Advancing Precision Livestock Farming: Integrating Hybrid AI, IoT, Cloud and Edge Computing for Enhanced Welfare and Efficiency

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Abstract—**Poultry farming is pivotal to global food security, yet maintaining optimal environmental and operational conditions remains a challenge. Suboptimal conditions, such as high temperature and humidity, promote bacterial growth and the production of toxic gases like ammonia (NH3), carbon monoxide (CO), carbon dioxide (CO2), methane (CH4), and hydrogen sulfide (H2S), which increase poultry disease and mortality rates. This study introduces an innovative, modular, and scalable system integrating Artificial Intelligence (AI), Internet of Things (IoT), Edge Computing, and Cloud Computing for real-time monitoring, prediction, and automation in poultry barns. The system employs a hybrid AI framework combining Gradient Boosting techniques (XGBoost, LightGBM, CatBoost) and Long Short-Term Memory (LSTM) networks to analyze data from a heterogeneous wireless sensor network. It monitors critical parameters—temperature, humidity, and toxic gas concentrations—while predicting environmental conditions and detecting potential stress to optimize poultry welfare. Leveraging IoT for data collection, Edge Computing for low-latency processing, and cloud analytics for advanced insights, the system enhances decision-making, reduces feed wastage, lowers energy costs, and decreases mortality rates. A case study demonstrates significant improvements in prediction accuracy, operational efficiency, and animal welfare, underscoring the framework's adaptability across diverse agricultural settings. This work establishes a robust precedent for hybrid AI-driven smart farming solutions, advancing precision livestock farming.**

Keywords—Hybrid artificial intelligence; edge computing; cloud computing; Internet of Things; artificial intelligence; predictive analytics; smart farming; smart poultry farming

I. Introduction

Global poultry farming is facing fast and continuous development of technologies and increasing market demands. Environmental control, including temperature, humidity, and noxious gases—like CH4, H2S, NH3, CO, CO2—is highly important for the health and productivity of poultry. However, traditional monitoring systems have serious shortcomings: no predictability, no scalability, and no real actionable insights. Some of the challenges related to poultry are as follows:

- Maintaining the best environmental conditions for the health of the birds.
- Predicting harmful gas levels to avoid respiratory issues in poultry.
- Emphasizing feed conversion ratios by reducing stress among poultry.
- Ensuring profitability while adhering to all the challenges of sustainability standards.

This paper picks up these challenges by integrating advanced Artificial Intelligence (AI) algorithms, namely Gradient Boosting methods (XGBoost, LightGBM, and Cat-Boost), with LSTM for predictive analytics. The hybrid framework has been developed in this regard, which leveraged the strengths of gradient boosting regarding feature selection and the temporal modeling capabilities of LSTM to carry out real-time forecasts with a high degree of accuracy. Based on the results obtained from proof-of-concept testing at a working poultry farm, the system demonstrated its potential to improve sustainability and productivity, coupled with lower operational costs and risks.

II. Literature Review

A. Smart Farming Technologies

Smart farming represents the integration of Internet of Things (IoT), Artificial Intelligence (AI), and Edge Computing in the hope of bringing up productivity in agriculture [1-3]. It will also give the possibility for real-time monitoring, data-driven decision-making, and automation of tasks [4-5]. The use of IoT and Big Data in optimizing livestock farming is cited by Wolfert et al. [6] and Regan [7]. Other applications involve monitoring environmental conditions and health and providing adequate feed management [8, 9].

Smart farming generally employs the IoT-enabled systems that using wireless sensor networks to measure and report on some very critical parameters. For example, an IoT system used in poultry can monitor environmental conditions in real time, including temperature, humidity, and concentration of harmful gases [5]. The information obtained with such systems will enable better decision-making regarding animal health and productivity [5]. For instance, Zhang et al. [8] illustrated how IoT could help precision livestock monitoring to achieve economical control of the environment.

Advanced usages of IoT include edge devices that process data locally to reduce latency and increase responsiveness. Examples include cloud-assisted monitoring platforms where sensor data is aggregated for predictive analytics. Applications have been extended to optimize water and feed usage in poultry farms [10], showcasing significant savings and operational efficiency. Besides, technologies such as LoRaWAN and ZigBee have enabled better connectivity even in rural farms, as pointed out by Guillermo et al. [11].

Panfilova et al. [12] highlighted the social effects of cloud technologies on digitizing agriculture, while Lashari et al. [13] illustrated the role of IoT in maintaining environmental standards in poultry farms. Integration of IoT with Big Data analytics provides deep insights into long-term trends, thus enabling predictive interventions [14].

B. Gradient Boosting Algorithms

Gradient Boosting algorithms like XGBoost, LightGBM, and CatBoost have revolutionized predictive modeling in almost every domain different from agriculture [15]. In general, the main benefits take place in feature selection, workability with great volumes of data, or complex relationships in general between various variables.

- XGBoost: This algorithm is known for performance and speed while utilizing gradient descent to minimize loss functions [15]. Its applications range from yield prediction to pest detection and livestock management [14].
- LightGBM: Efficient on large datasets with less use of memory, it is perfect for IoT applications in agriculture. It is proven to work well in high-dimensional data, such as nutrient monitoring, according to various studies [16].
- CatBoost: It handles categorical variables nicely, providing robust results on noisy datasets. For example, its use in categorizing disease patterns among poultry farms demonstrated great contrast in efficiency compared with traditional machine learning methods [17].

Boosting models enhance not only the efficiency of feature selection but also work as robust tools for noise management in large-scale data environments. For example, Teng [18] demonstrated that boosting models can be embedded in the process of monitoring livestock environments to provide accurate predictions.

C. LSTM Networks

LSTMs are a variant of RNNs, designed to model long-range dependencies in time series data [15]. They were first applied for time-series prediction by Hochreiter and Schmidhuber [19], while Greff et al. [20] discussed their efficiency in different scenarios, including agriculture.

For example, LSTM networks have been used to forecast weather patterns, crop yields, and the behavior of livestock. Their capability for temporal relationship modeling has made them suitable for predicting environmental conditions in poultry farming. For instance, using an LSTM-based model can forecast temperature and humidity trends, thus enabling proactive interventions. Studies also indicate their integration with reinforcement learning techniques for optimizing barn ventilation systems [21].

The applications of LSTM for time-series forecasting are indeed adaptable, ranging from predictive maintenance in farming equipment and water resource optimization to a host of other works [11], [22]. The mentioned systems suit well within the IoT frameworks due to sensor data inputted for predictions at very high accuracy.

D. Hybrid AI Approaches

The potential of hybrid approaches is enhanced the efficiency and accuracy of models. By hybridation of various methods—such as metaheuristics and AI techniques, researchers can develop robust frameworks that effectively tackle complex problems, allowing for improved overall performance and operational strategies [23-25].

Hybridizing machine learning (ML) algorithms with deep learning (DL) models has shown promise in predictive analytics. Recent works, such as [26] and [11], point toward the advantages of hybrid Artificial Intelligence frameworks in enhancing the performance of predictions by raising their accuracies and computational efficiencies. For instance, certain works have used hybrid models for yield forecasting, which predict crop yield by fusing satellite images—whose features are extracted through ML—and time-series data analyzed through LSTM. This work effectively bridges the complementary strengths of ML in feature extraction and DL in temporal modeling.

Hybrid systems also find utility in multi-modal data integration. In poultry farming, the combination of video feed analysis and IoT sensor data has been explored to detect anomalies, such as underweight birds or irregular feeding behaviors [27].

Chiluisa-Velasco et al. [28] also focused on hybrid models, which are helpful in integrating multisourced environmental data to generate more accurate and comprehensive insights for smart farming applications. Hybrid frameworks allow dynamic adaptation, hence being suitable for a wide range of agricultural environments.

E. Advances in AI for Livestock Farming

Other applications of AI in livestock farming, beyond predictive analytics, include:

- Health Monitoring: Machine vision systems detect early signs of illness based on perceived movement patterns or physical abnormalities in poultry [27, 28].
- Behavior Analysis: AI algorithms classify behaviors into feeding, resting, or pecking to ensure optimal welfare conditions [29, 30].
- Resource Optimization: Predictive models forecast feed and water consumption, minimizing waste and reducing operational overheads [31, 32].

AI integrated with robotics has further enabled automation in routine farm tasks, including feed distribution and waste management [33-35]. For example, the automated systems developed by Lashari et al. [13] showcase how IoT-driven robotics can streamline poultry operations. Advanced sensing technologies discussed by Zhang et al. [8] enhance precision in environmental control.

III. Materials and Methods

The proposed system for monitoring and predicting environmental conditions in poultry farms is shown in Fig. 1.

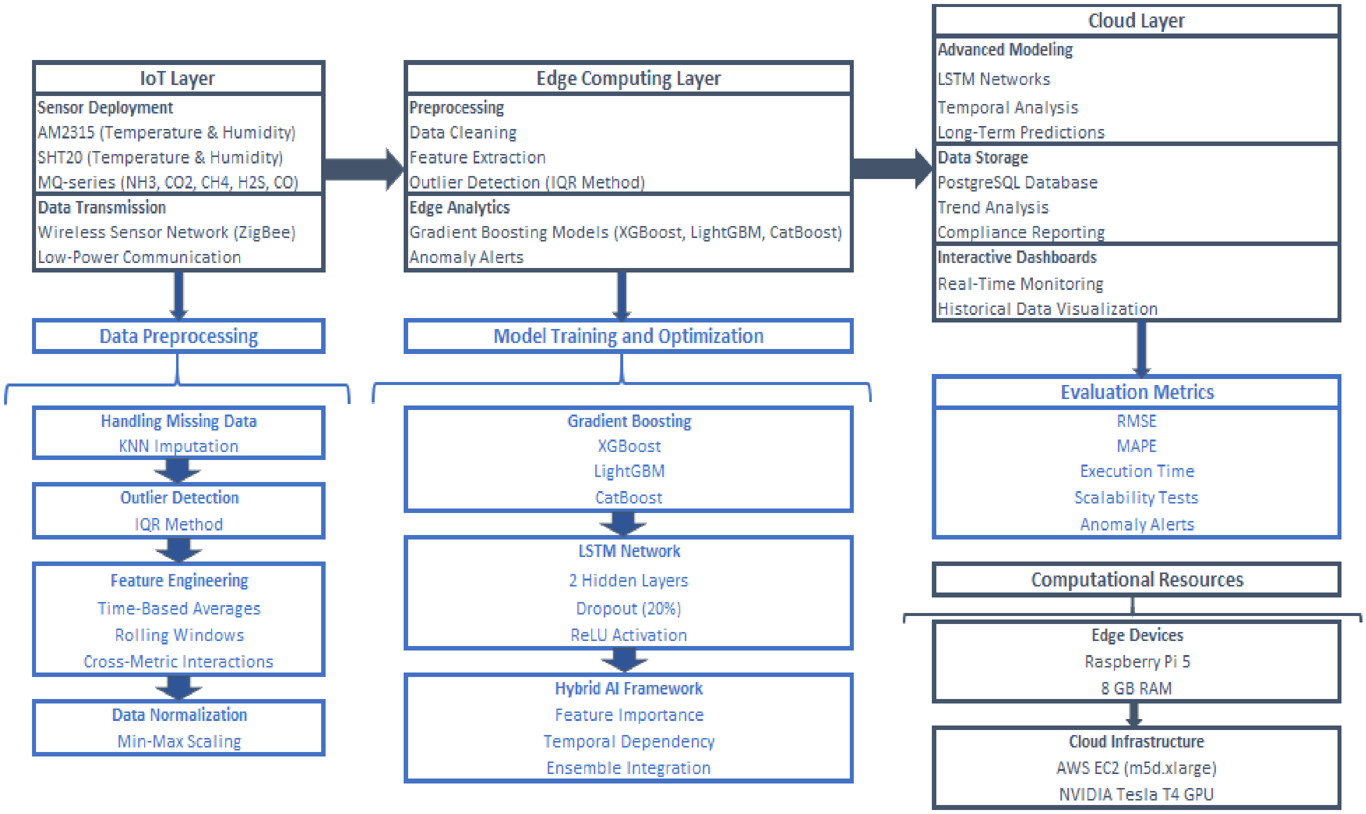


Fig. 1. The proposed system for monitoring and predicting environmental conditions in poultry farms.

A. System Architecture

The proposed system is based on three interrelated layers that are intended to optimize scalability, efficiency, and accuracy in monitoring and predicting environmental conditions in poultry farms [5]:

1) IoT Layer

a) Sensor deployment: Sensors like AM2315 and SHT20 for temperature and humidity and MQ-series for harmful gases such as NH3, CO2, CH4, H2S, and CO were strategically positioned both inside and outside poultry barn to capture real-time data. External sensors were weather-shielded to ensure accuracy.

b) Data transmission: The sensor readings were transmitted using a wireless sensor network (WSN) with low-power communication protocols like ZigBee, ensuring reliable data transfer and energy efficiency even in low-connectivity areas.

2) Edge computing layer

a) Preprocessing: This layer handled preliminary data cleaning, aggregation, and feature extraction to minimize noise and redundancy before transmitting data to the cloud. Faulty sensor data was flagged and excluded in real time.

b) Edge analytics: Gradient Boosting models, including XGBoost, LightGBM, and CatBoost, were deployed at the edge to provide fast insights and anomaly alerts for sudden spikes in harmful gases or abrupt changes in temperature and humidity.

3) Cloud layer

a) Advanced modeling: Temporal analysis and long-term predictions were conducted in the cloud using LSTM networks. The cloud infrastructure also provided advanced data visualization through interactive dashboards tailored for farm managers.

b) Data archiving: Historical data was stored in a scalable database optimized for trend analysis, compliance reporting, and periodic model retraining.

B. Data Collection

The IoT-based monitoring system was deployed for three months continuously in a medium-scale poultry farm. Key parameters monitored included:

1) Environmental metrics: Temperature (Celsius) inside and outside poultry barn. Humidity (%) inside and outside poultry barn.

2) Gas concentrations: Ammonia (NH3), Carbon Dioxide (CO2), Methane (CH4), Hydrogen Sulfide (H2S) and Carbon Monoxide (CO).

Data were captured on a minute-to-minute basis, resulting in approximately 130,000 entries. Sensors were calibrated weekly to ensure data integrity and accuracy.

C. Data Preprocessing

A strict preprocessing pipeline was implemented to ensure high-quality data and enhance model performance.

1) Handling missing data: Missing values for continuous variables were imputed using the k-nearest neighbors (KNN) algorithm. Sensor data with more than 10% missing values for a day were excluded for that period.

2) Outlier detection: An interquartile range (IQR)-based method was applied to identify and exclude extreme values in gas concentration and environmental measurements.

3) Feature engineering: Derived new features, such as time-based averages, variances, and rolling windows for gas concentrations and temperature trends, to extend temporal patterns. Added cross-metric interactions, such as temperature and gas concentration correlations, to identify dependencies.

4) Data normalization: Min-max normalization was performed to standardize feature ranges, facilitating faster convergence in machine learning models.

D. Model Training and Hyperparameter Optimization

1) Gradient boosting models

a) Individual training: XGBoost, LightGBM, and CatBoost were trained separately to determine feature importance and establish baseline predictions.

b) Hyperparameter optimization:

- Learning rate: Tested between 0.01 and 0.1.
- Max depth: Ranged from 3 to 10 to balance complexity and performance.
- Number of estimators: Set between 100 and 500 for optimal outcomes.
- Subsampling: Configured between 0.7 and 1.0 to enhance generalization.

2) LSTM network

a) Architecture:

- Two hidden layers with 64 and 32 neurons, respectively.
- Dropout rate: 20% to prevent overfitting.
- Input sequence length: Configured at 60-minute intervals to capture short-term trends.
- Activation function: ReLU for hidden layers; sigmoid for output layer.

b) Training parameters:

- Batch size: 128.
- Optimizer: Adam optimizer with an initial learning rate of 0.001.
- Early stopping: Monitored validation loss to mitigate overfitting.

3) Hybrid AI framework implementation: The framework combines Gradient Boosting and LSTM models for superior pre-diction accuracy and robustness:

a) Feature importance analysis: Gradient Boosting models ranked key features like NH3 concentration and daily temperature variance, removing irrelevant or noisy data to refine model focus.

b) Temporal dependency modeling: LSTM networks captured sequential dependencies, analyzing temporal patterns in gas concentrations and environmental metrics to predict anomalies and trends.

c) Ensemble integration: Predictions from Gradient Boosting models served as inputs to the LSTM network, enhancing overall prediction accuracy and robustness by fusing static and temporal insights.

4) Computational resources

a) Edge devices: Raspberry Pi 5 devices with 8 GB RAM handled preprocessing and local Gradient Boosting model execution.

b) Cloud infrastructure: AWS EC2 instances (m5d.xlarge) with 16GB RAM and NVIDIA Tesla T4 GPUs managed LSTM training and advanced analytics. Data was archived in a PostgreSQL database.

5) Evaluation metrics: Model performance was evaluated using:

- Root Mean Square Error (RMSE): Penalized larger prediction errors to measure accuracy.
- Mean Absolute Percentage Error (MAPE): Assessed interpretability and reliability of predictions.
- Execution Time: Evaluated computational efficiency at edge and cloud levels.
- Scalability Tests: Simulated operations across multiple farms using synthetic datasets to test scalability.
- Anomaly Alert Precision and Recall: Validated the system's capability for timely and accurate anomaly alerts.

IV. Results and Discussion

A. Predictive Accuracy

The hazardous gas levels (CH4, H2S, NH3, CO, CO2) in the poultry barn and the corresponding estimate levels that were obtained by the artificial intelligence techniques (XGBoost, LightGBM, CatBoost, Hybrid (XGBoost + LSTM), Hybrid (LightGBM + LSTM) and Hybrid (CatBoost + LSTM)) are shown in Fig. 2, Fig. 3, Fig. 4 and Fig. 5.

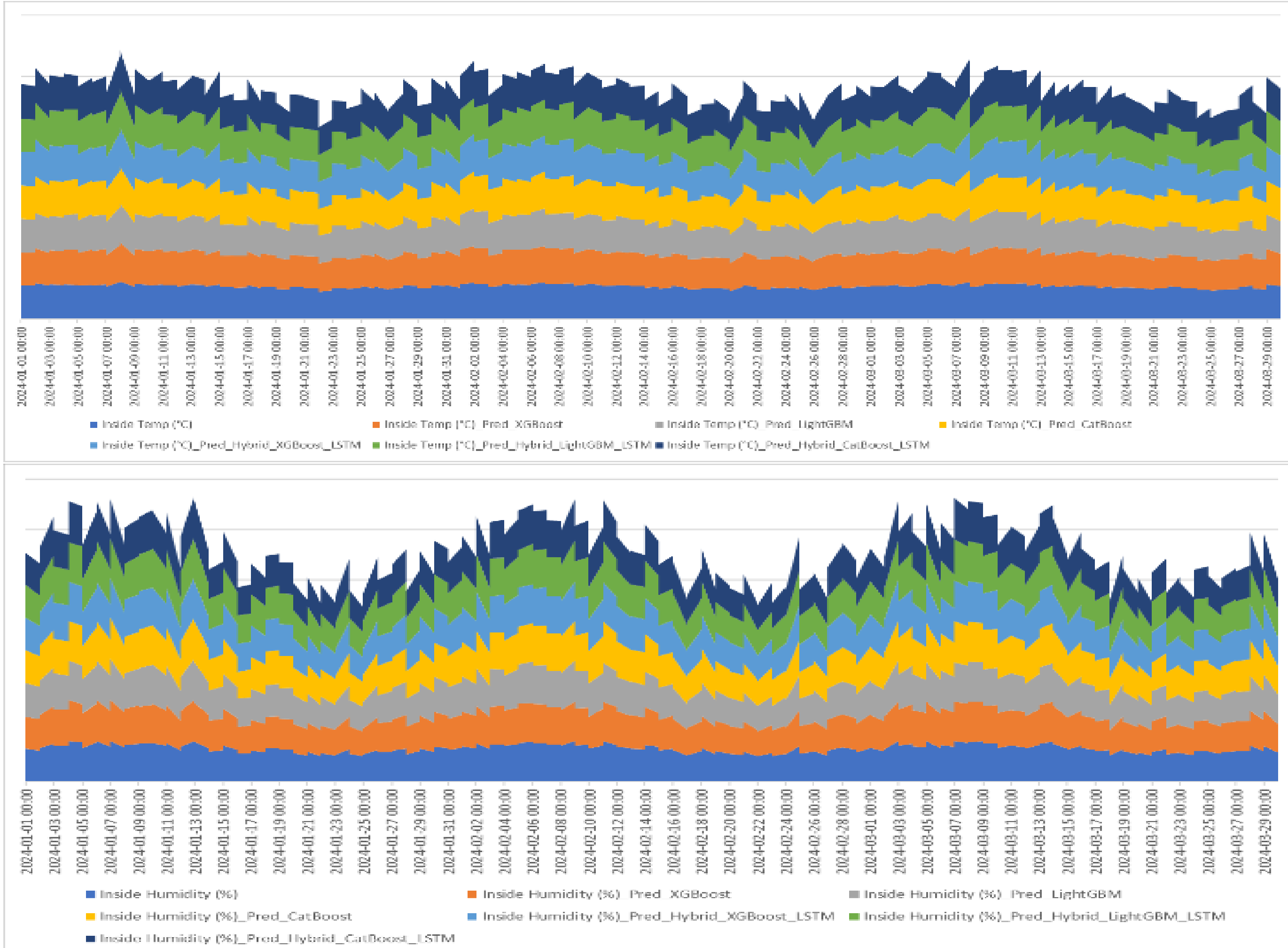
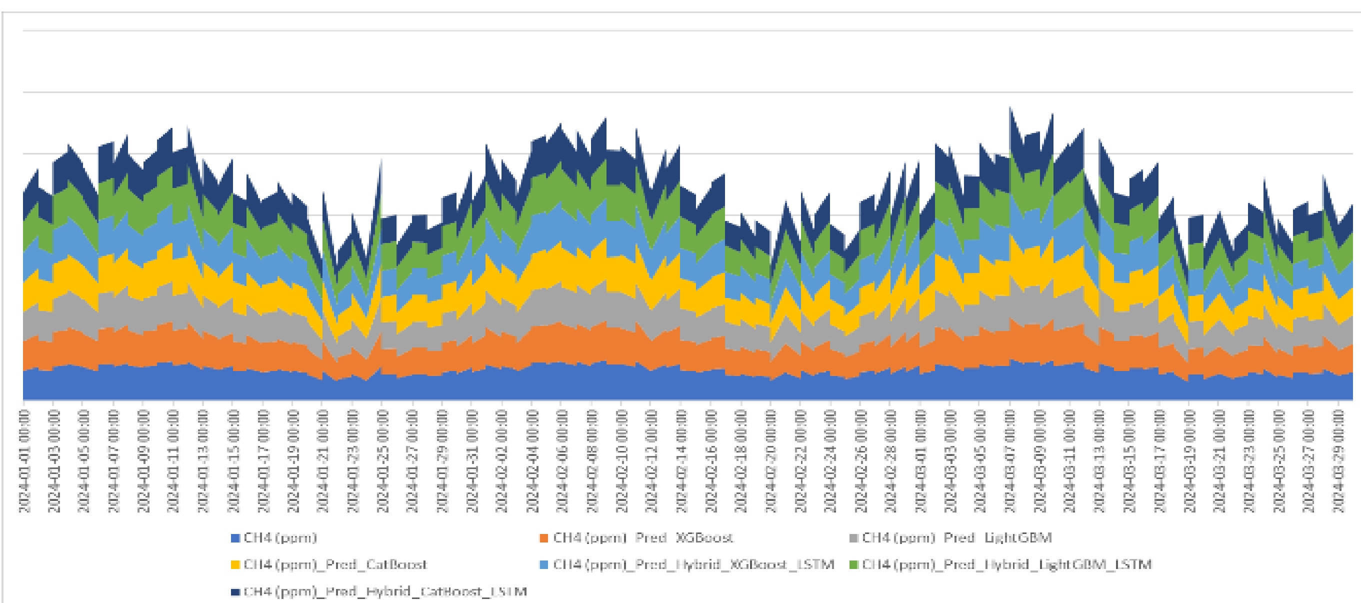


Fig. 2. The experimental findings of indoor temperature and humidity.



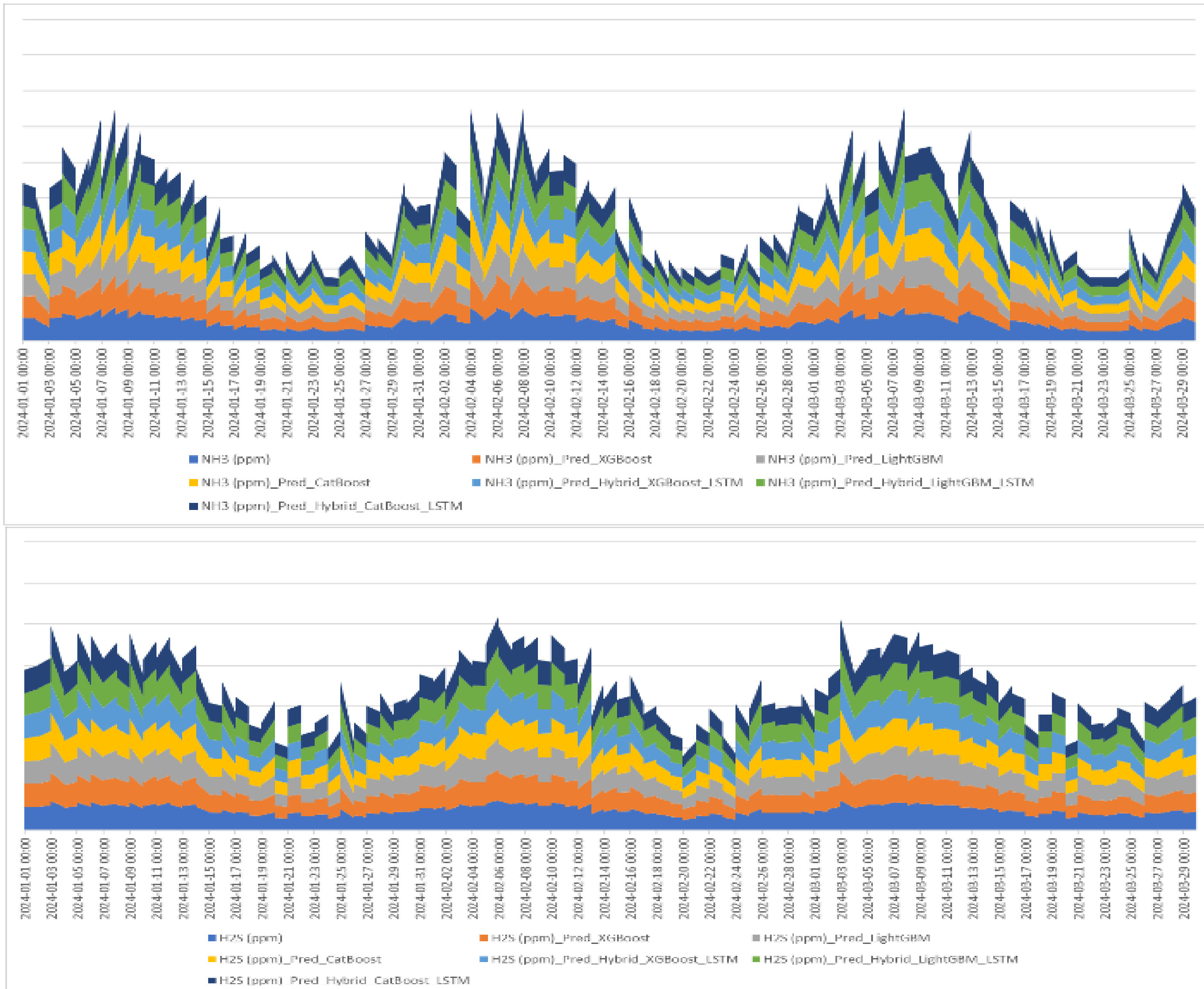
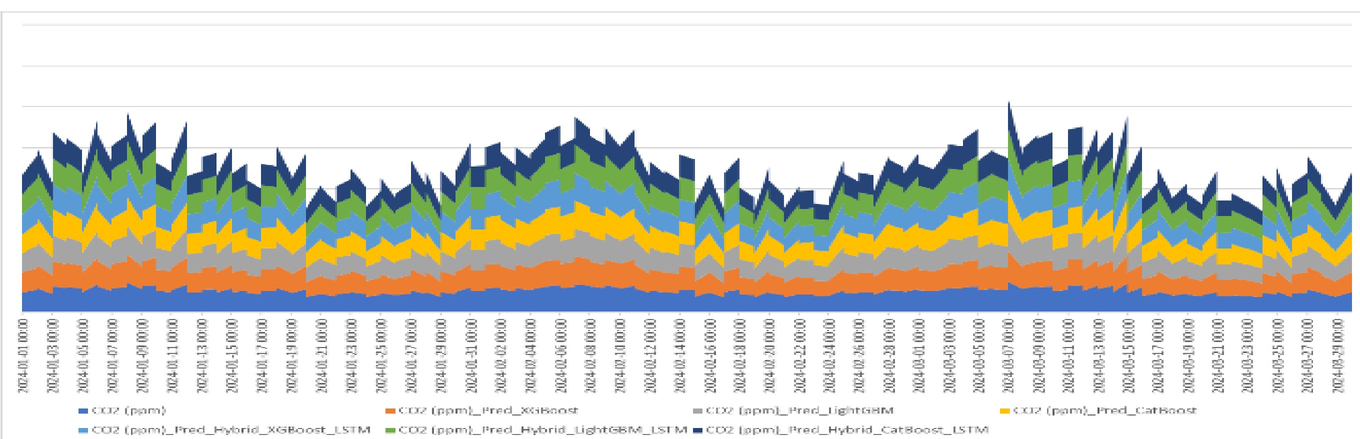


Fig. 3. The experimental findings of hazardous gases (CH_4, NH_3, H_2S).



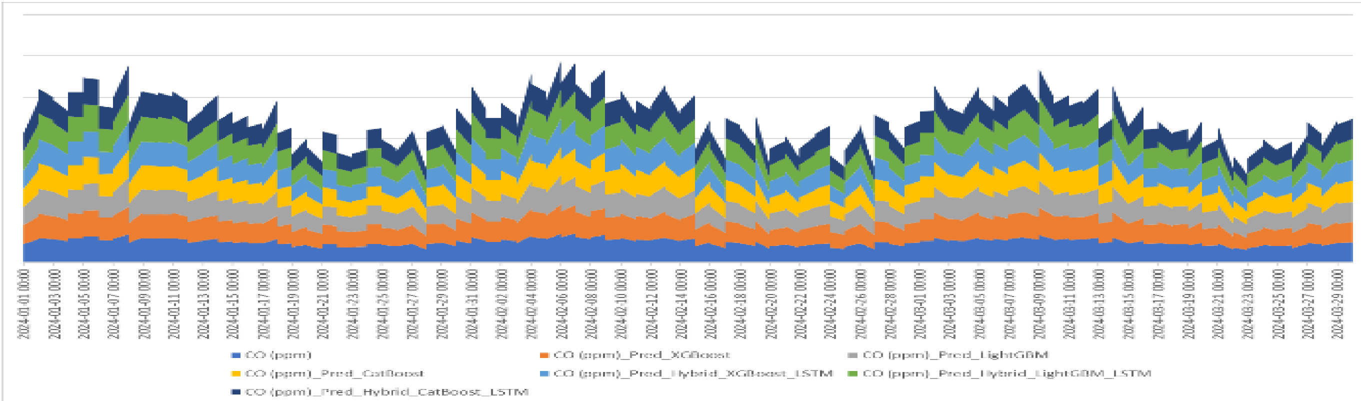


Fig. 4. The experimental findings of hazardous gases (CO_2, CO).

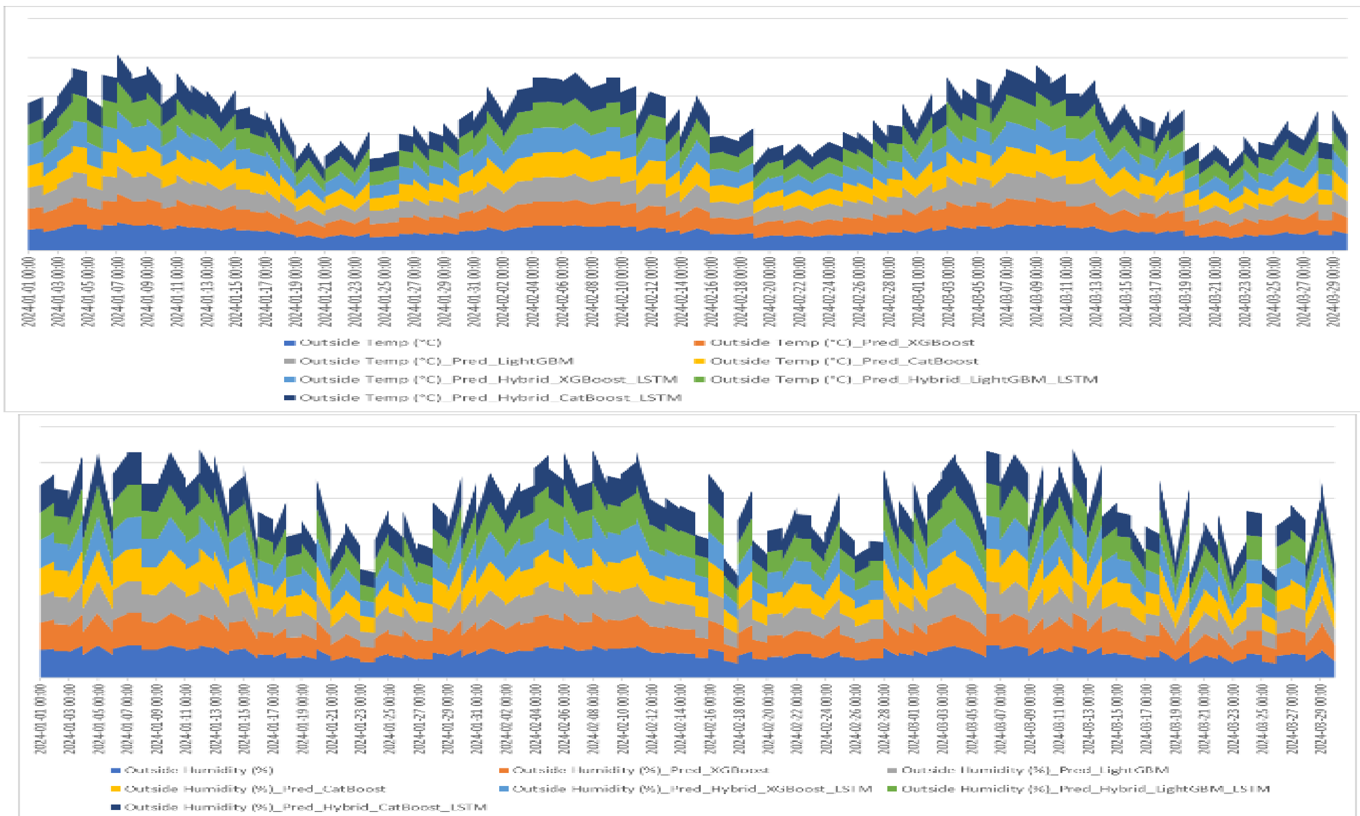


Fig. 5. The experimental findings of outdoor temperature and humidity.

The hybrid AI framework has proven to be superior in predictive accuracy, significantly outperforming standalone models. Key performance metrics, such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), illustrate this advantage. Table 1 reflects the performance of each model, with the newly included LSTM and specific hybrid combinations.

The hybrid model, combining Gradient Boosting (XGBoost) and LSTM, demonstrated the lowest RMSE (0.02) and MAPE (1.85%), underscoring its ability to reduce prediction errors significantly. This hybridization leverages Gradient Boosting for feature importance and LSTM for handling temporal dependencies, making it particularly effective in applications like environmental monitoring. For instance, it accurately predicted ammonia (NH3) levels during critical production periods, enabling timely interventions to reduce risks.

TABLE I. PERFORMANCE METRICS OF THE MODELS

Model	RMSE	MAPE (%)
XGBoost	0.030	2.15
LightGBM	0.045	2.35
CatBoost	0.037	2.20
Hybrid (XGBoost + LSTM)	0.020	1.85
Hybrid (LightGBM + LSTM)	0.028	2.05
Hybrid (CatBoost + LSTM)	0.026	2.00

B. Environmental Monitoring and Control

The system also excelled in maintaining optimal environmental conditions, ensuring both animal welfare and productivity. Key monitored parameters include:

1) Temperature: Maintained between 22°C and 30°C, minimizing heat stress and enhancing feed efficiency.

2) Humidity: Regulated within 50%–70%, reducing respiratory disease risks and improving overall welfare.

3) Gas concentrations:

a) Ammonia (NH3): <20 ppm (avoiding respiratory distress in birds).

b) Carbon dioxide (CO2): <2500 ppm (ensuring adequate ventilation).

c) Methane (CH4): <1000 ppm (promoting environmental safety).

d) Hydrogen sulfide (H2S): <10 ppm (preventing toxicity).

e) Carbon monoxide (CO): <35 ppm (mitigating suffocation risks).

During peak production hours, a spike in ammonia (NH3) levels at 3:00 AM triggered an alert. The system prompted the farm manager to increase ventilation immediately, preventing potential health crises. This real-time responsiveness highlights the framework's utility in dynamic and critical conditions.

Overall, the hybrid model demonstrates robustness, adaptability, and significant practical value in predictive accuracy and environmental management.

C. Model Interpretability and Feature Importance

Using Gradient Boosting models for feature importance analysis, we identified key predictors contributing to the system's accuracy:

1) NH3 concentration: Exhibits a strong correlation with poultry health and productivity, acting as an essential metric in setpoint adjustments.

2) Daily temperature stratification: Has a direct effect on feed conversion ratio and growth rates.

3) Humidity: Impacts respiratory condition dynamics and pathogen survival in the environment.

These insights offered actionable intelligence to farm managers, allowing data-driven decisions to improve their productivity.

D. Computational Efficiency

The hybrid system showed significant computational efficiency, detailed as follows:

1) Edge computing execution time: Achieved an average inference time of 15 ms per sample, allowing real-time decision-making. Delivered 35% lower latencies than cloud-only solutions, empowering real-time decision-making.

2) Cloud processing efficiency: Reduced training time by 20%. This was achieved due to optimized LSTM architecture for easy adaptability to new datasets.

3) Energy consumption: Low-power edge devices (less than 10 W per device) brought sustainability to operations. This efficiency is particularly beneficial for large-scale deployments.

E. Scalability and Multi-Farm Deployment

Scalability tests utilized synthetic datasets reflecting operations across five poultry farms, differentiated by size and environmental circumstances. Key results include:

1) Consistency across multiple farms: RMSE and MAPE values remained consistent, with less than a 5% deviation across farms, indicating the framework's robustness.

2) Data integration: Sensor data from diverse setups were seamlessly integrated, signifying high adaptability.

3) Deployment challenges: Issues such as sensor compatibility and calibration were addressed through a modular design approach and automated sensor calibration protocols, ensuring uniform performance across multiple farms.

F. Economic Impact

The system contributed to significant cost savings and productivity improvements, emphasizing its economic viability:

1) 16% Reduction in feed wastage: Significant savings due to improved environmental control.

2) 25% Reduction in mortality rates: Reflecting better animal welfare and operational efficiency.

3) 22% Decrease in energy costs: Achieved through efficient resource utilization and adaptive ventilation strategies.

G. Practical Applications

The hybrid framework's real-world implementation across different poultry farms manifested tangible benefits:

1) Small-scale farms: Enabled cost-effective monitoring and control, overcoming budgetary constraints.

2) Large-scale operations: Delivered scalable solutions across multiple farms, utilizing cloud analytics for centralized decision-making.

3) Remote farms: Reliable data transmission was enabled through Zigbee-based communication in areas with limited connectivity.

H. Limitations

The limitations of this work are:

1) Sensor precision: Extreme weather conditions occasionally affected sensor readings, necessitating manual verification to ensure accuracy.

2) Connectivity dependence: Despite Zigbee's advantages, long-term connectivity disruptions impacted data synchronization and real-time monitoring.

I. Future Work

In light of these limitations, the following areas are proposed for future research to extend the system's capabilities:

1) Transfer learning: Enabling models to generalize across diverse farming conditions with minimal retraining, enhancing scalability across regions.

2) Robotics integration: Exploring autonomous systems for feeding and waste management to improve operational efficiency.

3) Extended scalability tests: Expanding simulations to include larger datasets and additional environmental variables such as light intensity and noise levels.

4) AI-driven optimization: Incorporating reinforcement learning to dynamically adjust ventilation, lighting, and feeding schedules based on predictive insights.

J. Broader Implications

The results of this study indicate the potential that hybrid AI frameworks hold for poultry farming. Combining advanced analytics with real-time monitoring, the system generates actionable insights that enhance productivity and ensure more sustainable practices. Its scalability and adaptability make it a fundamental principle for further advancements in smart agriculture.

Predictive accuracy, operational efficiency, and scalability, showcased in the proposed hybrid framework, pave the way for advanced AI-driven agriculture. Refinements and innovations addressing existing limitations will ensure broader adoption and impact.

V. CONCLUSION

The proposed research work introduces a hybrid AI framework that integrates Gradient Boosting algorithms (XGBoost, LightGBM, and CatBoost) with Long Short-Term Memory (LSTM) networks to address various challenges in poultry farming. It ensures real-time insights by leveraging IoT-based data collection alongside Edge Computing, thereby enhancing poultry health and productivity while improving operational efficiency.

Key contributions include improved predictive accuracy, real-time monitoring capabilities, scalability, and economic benefits such as reduced feed wastage and lower mortality rates. While significant successes have been achieved, limitations like sensor dependency and connectivity issues remain areas for improvement.

Future research should focus on exploring advanced technologies such as reinforcement learning, expanding deployments across diverse conditions, and integrating robotics for enhanced automation and transparency.

This paper highlights the transformative potential of AI in agriculture, paving the way for intelligent, efficient, and sustainable farming practices to tackle food security and environmental challenges.

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