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IoT – INTEGRATED SMART POULTRY FARMING SYSTEM

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Abstract: This project introduces an intelligent, automated system designed for bird feeding and poultry management. Traditional poultry systems rely heavily on manual monitoring, which often results in significant food wastage and inefficient tracking of bird health. To overcome these challenges, we propose a "Smart Poultry System" that integrates automated temperature adjustment and real-time health monitoring.

The system automates feeding schedules based on specific phases of bird growth. The architecture combines Arduino-based hardware with Machine Learning (ML) synergy, utilizing a multi-sensor array for real-time data acquisition and autonomous decision-making. By leveraging these technologies, the system ensures optimal environmental conditions and precise resource management, significantly improving the efficiency of poultry farming.

Keywords: Internet of Things (IoT), Machine Learning (ML), Data Acquisition (DAQ), Real-time Monitoring, Smart Poultry Management, Automatic Feeding System.

I. INTRODUCTION

In the agricultural landscape, the combination of the Internet of Things (IoT) and ML has revolutionised. Poultry farming is a critical sector of the global food supply chain although it faces several challenges such as feed wastage, inefficient nutritional schedules, and difficulty of monitoring in real-time. Traditional manual methods are often labour-intensive and time-consuming processes. In order to overcome this limitation, there is a need to grow an automated system that is used to execute environmental patterns and to make intelligent decisions.

This method proposes an innovative solution through the development of an IoT-based Smart Feeding and Poultry Farming System and it uses synergy between Arduino hardware and machine learning algorithms. Here, the system has multiple sensors that are used to collect critical data like feed levels, room temperature, humidity, and bird health. Unlike traditional automatic feeders, which operate on fixed times. This system allows us to observe and analyse consumption patterns and environmental variables. It also predicts optimal feeding times, quantities, and required nutrients. The integration of the ML model further enhances the system utility by identifying the odd behaviour of a bird so that it can easily be able to identify the unhealthy bird. By analysing the data that is driven by the sensor, the system can predict exactly when the bird needs food or when the environment needs to be adjusted.

II. LITERATURE SURVEY

In the Internet of Things(IoT), there has been a significant rise in the use of intelligent technologies for optimising efficient nutrition and health monitoring, especially in automated poultry systems and smart bird feeders. In [1], the author discussed IoT-based advanced feeding systems to focus on automated devices that replace manual work with automated devices, and the limitation is that this system cannot able to find whether the bird has taken food or not. In(2), the author focused on the environment and health monitoring using sensors to track the ammonia levels and temperature. It is critical because poultry health is highly sensitive to air quality, and the limitation is that any lag in the network can delay life-saving ventilation adjustment.

In the research paper [3], the author discussed AI and machine learning integration, which analyses bird behaviour through camera feeds, and the limitation is that if AI is at the edge, it is difficult due to the limited power cost of IoT hardware. Remote accessibility for domestic Bird care [4] focuses on the pet bird keepers. These systems use the Blynk IoT platform to allow owners to feed their birds from anywhere in the word and the limitation is that it is highly dependent on the stability of the home Wi-Fi. In [5], Visual monitoring and activity analysis by using IoT devices and ESP32, and the limitation is High computational load for edge devices, sensitive to lighting.

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IoT sensors to track the Feed Conversion Ratio were introduced in [6], where the author utilises IoT as a key metric for poultry profitability. The limitation is that minimum measurement intervals (e.g., 40kg) are required for high accuracy. The use of Voice Assistants for poultry management was examined in [7], where the author used a NodeMCU and the IFTTT (If This Then That) protocol. Owners can trigger feeding cycles via voice commands, and the limitation is it Reliability depends on the third-party cloud stability (IFTTT, Google).

In [8], the author focuses on an all-in-one "Smart Cage" for domestic birds or small poultry batches. It integrates feeding with water quality filtering and waste processing, all monitored via the ESP32 microcontroller. A limitation is that while highly effective for bird well-being, the integration of water filters and waste motors increases the risk of mechanical clogs. Multi-Tiered Remote Monitoring was examined in [9], which proposes a robust architecture using a Raspberry Pi as a central Linux-based web server and Arduinos as edge nodes. This allows for a detailed dashboard that tracks humidity, temperature, and light levels across large-scale farms. The limitation is that using a Raspberry Pi as a 24/7 server increases electricity.

Finally,[10] proposes an IoT for Crop & Feed Protection, which explores "Smart Scarecrows." These use PIR (Passive Infrared) sensors to detect wild birds or predators. When movement is detected, the system activates mechanical flapping and buzzers to protect the feed and crops. In this, the drawback is birds eventually learn that the device is not a real threat and return to the feeding area.

III. EXISTING SYSTEM

The evolution of poultry management has transitioned from labour-intensive manual monitoring to sophisticated, cloud-integrated automation. Traditional methods rely entirely on physical inspections and analogue tools, which are prone to human error and lack the responsiveness needed to handle sudden environmental shifts. While microcontroller-based systems improve efficiency by using threshold logic to automate tasks like heating and cooling, they operate as isolated units. This lack of remote connectivity prevents long-term data logging and keeps farmers physically tethered to the site for status updates.

In contrast, IoT and cloud-integrated systems represent a modern, data-driven approach that utilises wireless sensor networks and advanced microcontrollers like the ESP32. By leveraging the MQTT protocol and cloud platforms, these systems offer real-time data visualisation and instant mobile alerts. This shift from reactive to proactive management allows for superior risk mitigation and scalability, enabling farmers to oversee operations from any location while maintaining precise control over the poultry environment.

IV. PROPOSED SYSTEM

The proposed SHIELD-A system utilizes a simulation-based framework combined with machine learning techniques to predict aerial threat behavior. The system processes pre-existing datasets to estimate parameters such as trajectory, velocity, altitude, and estimated time of arrival.

A visualization interface presents real-time information through graphs and geospatial mapping. Parameters such as signal density, altitude variation, and threat movement are displayed to enhance situational awareness. The system also includes an alert mechanism that delivers timely notifications to users for critical threats.

A. Technologies Used

Technology	Purpose
Python	Core logic and simulation
Streamlit	Dashboard Interface
Pandas &Numpy	Data Preprocessing
Plotly	Visualization
Pushbullet	Alert System
Built-in Modules	Simulation And Logging

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V. FUNCTIONAL MODULES DESCRIPTION

1.Threat Processing Unit
The system generates simulated threat scenarios with parameters such as direction, velocity, altitude, and estimated time of arrival. This enables accurate modeling of real-world conditions.
2.Data Processing Unit
Collected data is refined to extract relevant features, ensuring consistency and improving system performance.
3 Visualization Module
Graphical representations and geospatial mapping are used to display threat information clearly and effectively.
4 Risk Assessment Unit
The system evaluates threat severity and determines appropriate responses based on predefined criteria.
5 Alert System
Critical threats trigger notifications through a push-based alert mechanism, ensuring rapid communication.
6 Logging Module
All system activities are recorded for analysis, performance evaluation, and future improvements.

VI. PROPOSED SYSTEM BLOCK DIAGRAM

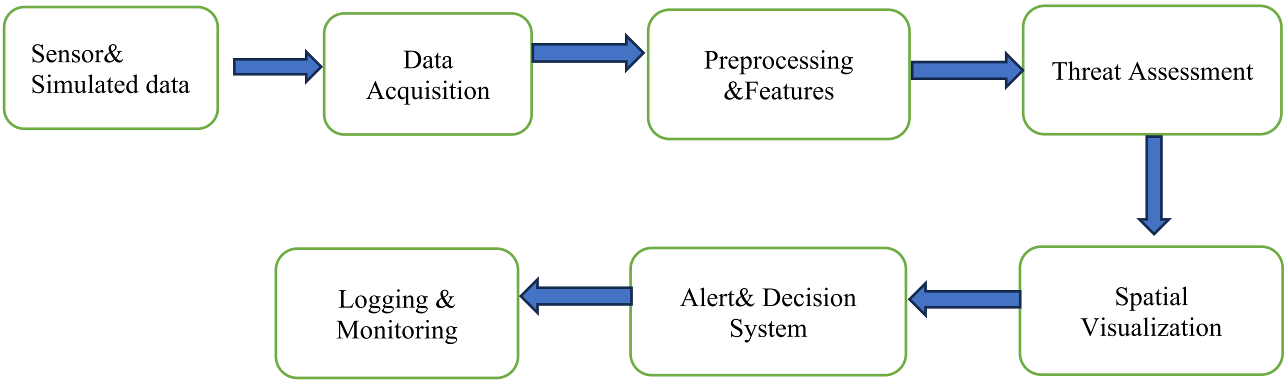

Figure 1. Proposed System Block Diagram

VII. IMPLEMENTATION DETAILS

This section explains how the system is actually built and works technically

[1]. **System Design Approach**
The SHIELD-A system is implemented using a modular design strategy that integrates simulation, machine learning, and visualization components to enable real-time threat analysis.

[2]. **Simulation Environment**
A virtual simulation model is developed to generate dynamic aerial objects. These objects continuously update their parameters, allowing the system to mimic real-time operational scenarios.

[3]. **Data Handling and Preprocessing**
Incoming simulation data is processed through preprocessing techniques such as scaling and noise removal. This step ensures that the dataset is structured and suitable for model training and evaluation.

[4]. **Machine Learning Model Implementation**
A neural network algorithm is implemented to analyze input features and categorize threats. The model is trained using simulated datasets to recognize complex patterns and improve classification accuracy.

[5]. **Priority Assignment Mechanism**
Based on model output, a ranking system is applied to assign priority levels to detected threats. This mechanism ensures that critical threats are addressed first.

[6]. **Alert Mechanism Integration**
The system incorporates a real-time alerting feature that is triggered when high-priority threats are identified. Notifications are generated instantly to facilitate rapid response.

[7]. **Data Logging and Storage**
System outputs and operational data are continuously recorded in log files. This information is used for performance tracking and system validation.

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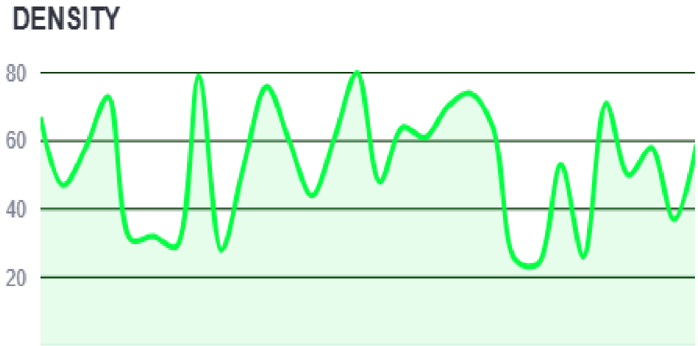
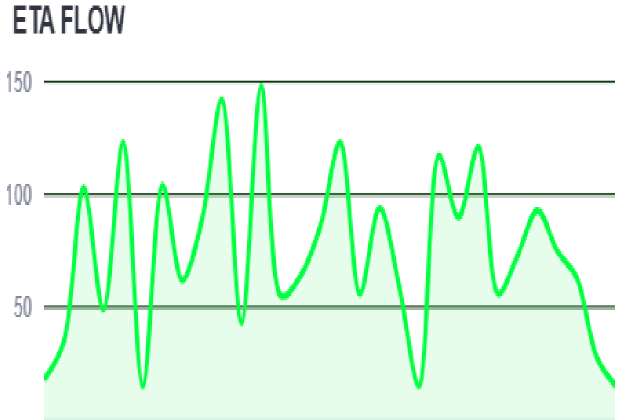
[8]. **User Interface Development**
A visualization dashboard is implemented to display real-time threat information, system status, and analytical results in an intuitive format.

VIII. EXPERIMENTAL RESULTS

The proposed system was evaluated under multiple simulated scenarios and demonstrated effective handling of dynamic threats with timely classification. It reduces latency through real-time monitoring and improves decision-making speed. The system achieves accurate threat-level identification and enhances understanding through better visualization. Additionally, it maintains stability under varying conditions while outperforming traditional methods in both accuracy and response time.





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IX. CONCLUSION

The smart poultry highlights the transformative impact of integrating IoT and Machine Learning within the poultry industry to address long-standing inefficiencies. By moving away from traditional, labour-intensive manual methods and rigid automated timers, this system provides a sophisticated, data-driven approach to livestock management. The synergy between Arduino-based hardware and ML algorithms allows for real-time monitoring of critical environmental factors such as temperature, humidity, and feed levels, while also enabling the early detection of health issues through behavioural analysis.

Ultimately, this smart poultry farming solution not only optimizes resource consumption and reduces feed wastage but also significantly improves bird welfare and productivity, paving the way for more sustainable and intelligent agricultural practices.

X. FUTURE SCOPE

In the future, this system can be expanded and improved in several key ways. Firstly, it lies in the expansion of its analytical capabilities and the scaling of its automation features to enhance large-scale poultry operations. Future iterations could incorporate advanced computer vision to monitor bird growth rates and detect physical injuries or specific diseases in real-time without human intervention. Integrating a cloud-based dashboard would allow farmers to manage multiple poultry farms remotely through a centralized mobile application, providing predictive analytics for market demand and supply chain logistics.

Additionally, the system could be optimized for sustainability by incorporating renewable energy sources, such as solar power, to run the sensors and hardware, and by implementing automated waste management systems that convert poultry droppings into organic fertilizer using specialized IoT sensors. These advancements would further transition poultry farming toward a fully autonomous, high-yield, and eco-friendly industry.

REFERENCES

[1]. M. Sakib et al., "IoT Enabled Smart Poultry Farming System With Deep Learning for Chicken Health Detection in Real-Time," Journal of Sensors, vol. 2026, no. 3, pp. 45–58, 2026.
[2]. A. K. M. S. Islam et al., "Lightweight model for poultry disease detection from faecal images using multi-colour space feature optimization and machine learning," Smart Agricultural Technology, vol. 10, no. 1, pp. 100412, 2025.
[3]. H. Miller et al., "From Sensor to Strategy: Leveraging IoT and Real-Time Data Analytics for Poultry Disease Management," IRE Journals, vol. 8, no. 9, pp. 112–125, 2025.
[4]. S. A. Dantata et al., "Poultry disease detection using machine learning: A review," Journal of Scientific Development Research, vol. 8, no. 9, pp. 29–40, 2025.
[5]. T. V. Tran, "Enhancing poultry disease classification with data augmentation and ensemble learning," Proceedings of Computational Data and Social Networks (CSoNet), vol. 14, no. 1, pp. 122–133, 2025.
[6]. E. C. Lira et al., "Automated classification of chicken diseases using dense CNN architectures," International Journal of Academic Information Systems Research, vol. 8, no. 4, pp. 9–17, 2024.
[7]. P. Sharan Kumar et al., "IoT-Based Automated Poultry Farm for Layer Chicken using Artificial Intelligence Techniques," International Conference on Computer Science and Engineering (ICITISEE), vol. 7, no. 2, pp. 210–216, 2023.
[8]. T. V. Tran, "Enhancing poultry disease classification with data augmentation and ensemble learning," Proceedings of Computational Data and Social Networks (CSoNet), vol. 14, no. 1, pp. 122–133, 2025.
[9]. V. Shwetha et al., "Latest trends and challenges in machine learning and deep learning-based computational techniques in poultry health and disease management: A review," Poultry Science Reviews, vol. 103, no. 2, pp. 400–415, 2024.
[10]. O. Adebayo et al., "Development of an IoT-based automated poultry feed and water dispensing system," Scientific African, vol. 11, no. 1, pp. e00684, 2021.
[11]. L. Zhu et al., "Machine learning in poultry science: Current status and future prospects," Poultry Science Journal, vol. 100, no. 2, pp. 100–112, 2021.
[12]. S. A. Dantata et al., "Poultry disease detection using machine learning: A review," Journal of Scientific Development Research, vol. 8, no. 9, pp. 29–40, 2025.