI results, communicates with the database, prepares dashboard information and manages notifications. Major responsibilities include user authentication, sensor-data processing, validation, database communication, AI-result handling, rule-based decision making, actuator commands, alert generation, report generation and external-service integration. A suitable web framework such as FastAPI, Flask or another backend framework can be selected according to implementation requirements. The literature reviewed includes FastAPI [1] and Streamlit-based [2] deployment approaches.

F. AI and Computer Vision Engine

The AI component analyses camera images or video to provide bird-level information that cannot be obtained from environmental sensors alone. Possible functions include bird detection, counting, tracking, activity monitoring, abnormal appearance detection and selected health observations.

The reviewed literature demonstrates the use of EfficientNet-B0 for chicken health detection [1], YOLOv5 for real-time detection and tracking [2], and deep-learning/edge-AI approaches for detection and segmentation [4]. The selected

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model should depend on the available dataset, computing resources and required response time. Model performance should be evaluated using appropriate metrics rather than accuracy alone where object detection is involved.

G. Environmental Status Classification

Sensor readings can be converted into understandable status categories using configured safe ranges. For example, a reading within the acceptable range can be classified as Normal, a reading near a configured boundary can be classified as Warning, and a reading outside the safe range can be classified as Critical. The exact threshold values should be configured according to the poultry-management requirements used for the project and should not be assumed universally. This rule-based layer can operate alongside AI predictions so that the system does not depend only on one type of information.

H. Alert and Notification Module

The alert module converts abnormal sensor conditions or AI observations into user-readable notifications. Alerts may be displayed on the dashboard and, where configured, sent through email, SMS or another supported channel. Examples include: high temperature detected; humidity outside configured range; water level low; harmful gas level high; abnormal bird activity detected; camera/AI monitoring unavailable; or equipment failure detected.

The process can be represented as: Sensor/AI Analysis → Status Classification → Alert Generation → Notification → User Action. Alerts should clearly communicate the condition, time and recommended next action rather than relying only on visual colours.

I. Dashboard and Visualization

The dashboard provides a centralized view of the poultry farm. It can display current temperature, humidity, gas status, water level, lighting status, fan/pump/heater state, bird count, bird activity, recent alerts and historical trends. Charts can show temperature and humidity trends, gas-level changes, water consumption, device activity and bird-count history. A centralized dashboard reduces the need to inspect separate devices and helps the farm owner prioritize conditions requiring immediate attention.

J. Search and Filtering

The system can provide search and filtering for historical records. Users may filter data by date/time, sensor type, alert severity, device, bird-monitoring event or status. This functionality helps identify when an abnormal condition occurred and supports later evaluation of the system.

K. Reports and Analytics

Possible reports include environmental monitoring reports, alert reports, device-activity reports, water-level reports, bird-count reports, AI detection summaries and historical trend analysis. If sufficient historical data become available, advanced analytics can be added for disease-risk estimation, growth trends, resource consumption and predictive maintenance. Such advanced models should be introduced only after collecting reliable and representative data.

L. External Services Integration

The proposed architecture can integrate cloud storage, email/SMS notification services, remote dashboards, camera streams and optional edge-AI hardware. Edge processing can reduce the need to continuously transmit large video streams to a remote server. External services should be selected according to cost, network availability and privacy requirements. The core monitoring system should remain functional for essential operations even when an external service is temporarily unavailable where practical.

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M. Security and Access Control

Security is important because the system stores user information and controls physical devices. Authentication should be required for protected functions. Authorization can provide different permissions for farm owners, operators and administrators. Communication between client and server should use secure protocols where supported. Database access should be restricted. Important operations, especially actuator commands and configuration changes, should be logged. Critical operations such as medicine dispensing should use explicit human approval and appropriate safety controls.

N. Complete System Workflow

The complete workflow of the system is summarised in Table III.

TABLE III COMPLETE SYSTEM WORKFLOW

Step	Activity	Description
1	User Registration/Login	The authorized user accesses the system.
2	Sensor and Camera Collection	Sensors and cameras collect farm information.
3	Input Validation	The controller/application checks data quality and device status.
4	Data Storage	Valid records are stored in the database.
5	Environmental Analysis	Sensor readings are compared with configured conditions.
6	AI Analysis	Images/video are processed for bird detection, counting, tracking or selected health observations.
7	Decision Making	Sensor rules and AI outputs are combined where appropriate.
8	Actuator Control	Safe predefined actions activate fans, pumps, heaters or lights.
9	Alert Generation	Abnormal conditions generate notifications.
10	Dashboard Visualization	Current and historical information is displayed.
11	Human Action	The owner reviews alerts and approves actions requiring judgement.
12	Logging and Evaluation	Events are recorded for reports, maintenance and future improvement.

VII. ALERT GENERATION AND STATUS CLASSIFICATION

The alert system converts measurements and AI outputs into user-readable conditions. A normal environmental condition is marked Normal. A condition approaching a configured limit can be marked Warning. A condition outside the configured safe range can be marked Critical. Example messages are given in Table IV.

TABLE IV EXAMPLE ALERT MESSAGES

Type	Example Message
Warning	“Water level is low. Please inspect the water supply.”
Environmental alert	“Temperature is above the configured threshold. Fan control has been activated according to the predefined rule.”
AI alert	“Abnormal bird activity detected. Please inspect the poultry house.”

The threshold values and automatic actions should be configured according to the project’s selected poultry-management requirements. Critical actions should not be performed automatically unless they are explicitly designed, tested and approved for safe operation.

VIII. USER INTERFACE DESIGN

The interface should be simple and task-oriented. Proposed screens include Login/Registration, Dashboard, Live Monitoring, Add/Configure Device, Sensor Data, Bird Monitoring, Alerts, Historical Reports, Device Control and User Management. The Dashboard should summarize current environmental values, equipment state, bird count/activity and

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active alerts. The Bird Monitoring screen can display camera results and AI predictions. The Alerts screen should show the condition, timestamp, severity and acknowledgement state.

IX. SYSTEM TESTING AND EVALUATION

Testing should be performed using controlled sensor readings, simulated abnormal conditions, representative camera images and different device states. The purpose is to verify sensor communication, data validation, database storage, threshold classification, AI predictions, actuator responses, notifications and dashboard updates.

AI evaluation should use appropriate metrics such as precision, recall, F1-score and mAP where applicable, while classification tasks can additionally report accuracy. System-level evaluation should include response time, reliability, false-alert rate, hardware cost, network dependence, maintainability and performance under varied farm conditions. The literature specifically indicates that laboratory performance may not remain identical under different field conditions; for example, the EfficientNet-B0 classifier in [1] dropped from 99.19% on a public benchmark to 95.62% on real farm images.

X. EXPECTED OUTCOME

The expected outcome is a functional Smart Poultry Farm prototype that continuously monitors important farm conditions, supports selected automatic controls, analyses bird images using AI/computer vision, generates alerts and presents information through a centralized dashboard. The system is expected to reduce repetitive manual monitoring and help the farm owner identify conditions requiring attention more quickly. The contribution is primarily an integrated and practical architecture combining IoT sensing, automation, AI/computer vision and remote monitoring rather than a claim of a new AI algorithm.

XI. FUTURE SCOPE

Future versions can add larger and more diverse poultry datasets, disease-risk prediction, growth estimation, feed-consumption analytics, predictive maintenance, edge-AI deployment, mobile applications, cloud synchronization, improved bird re-identification, dead-bird detection, unwanted-animal detection and advanced resource optimization.

Computer-vision models can be retrained using field data collected from different poultry houses. The system can also be extended with additional sensors if required. Any medicine-related automation should include human approval, dosage safeguards and appropriate responsible-person supervision rather than relying solely on an AI prediction.

XII. DISCUSSION

The reviewed literature supports the use of IoT, AI and computer vision as complementary technologies for poultry farming. IoT studies [1], [3] demonstrate the usefulness of low-cost sensors, remote monitoring and automatic control. Computer-vision studies [2], [4] demonstrate the potential for bird-level detection and tracking. Deep-learning studies [1] show that AI can support health-related analysis, while edge-AI approaches [4] provide a path toward local image processing.

A major design consideration is integration. Sensors can describe environmental conditions but cannot provide complete bird-level information. Cameras can observe birds but are affected by occlusion, lighting and camera position. AI models can identify patterns but require representative data and validation. Dashboards improve accessibility but depend on reliable data and meaningful alerts. Therefore, the proposed system assigns different tasks to suitable components and keeps human supervision for critical decisions.

XIII. CONCLUSION

This literature paper reviewed research related to IoT-based poultry monitoring, farm automation, AI-based health detection, bird detection/tracking and edge computer vision. The reviewed studies demonstrate strong potential for

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reducing manual monitoring and supporting faster farm decisions, while also identifying limitations such as limited field datasets, occlusion, camera dependence and incomplete integration.

The proposed Smart Poultry Farm system combines environmental sensing, automated control, AI/computer vision, remote alerts, database storage and dashboard visualization in one modular architecture. The most important research opportunity is not simply adding more technologies, but connecting them into a reliable workflow that works under real poultry-farm conditions. With robust sensing, representative datasets, appropriate human approval and practical evaluation, the system can provide a strong foundation for a major-project smart poultry farm prototype.

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