UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 3(5), December (2024), 1344 - 1353
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

Modelling of Machine Learning-based Poultry Farm Environmental Monitoring System with Internet of Things

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Abstract
This research presents an environmental monitoring system designed for poultry farms by integrating Internet of Things (IoT) technologies with Machine Learning (ML) algorithms. Conducted in Uyo, Nigeria, from June 2023 to April 2024, the study collected and labeled 8,412 samples of key environmental parameters—including ambient temperature, humidity, air quality, and the average age of chickens in weeks—with guidance from poultry farming experts. These data were used to train and validate three Machine Learning models: Random Forest, K-Nearest Neighbors, and Support Vector Classifier and each was evaluated for accuracy and reliability. The Random Forest model achieved the highest accuracy at 98%, outperforming the other models and indicating its robustness in environmental monitoring tasks. The study highlights the potential of IoT and ML technologies to improve farm productivity and animal welfare through proactive, data-driven management strategies. This work advances existing solutions by enhancing precision through data-driven insights, leveraging IoT to capture real-time data and ML algorithms to analyze environmental conditions with exceptional accuracy unlike traditional monitoring methods that rely solely on manual checks.

Keywords: Internet of Things, Sensors, Machine Learning, Smart Environmental Monitoring

1. Introduction

Effective monitoring of poultry farms is essential for maintaining animal welfare, enhancing productivity, and promptly addressing environmental issues that may adversely affect farm operations (Meseret, 2016; Ben et al., 2016). Recent advancements in Internet of Things (IoT) technologies have significantly transformed agricultural practices by facilitating real-time data collection and remote monitoring of critical environmental parameters such as temperature and humidity (Zhang et al., 2018; Ayaz et al., 2019; Khanna et al., 2019; Dhanaraju et al., 2022). These innovations allow for the creation of smart poultry farms, where wireless sensor networks automate operational processes, improving farm management efficiency and reducing costs. While IoT has been instrumental in enhancing agricultural practices, its integration with machine learning (ML) algorithms for comprehensive environmental monitoring in poultry farms remains underexplored.

This study addresses the need for an integrated solution by combining IoT devices for continuous data collection with ML algorithms to monitor environmental conditions in poultry farms. The proposed system focuses on key parameters such as temperature, humidity, and air quality, utilizing real-time data analysis to optimize farm management. The novelty of this research lies in its dual approach, leveraging IoT and ML to create a more effective monitoring system that not only enhances operational efficiency but also ensures better animal welfare. Additionally, while previous studies have investigated various IoT applications in agriculture (Ojo et al., 2022;

Choukidar et al., 2017; Lufyagila et al., 2022), they often operate in isolation, failing to explore the synergistic potential of integrating ML for deeper insights into environmental monitoring. This research addresses this gap by providing an integrated solution that utilizes IoT devices and ML algorithms for continuous monitoring of environmental parameters, such as temperature, humidity, and air quality. By optimizing farm management through this data-driven approach, the study aims to improve operational efficiency and reduce costs while also acknowledging challenges like data privacy concerns and the need for reliable internet access in remote areas.

The Internet of Things connects different devices to the Internet and transforms poultry farms into smart farms. It does this by monitoring critical conditions such as temperature, gas and humidity. The sensors collect data and send it to a central database (Faysal et al., 2021). IoT bridges the gap between digital and physical systems (Farooq et al., 2022). Machine learning is a form of artificial intelligence that learns from data without needing help from people. It can be used to look at pictures taken by cameras in a poultry house. This makes it easier to monitor the number of birds in these areas (Faysal et al., 2021).

The integration of the Internet of Things (IoT) in agriculture has helped to transform the sector by aiding interconnected devices to seamlessly exchange data across both wired and wireless networks (Shafik et al., 2024). This technology is important for making farming better. Tools like sensors and communication methods such as Wi-Fi, LoRaWAN, mobile networks, ZigBee, and Bluetooth are crucial for these improvements. IoT (Internet of Things) in farming doesn't just connect devices; it also helps manage information and keep track of different systems (Ali et al., 2024). These systems give farmers important, timely updates so they can make better decisions. They help use water more efficiently and cut down on labor costs. Information and Communication Technology (ICT) supports these IoT advancements in farming. IoT is improving how we monitor food quality. For instance, mobile apps that use IoT technology allow people to check how fresh their food is, helping to ensure it meets high safety standards. This technology changes how we manage food quality and safety from the farm to our plates.

IoT and machine learning are revolutionizing agriculture by offering farmers cutting-edge tools for real-time monitoring, automation and data-driven decision-making (Slimani et al., 2024). These technologies are helping to boost farm efficiency, productivity and sustainability. Farmers can track critical factors like temperature, humidity and gas levels with IoT platforms which use sensors and controllers. These systems provide continuous updates and can automatically adjust conditions to create the best environment for crops and livestock. By automating things such as irrigation, feeding and climate control, IoT reduces the need for manual labor, cuts down on costs and streamlines farm management (Lamsal et al., 2023; Ezema et al., 2019; Gbadamosi et al., 2020). Machine learning improves Internet of Things systems by predicting future occurrences based on sensor data (Nozari et al., 2024). Algorithms like Random Forest and SVC process sensor data and estimate future trends. This enables farmers to make better informed judgments when managing their crops and livestock. The models are accurate and allow farmers to avoid potential risks caused by sudden changes in the environment [(Goyal et al., 2022).

Deep learning models such as CNNs are also being used for tasks such as detecting objects, monitoring livestock behavior and spotting diseases early. For example, CNN models can process live video footage to evaluate the health of animals, enabling earlier intervention and more efficient farm management (Guo et al., 2022). By combining IoT and machine learning, agriculture is moving toward smart farming solutions that not only automate everyday tasks but also provide valuable insights to optimize farm operations. This integration of technology has the potential to manage resource usage, improve sustainability and increase farm yields (Chigwada et al., 2022; Perdanasari et al., 2023).

2.0 Material and methods

2.1 System Design and Components

The environmental monitoring system was designed using a combination of IoT devices, communication modules, and machine learning software. Figure 2.1 shows the overall flowchart illustrating the data acquisition and processing flow within the system. Figures 2.2 and 2.3 visually represent the system's architecture and alert mechanism, respectively, illustrating how data flows from sensor simulation to alert generation within the modelled environment. The key components include:

- **Sensors**: DHT22 sensors were used to measure temperature and humidity levels, while MQ135 sensors were employed to monitor air quality by detecting gas levels, such as CO_2.

- **Communication Devices**: An Arduino microcontroller serves as the central processing unit, receiving data from the sensors. A GSM module was used to transmit alerts to the user via SMS.
- **Software**: The machine learning models were developed and implemented using Python programming language, utilizing libraries such as scikit-learn and pandas within the Jupyter Notebook environment. Proteus Simulation Software was used to simulate the system before deployment.

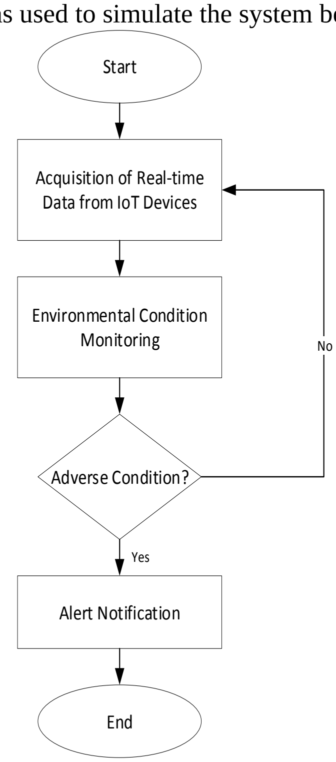

Fig. 2.1: Flowchart of the working principle of the developed system

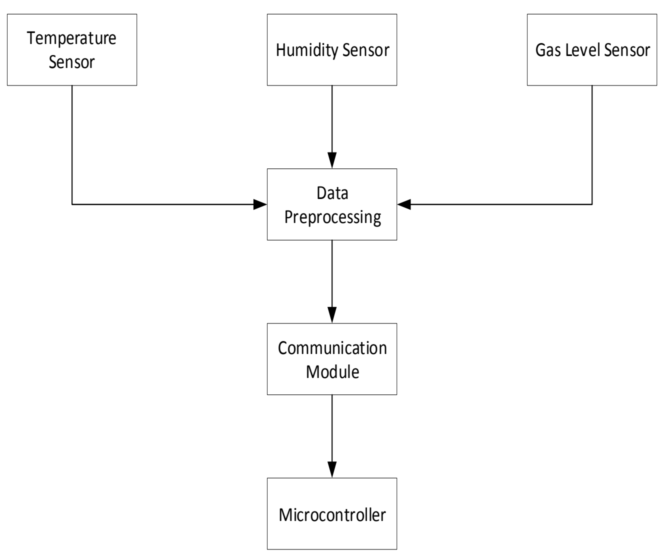

Fig. 2.2: Block diagram of IoTs architecture for poultry environmental conditions monitoring

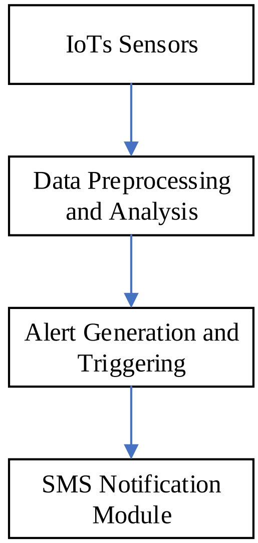

Fig. 2.3: Block diagram of the alert system for poultry condition monitoring

2.2 Data Acquisition and Processing

Data is acquired in real-time from the IoT sensors deployed within the poultry farm. The sensors were strategically placed to ensure accurate monitoring of environmental conditions. Data was collected every 15 minutes and transmitted to the Arduino microcontroller, which processed the data in real-time. Prior to analysis, the data was pre-processed to handle any missing values and normalize the inputs.

2.3 Machine Learning Model Development

Three machine learning models—Random Forest, K-Nearest Neighbours (KNN), and Support Vector Classifier (SVC)—were developed to analyze the sensor data. The dataset was divided into training (80%) and testing (20%) sets to evaluate the model's performance. Hyperparameter tuning was performed using grid search to optimize the models. The models were trained to recognize patterns that indicate normal or abnormal environmental conditions, based on historical data.

2.3.1 Random Forest Model

The Random Forest Classification algorithm has been selected to monitor environmental conditions in poultry farms due to its robustness and effectiveness in handling complex datasets. This algorithm processes training data that includes various features related to environmental parameters and corresponding target labels. It takes training data with features and target labels, test data, and a range of hyperparameters as input. The algorithm tunes hyperparameters to optimize model performance using cross-validation. It then trains a final Random Forest model on the entire training dataset. For prediction, each data point from the test set is evaluated by passing it through all decision trees in the ensemble, with the final environmental condition being determined by aggregating the predictions. This ensemble approach not only improves accuracy but also increases the model's resilience to overfitting, making it particularly suitable for the dynamic nature of environmental monitoring in poultry farming.

2.3.2 K-Nearest Neighbours

The K-Nearest Neighbors (KNN) algorithm is well-suited for monitoring environmental conditions in poultry farms due to its simplicity and effectiveness in handling the types of data typically encountered in this domain. It takes training data with features and target labels, test data, and a range of hyperparameters as input. The algorithm tunes hyperparameters to optimize model performance using cross-validation. Once trained on the complete dataset, KNN predicts environmental conditions for new test data points by identifying the k nearest neighbors within the training data and determining the majority class among them. This approach is particularly beneficial in poultry farming, where real-time decision-making based on environmental factors is critical for maintaining animal welfare and optimizing production. The ability of this model to adapt to changing conditions and its straightforward interpretability makes it a valuable choice for effective environmental monitoring.

2.3.3 Support Vector Classifier

The Support Vector Classifier (SVC) algorithm is selected for monitoring environmental conditions in poultry farms due to its effectiveness in handling complex, high-dimensional data and its robustness in classification tasks. It takes training data with features and target labels, test data, and a range of hyperparameters as input. The algorithm tunes hyperparameters to optimize model performance using cross-validation. Once optimized, the final SVC model is trained on the complete training dataset, allowing it to learn the underlying patterns. Subsequently, the model predicts the environmental condition of test data points by utilizing the coefficients of the hyperplane, classifying each point into one of the predefined environmental conditions. This ability to discern subtle variations in environmental factors makes SVC particularly suitable for the poultry domain, where precise monitoring is crucial for maintaining animal welfare and optimizing farm productivity.

2.4 Performance Metrics

The performance of the models was assessed using several key metrics: accuracy, precision, recall, F1 score and confusion matrix. Each provided distinct insights into the effectiveness of the models in monitoring environmental conditions in poultry farms. Accuracy measures the proportion of correctly classified instances out of the total, giving a straightforward indication of overall performance. Precision evaluates the model's ability to correctly identify positive instances (e.g., abnormal environmental conditions) among all predicted positives, while high precision indicates that positive predictions are likely correct. Recall (sensitivity) measures the ability of the models to identify all actual positive instances, ensuring that most abnormal conditions are detected, which is crucial for animal welfare. The F1 score, which is the harmonic mean of precision and recall, provides a balanced measure of model effectiveness, particularly in imbalanced datasets. Finally, the confusion matrix visualizes the performance of the models by outlining true positives, true negatives, false positives, and false negatives. This provides a detailed analysis of misclassification errors.

3.0 Results and Discussions

The accuracy and other performance metrics results for each model are summarized in Table 3.1, Table 3.2, Table 3.3 and Table 3.4. The Random Forest model achieved the highest accuracy at 98%, followed by SVC at 93% and KNN at 88%. These results indicate that the Random Forest model is the most effective at classifying the environmental data, likely due to its ensemble approach, which reduces variance and avoids overfitting.

Table 3.1: Accuracy Results for Environment Monitoring Models.

Models	Accuracy
Random Forest	98%
KNN	88%
SVC	93%

Table 3.2: Performance Analysis for Random Forest-Based Environment Monitoring Model

	Precision	Recall	F1-Score	Overall
Ab_T1	0.98	0.99	0.98	-
Ab_T2	0.95	0.99	0.97	-
Ab_T3	0.98	1.00	0.99	-
Ab_T4	1.00	0.96	0.98	-
Normal	0.98	1.00	0.99	-
Accuracy	-	-	-	0.98

Table 3.3: Performance Analysis for KNN-Based Environment Monitoring Model

	Precision	Recall	F1-Score	Overall
Ab_T1	0.76	0.92	0.83	-
Ab_T2	0.79	0.87	0.83	-
Ab_T3	0.99	0.92	0.91	-
Ab_T4	0.92	0.87	0.93	-
Normal	0.98	0.84	0.88	-
Accuracy	-	-	-	0.88

Table 3.4: Performance Analysis for SVC-Based Environment Monitoring Model

	Precision	Recall	F1-Score	Overall
Ab_T1	0.86	0.94	0.90	-
Ab_T2	0.87	0.90	0.88	-
Ab_T3	0.93	0.93	0.93	-
Ab_T4	1.00	0.95	0.98	-
Normal	0.93	0.89	0.91	-
Accuracy	-	-	-	0.93

In addition to accuracy, the confusion matrices for each model (Figures 3.1, 3.2, and 3.3) provide further insights into model performance. The Random Forest model's confusion matrix shows a high number of true positives and true negatives, with minimal misclassifications. In contrast, the KNN and SVC models exhibit more false positives and false negatives, which could lead to less reliable environmental monitoring in practice.

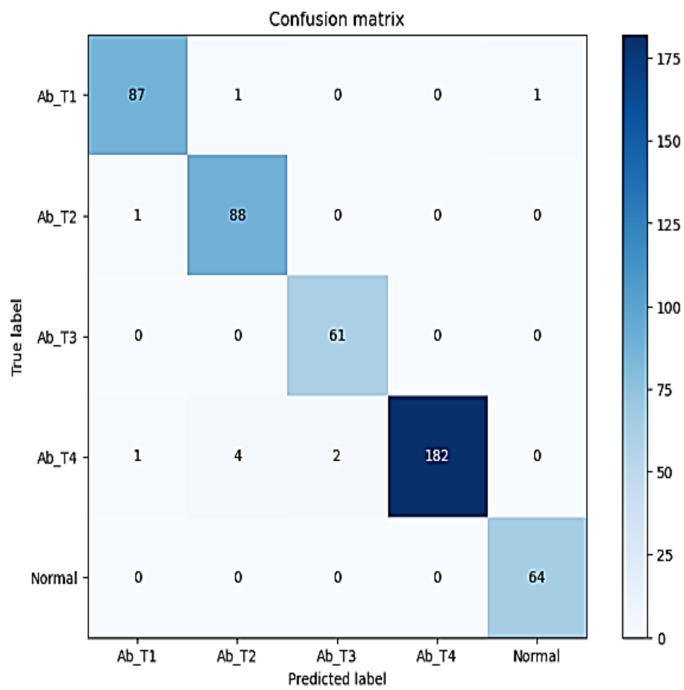

Fig. 3.1: Confusion Matrix for Random Forest-Based Environment Monitoring Model.

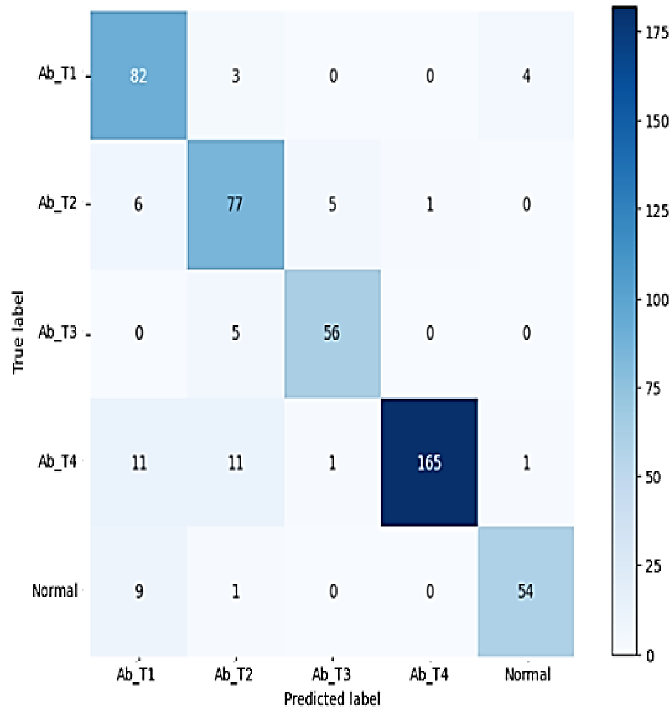

Fig. 3.2: Confusion Matrix for KNN-Based Environment Monitoring Model.

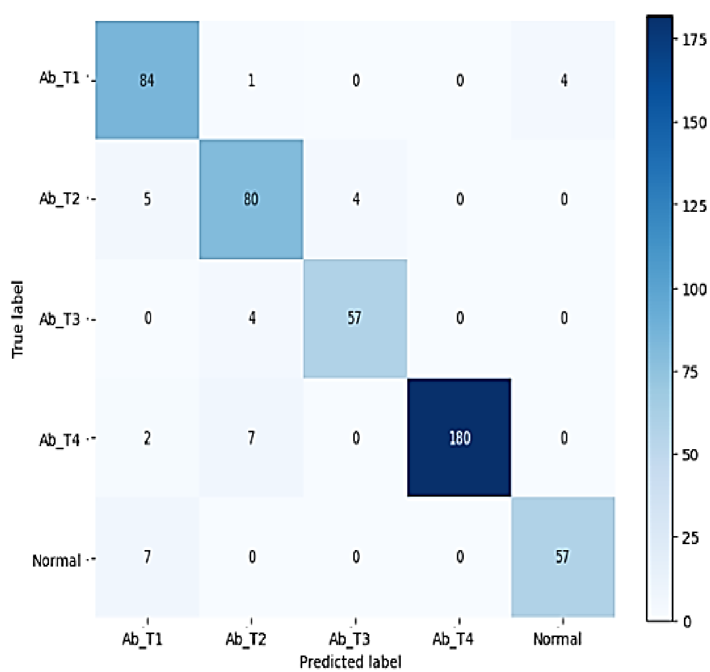

Fig. 3.3: Confusion Matrix for SVC-Based Environment Monitoring Model.

The superior performance of the Random Forest model can be attributed to its ability to handle complex data patterns through the aggregation of multiple decision trees. This model is particularly effective in dealing with the variability present in the environmental data collected from the poultry farm. On the other hand, the lower performance of KNN and SVC may be due to their sensitivity to the dataset's dimensionality and their reliance on predefined decision boundaries, which may not capture the nuances of the environmental conditions as effectively.

The high accuracy of the Random Forest model suggests it is well-suited for real-time monitoring of poultry farm environments. The model's robustness can lead to more reliable alerts and timely interventions, potentially reducing the risk of adverse conditions affecting poultry health. However, challenges such as the computational cost of running Random Forest in real-time must be considered.

4.0. Conclusion

This study demonstrates the effectiveness of using machine learning models, particularly the Random Forest algorithm, to monitor environmental conditions in poultry farms, achieving an accuracy rate of 98%, which outperformed other tested models. By integrating IoT devices with machine learning algorithms, this system offers a reliable solution for real-time monitoring and timely interventions, which are crucial for maintaining optimal conditions in poultry farms. However, despite these promising results, several limitations warrant attention. The performance of the system in real-world scenarios may be affected by data variability due to changing environmental conditions and the need for scalable solutions in resource-constrained environments. These challenges include ensuring cost-effective deployment and maintenance of the monitoring system in diverse operational contexts, which were not fully addressed in this study.

5.0 Recommendation

Looking ahead, future improvements should focus on enhancing the system’s scalability, developing strategies to mitigate costs, and conducting field trials to assess its effectiveness in various settings. Such efforts could lead to the adaptation of the system for broader use across different types of farms. The implementation of this developed monitoring system has the potential to revolutionize poultry farm management practices. It is recommended for several stakeholders, including poultry farm owners and managers, veterinarians, research institutions, and government agencies. Poultry farm owners and managers can utilize the system to gain valuable insights into environmental conditions and disease outbreaks, optimizing farm conditions and enhancing productivity while minimizing economic losses through early disease detection. Veterinarians can make informed decisions and implement targeted interventions to improve poultry health outcomes. Research institutions may benefit from the integration of IoT devices with advanced machine learning techniques, contributing to agricultural technology advancements. Lastly, government agencies and regulatory bodies can leverage insights from the system to develop policies promoting the adoption of advanced monitoring technologies, thereby enhancing industry standards and ensuring compliance with animal welfare and safety regulations. Ultimately, this study not only contributes to the field of agricultural technology but also lays the groundwork for future innovations that could significantly impact the poultry industry and improve animal welfare.

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