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# An LSTM-SARIMA-based forecasting method for environmental quality in enclosed poultry houses

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## Abstract

*Closed-type poultry houses support stable production performance by maintaining a controlled microenvironment that promotes optimal poultry growth. However, many farms still rely on manual monitoring of environmental parameters such as temperature, humidity, and ammonia concentration, resulting in delayed responses, reduced productivity, and increased environmental stress on poultry. These limitations highlight the need for predictive and automated systems that can monitor and forecast environmental conditions in real time. Previous studies have shown that LSTM networks are effective for nonlinear time-series forecasting. However, when applied independently, LSTM models often face difficulties in capturing linear seasonal patterns and long-term trends inherent in poultry house environmental data. Therefore, this study proposes a hybrid forecasting framework that integrates LSTM and SARIMA models to simultaneously capture nonlinear temporal dependencies and linear seasonal components. Environmental parameters, including temperature, litter moisture, and ammonia concentration, were collected using SHT31, Soil Moisture, and MQ137 sensors. The collected data were processed using a Python-Flask backend system, stored in MongoDB, and visualized through a cross-platform web interface developed using Flutter. Experimental results demonstrate that the proposed LSTM–SARIMA model achieves strong predictive performance, with MAE = 0.62, MSE = 0.55, RMSE = 0.58, MAPE = 7.89%, and $R^2$ = 0.86. These findings indicate that the proposed method effectively supports early warning systems and real-time microclimate monitoring, enabling faster environmental control responses and reducing production losses caused by unstable poultry house conditions.*

## 1. Introduction

Poultry meat serves as an essential source of animal protein in Indonesia, making broiler production an important component of national food security [1]. The productivity and sustainability of poultry farming are strongly influenced by effective environmental management, particularly in closed-house systems designed to maintain stable microclimatic conditions regardless of external weather fluctuations.

Environmental parameters such as temperature, humidity, and ammonia concentration significantly affect feed conversion efficiency, growth performance, and mortality rates, thereby influencing overall farm profitability. Prolonged exposure to ammonia concentrations exceeding 25 ppm has been shown to reduce weight gain, increase feed consumption, induce respiratory disorders, and increase mortality rates by 10–15%, leading to significant economic losses [2]. Furthermore, unstable temperature and humidity conditions can cause heat stress and immune suppression, increasing susceptibility to infectious diseases and further reducing production efficiency [1].

This study addresses the problem that environmental management in many closed-type poultry housing systems remains inadequate and highly dependent on manual monitoring and operator experience. Field observations conducted at CV. Berkah Bersama Farm in Kota Batu indicate that poultry house conditions are commonly assessed using subjective indicators such as litter moisture, ammonia odor, and poultry behavior, which are intrinsically imprecise and often result in delayed corrective actions.

Poor ventilation and excessive litter moisture contribute to ammonia accumulation, creating serious health risks including respiratory disorders, eye irritation, immune suppression, and increased susceptibility to pathogens such as Escherichia coli and Mycoplasma gallisepticum [3]. Although several monitoring technologies have been introduced, most systems still operate primarily as passive real-time monitoring tools without predictive or early warning capabilities, causing environmental management to remain reactive rather than proactive.

Recent studies indicate that hybrid time-series models can improve forecasting accuracy by integrating linear seasonal modeling with nonlinear learning approaches. Panicker and Valarmathi developed a SARIMA-LSTM model for predicting Aerosol Optical Depth, where SARIMA identified seasonal trends and LSTM discerned nonlinear residual patterns, resulting in lower RMSE and MAE values compared to standalone models [4]. Naidu and Chandniha proposed a SARIMA-BiLSTM model for monthly rainfall forecasting, demonstrating improved predictive accuracy by effectively handling seasonality and non-stationarity in agro-environmental time series data [5].

Although these hybrid models exhibit promising performance, they are primarily designed for offline analysis using historical datasets and generally lack integration with real-time sensor data streams. Furthermore, existing studies mainly focus on large-scale atmospheric or climatic phenomena, limiting their applicability to enclosed livestock environments characterized by rapid microclimatic fluctuations and the need for continuous early-warning systems [6], [7].

To address these limitations, this study proposes a hybrid forecasting framework that combines SARIMA and LSTM models using a residual learning mechanism. Within this framework, SARIMA is first employed to model the linear, seasonal, and cyclical characteristics of poultry house microclimate data. The residual errors generated by the SARIMA model, which contain nonlinear and complex temporal patterns, are subsequently assimilated by the LSTM network.

By separating linear seasonal modeling from nonlinear temporal learning, the proposed method improves prediction accuracy and robustness for microclimate forecasting in closed-type poultry houses [8]. The main contributions of this research are summarized as follows:

1. A residual-based LSTM-SARIMA hybrid model for jointly modelling nonlinear temporal dynamics and linear seasonal patterns in poultry house environments
2. Real-time integration of the proposed model with IoT-based ammonia, temperature, and litter moisture sensing systems for continuous microclimate monitoring.
3. Comprehensive performance evaluation using multiple error metrics to validate early warning capability and support proactive environmental control.
4. A scalable web-based monitoring architecture that enables real-time visualization and supports multi-farm deployment for precision poultry farming.

## 2. Research Method

### 2.1 System Design

Figure 1 illustrates the proposed system architecture for the predictive environmental monitoring framework. The procedure begins with real-time data acquisition from three primary sensors [9]. The hybrid forecasting model integrates a three-layer LSTM architecture consisting of 16, 32, and 64 units with a SARIMA configuration of (2, 1, 2) (1, 0, 1, 7). Dropout regulation (0.3) and kernel regularization (1e-4) are applied to mitigate overfitting, while the Adam optimizer is used for model optimization.

Within the hybrid framework, the LSTM component is responsible for learning nonlinear temporal dependencies, whereas SARIMA identifies linear seasonal patterns. The deployment architecture utilizes Flask, MongoDB, and Flutter to support real-time environmental monitoring and predictive notification systems.

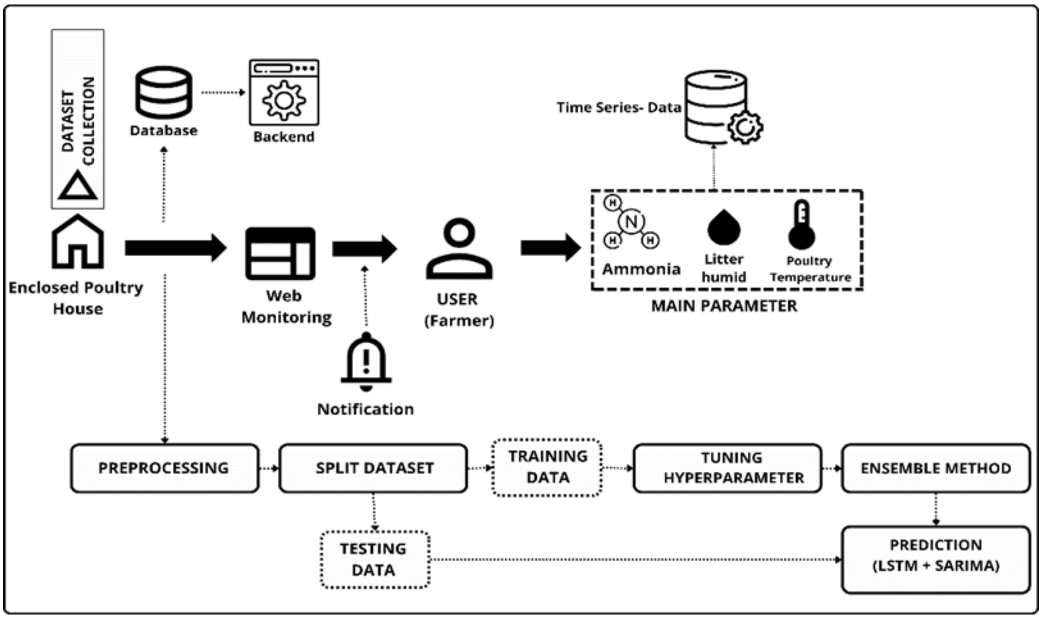


*Figure 1. System Design*

### 2.2 Dataset Preparation

The dataset consisted of 2,000 time-series samples containing ammonia concentration, temperature, and litter moisture measurements. Of these samples, 1,350 were obtained from manual environmental records collected at CV. Berkah Bersama Farm, while the remaining 650 samples were collected directly through real-time sensor monitoring.

During the preprocessing stage, missing values were handled using interpolation techniques to maintain temporal continuity within dataset. To accelerate LSTM convergence and ensure consistent data scaling, Min-Max normalization within the range of 0–1 was applied. Min–Max normalization was selected instead of standard normalization because the sensor-based environmental parameters possess fixed physical ranges, and preserving their relative scale improves LSTM training stability while reducing distortion of temporal patterns caused by variance-based scaling [7].

To ensure fair model evaluation, the dataset was divided into 70% training data, 15% validation data, and 15% testing data. This systematic preparation enabled the model to identify linear seasonal structures using SARIMA while simultaneously learning nonlinear temporal relationships using LSTM. By integrating preprocessing strategies suitable for both statistical modeling and deep learning apporaches, the dataset was optimized for hybrid forecasting performance [10]. Consequently, the proposed framework demonstrated improved capability in reliably detecting variations in ammonia concentration, temperature, and litter moisture with minimal computational bias.

### 2.3 SARIMA Construction

This study aimed to improve the nonlinear learning capability of the LSTM model by first identifying the linear and seasonal patterns present in environmental variables such as ammonia concentration, temperature, and litter moisture. The SARIMA model configuration was determined through systematic parameter optimization using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses to identify the most relevant lag orders [11].

The optimal parameters obtained were (p, d, q) = (2, 1, 2) for the non-seasonal component and (P, D, Q, s) = (1, 1, 1, 7) for the seasonal component, where s = 7 represents a weekly seasonal cycle within the hourly dataset. This seasonal periodicity reflects recurring poultry house operational activities, including scheduled litter management, ventilation adjustments, feeding routines, and waste accumulation patterns that commonly repeat within a weekly production cycle. These repetitive management activities generate regular fluctuations in ammonia concentration, temperature, and litter moisture, making weekly seasonality an important component in environmental forecasting.

The model parameters were evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to ensure model simplicity while minimizing the risk of overfitting. Prior to model training, differencing was applied to the dataset to achieve stationarity, and residual diagnostic analysis was conducted to verify that the residuals followed a white-noise distribution, thereby confirming model adequacy [12].

The SARIMA model was implemented using the statsmodels library in Python and trained separately for each environmental variable to account for distinct seasonal characteristics. By focusing on linear and periodic dynamics, SARIMA established a robust statistical forecasting foundation that was subsequently integrated with the LSTM model within a hybrid ensemble framework. This integration improved overall forecasting accuracy and prediction stability across varying environmental conditions.

### 2.4 LSTM Construction

This study utilized an LSTM model with a Sequential architecture consisting of three stacked layers containing 16, 32, and 64 units to effectively capture both short-term and long-term temporal dependencies within environmental time-series data [13], [14], as illustrated in Figure 2. The gradual increase in number of neurons enables hierarchical feature learning, allowing the lower layers to capture short-term fluctuations such as transitory ammonia spikes, while deeper layers model delayed and long-term environmental responses commonly observed in closed-type poultry houses. This architecture balances predictive capability and computational efficiency, making it suitable for real-time IoT-based environmental monitoring applications [15].

To mitigate overfitting, a dropout rate of 0.3 and L2 kernel regularization (1e−4) were applied, providing an effective balance between regularization strength and information preservation for moderately sized and noise-sensitive sensor datasets. This strategy improves model generalization while preserving important temporal patterns.

A Dense output layer was employed for continuous-value prediction, while the Adam optimizer with a learning rate of 0.001 was utilized because of its adaptive learning capability and stable convergence behavior in non-stationary time-series environments [16]. Furthermore, the Huber loss function was utilized to enhance robustness against outliers caused by sudden environmental disruptions [17], such as ventilation system failures or excessive litter accumulation. The model was trained for 200 epochs using a batch size of 16, resulting in stable convergence and effective nonlinear temporal modeling within the proposed LSTM–SARIMA hybrid framework.

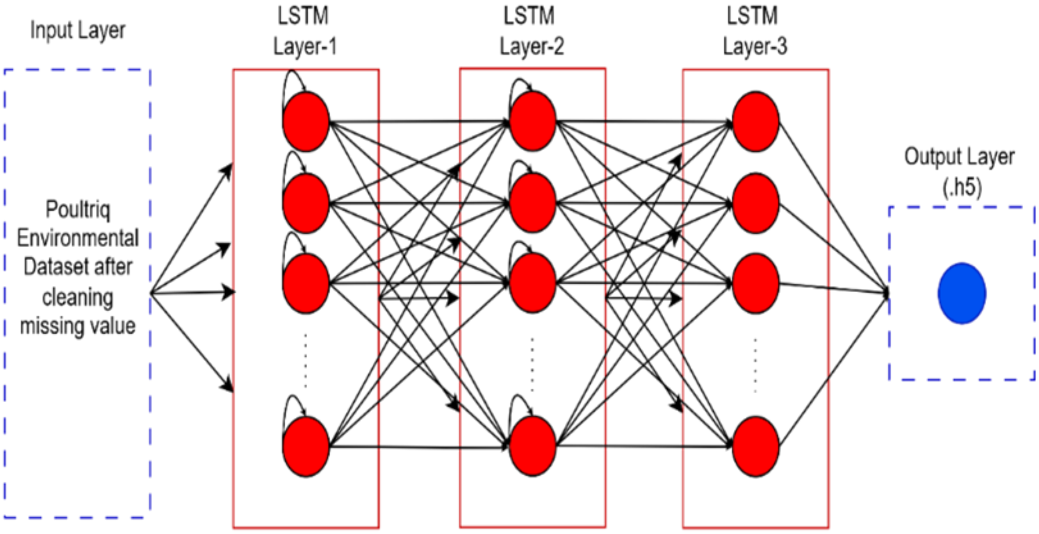


*Figure 2. LSTM Architecture*

### 2.5 Pre-Trained Model and Hybrid Integration

The initial training phase (pre-training) employed a dual-model architecture integrating LSTM and SARIMA using time series dataset collected from environmental sensors installed in a closed-type poultry house over a one-month observation period. The dataset consisted of environmental measurements including air temperature and humidity obtained from the SHT31 sensor, litter moisture measurements from the Soil Moisture Sensor, and ammonia concentration data from the MQ137 sensor, collected at regular time intervals.

The proposed LSTM-SARIMA pre-trained model was developed using these multivariate environmental time-series data. Prior to modeling, all features were normalized within a 0–1 range using Min-Max scaling to improve training convergence. Subsequently, the dataset was transformed into sequential input structures with the format (samples, time_steps, features).

The LSTM architecture consisted of three stacked layers containing 16, 32, and 64 units, combined with dropout regularization (0.3) and a Dense output layer designed for regression tasks. Simultaneously, SARIMA models were trained independently for each environmental feature, where the optimal parameters (p, d, q, P, D, Q, s) were determined using AIC/BIC evaluation and residual diagnostic analysis.

The final hybrid prediction was generated through a weighted ensemble mechanism in which SARIMA provided baseline seasonal forecasting, while the LSTM component performed nonlinear residual correction [18]. The hybrid model was trained using the Adam optimizer together with the Huber and MSE loss functions to improve prediction robustness and convergence stability. Model performance was evaluated using MAE, RMSE, $R^2$, and MAPE metrics. The final hybrid predictions were validated on the testing dataset, demonstrating reliable forecasting performance and enabling early detection of environmental problems within closed-type poultry houses.

### 2.6 Preprocessing Model

During the preprocessing stage, environmental time-series data collected from the closed-type poultry house were optimized to enhance forecasting accuracy and reduce the risk of overfitting [19]. Data acquisition was conducted at three-hour intervals using environmental sensors.

During model preparation, the LSTM input features were normalized using Min–Max scaling, as expressed in Equation 1, whereas the SARIMA model utilized raw input values to preserve the original data scale required for effective seasonal modeling. The LSTM input data were subsequently transformed into temporal sequences to capture nonlinear temporal dependencies, as formulated in Equation 2. Meanwhile, SARIMA utilized time-series decomposition and seasonal differencing to discern linear and periodic patterns, thereby ensuring coherent integration within the proposed hybrid forecasting framework.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$$X_t = [x_{t-T-1,} x_{t-T+2,\dots,} x_t] \rightarrow Y_{t+1} \quad (2)$$

Explanation:
$X_{norm}$ : Normalized value
$X$ : Original value of the sensor parameter

$X_{min}$ : Minimum parameter value in the dataset

$X_{max}$ : Maximum parameter value in the dataset

$X_t$ : Input data sequence at time step $t$

$x_{t-T-1,}$ : Environmental parameter values from the previous $T$ time steps up to time step $t$.

T : Time-window size

$Y_{t+1}$ : Target value (label) to be predicted at the next time step $(t+1)$.

**2.7 Splitting Dataset**

Following preprocessing, the dataset was partitioned into training, validation, and testing subsets. The dataset consisted of 2,000 data points, divided into 1,400 training samples, 300 validation samples, and 300 testing samples. The time-series data acquired from environmental sensors together with timestamp information were processed using a sliding-window approach to generate sequential input-output pairs ($Xseq$, $Yseq$) for LSTM training.

The training size was defined as 70% of the total sequence length, ensuring proportional data partitioning, as expressed in Equation 3. The training dataset ($X$train, $Y$train) was obtained from the initial segment of the sequence, as formulated in Equation 4. Subsequently, 15% of the data were allocated for validation ($X$val, $Y$val), following the training segment, as described in Equation 5. The remaining 15% of the data were assigned as the testing dataset ($Xtest$, $Ytest$), as presented in Equation 6.

Within the LSTM processing stage, all input features underwent Min–Max normalization, whereas SARIMA maintained raw numerical values to preserve the original temporal distribution of the data. For both models, the dataset partitioning was performed chronologically based on timestamps order to maintain temporal consistency and ensure synchronized learning within the hybrid forecasting framework [20].

$$TrainSize = int\left(len\left(X_{seq}\right) x \ 7\right) \tag{3}$$

$$X_{train} = X_{seq}[1 : TrainSize], Y_{train} = Y_{seq}[\, 1 : TrainSize] \tag{4}$$

$$X_{Val} \ = X_{seq}\ [TrainSize + 1 : TrainSize + 0.15N], Y_{val} = \ Y_{seq}[TrainSize + 1 : TrainSize + 0.15N] \tag{5}$$

$$X_{test} \ = X_{seq}\ [TrainSize + 0.15N + 1 : N], Y_{test} = \ Y_{seq}[TrainSize + 0.15N + 1 : N] \tag{6}$$

Explanation:
*TrainSize* : Number of samples allocated to the training subset, representing 70% of the total dataset
$X_{seq}, Y_{seq}$ : Sequential input-output data generated from the time-series dataset
$X_{train}, Y_{train}$ : Training dataset pair consisting of the first 70% of sequential samples used for model training
$X_{val}, Y_{val}$ : Validation dataset pair consisting of 15% of the sequential samples used for model validation
$X_{test}, Y_{test}$ : Testing dataset pair consisting of 15% of the sequential samples used for model evaluation

**2.8 Build Modified LSTM-SARIMA Model**

As illustrated in Figure 3, the proposed hybrid forecasting framework combines linear seasonal modeling and nonlinear temporal learning by integrating SARIMA and LSTM through a residual learning mechanism. This framework utilizes SARIMA to model deterministic linear components and seasonal periodicity present in poultry environmental data, including daily ventilation cycles and recurring management activities. This initial forecasting stage establishes a stable baseline that captures expected trends while reducing noise and trend bias.

Residual learning is introduced to address the limitations of SARIMA in handling nonlinear and sudden environmental fluctuations. SARIMA first generates the baseline prediction as formulated in Equation 7, followed by residual error calculation representing the difference between the actual observations and SARIMA forecasts, as expressed in Equation 8. These residuals sequences contain complex nonlinear dynamics, including sudden ammonia accumulation, temperature increases, and delayed microclimate responses that cannot be adequately represented using linear statistical models alone.

The LSTM network is subsequently trained exclusively on the residual sequences, allowing it to focus on learning nonlinear temporal dependencies without interference from linear or seasonal structures already modeled by SARIMA. The final forecast is obtained by combining the SARIMA baseline prediction with the residual corrections generated by the LSTM model, as formulated in Equation 9.

This separation of learning responsibilities improves model interpretability, enhances forecasting stability, and reduces the risk of overfitting. By explicitly separating linear-seasonal modeling from nonlinear temporal learning, the residual-based LSTM-SARIMA hybrid framework achieves superior prediction accuracy and robustness compared to standalone forecasting models, making it highly suitable for real-time microclimate monitoring in closed-type poultry houses [21].

$$A_t = L_t + N_t \tag{7}$$

$$R_t = A_t + \hat{L}_t \tag{8}$$

$$\hat{A}_t = \hat{L}_t + \hat{N}_t \tag{9}$$

Explanation:
$A_t$ = Data at Time
$L_t$ = Linear Data
$N_t$ = Non-linear Data
$R_t$ = Residual learning

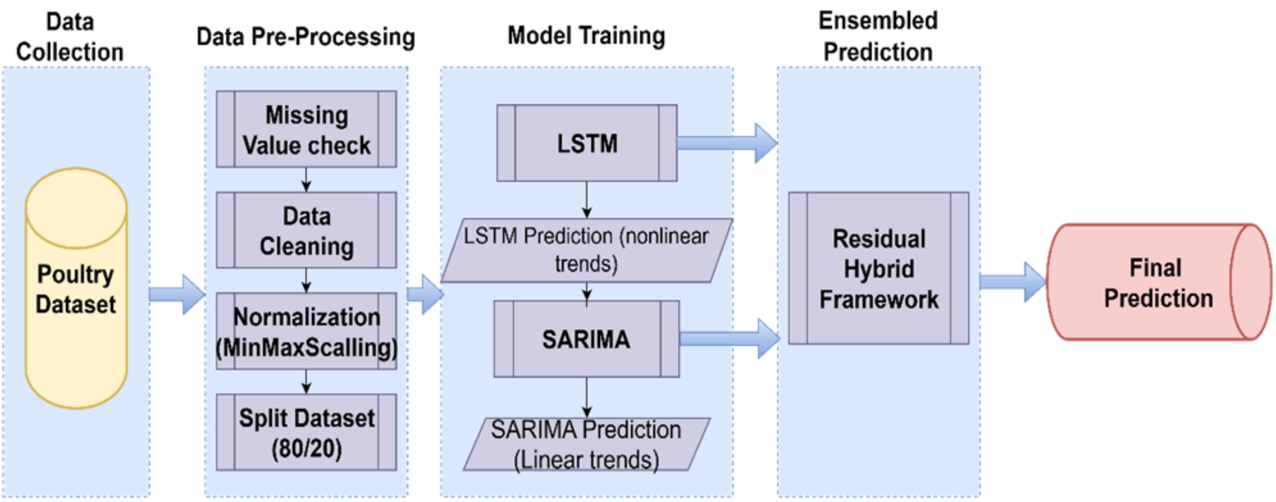


*Figure 3. LSTM+SARIMA Architecture*

**2.9 Set Hyperparameter and Training**

The experiment conducted using several batch size configurations (16, 32, and 64) with 200 training epochs to determine the optimal learning stability for the LSTM model. The final configuration consisted of three stacked LSTM layers containing 16, 32, and 64 units, combined with a dropout rate of 0.3 and an L2 regularization parameter of (1e-4) to mitigate overfitting.

The Adam optimizer together with the Huber loss function was employed to improve convergence stability and enhance robustness against outliers. The combination of Huber loss and residual learning increases resilience to sensor noise and transient measurement inaccuracies frequently encountered in IoT-based poultry environmental monitoring systems [22]. Based on the experimental evaluation, a batch size of 16 and 200 epochs provided the most balanced performance and training stability.

Hyperparameter optimization for the SARIMA model involved tuning both the non-seasonal (p, d, q) and seasonal (P, D, Q, m) components to achieve minimal Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. Following iterative evaluation, the optimal configuration was determined as (p, d, q) = (2, 1, 2) and (P, D, Q, m) = (1, 0, 1, 7), which effectively captured weekly seasonal patterns and linear relationships.

Residual diagnostic analysis was subsequently conducted to verify that the SARIMA residuals followed a white-noise distribution [23], thereby confirming the suitability of the model for linear trend forecasting. The integration of SARIMA and LSTM enabled the hybrid framework to simultaneously model linear seasonality and nonlinear temporal dynamics, resulting in a balanced and accurate forecasting system.

Model performance was evaluated using several standard forecasting error metrics. RMSE, as formulated in Equation 10, measures the overall magnitude of prediction error, while MAE, presented in Equation 11, quantifies the average prediction deviation. MAPE, shown in Equation 12, evaluates relative forecasting accuracy, whereas the coefficient of determination ($R^2$), formulated in Equation 13, measures the overall goodness-of-fit of the model. These evaluation metrics provide objective validation of predictive reliability within the proposed hybrid framework, where SARIMA captures linear-seasonal structures and LSTM learns nonlinear temporal dynamics [24].

$$RMSE \sqrt{\frac{1}{n}\sum_{i=1}^{n} (Yi - \hat{Y}i)^{2}} \tag{10}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|Yi - \hat{Y}i\right| \tag{11}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{Yi - \hat{Y}i}{Yi}\right| \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(d_i - \widehat{d_\iota})^2}{\sum_{i=1}^{n}(d_i - \widehat{d_\iota})^2} \tag{13}$$

### 2.10 Creating Web Monitoring and Database

Figure 4 illustrates the architecture and development process of the web monitoring system and database integration. The system utilizes the Flutter framework for web-based environmental monitoring, enabling cross-platform accessibility across desktop computers, smartphones, and tablets [25], [26]. The frontend was developed using Visual Studio Code and provides modules for real-time environmental visualization and alarm notifications. User authentication is implemented through Google Sign-In, where login and registration are restricted to Google accounts. User credentials are securely stored and managed within the Firebase database to ensure data integrity and controlled system access. The backend system was developed using Python with the Flask framework, enabling the trained LSTM and SARIMA models to process historical and real-time sensor data and generate forecasting outputs through a JSON API [27]. MongoDB function as the primary database for storing sensor data with timestamped sensor measurements and prediction results for future analysis and monitoring purposes. The development process also included debugging, synchronization testing between the web application and database system [28], and deployment validation to ensure stable real-time operation.

Figure 5 presents the implemented monitoring interface named *PoultriQ*. During system observation, the recorded environmental parameters included an ammonia concentration of 0.87 ppm, litter moisture of 100%, and a temperature of 31.40 °C. These measurements were obtained during a maintenance phase in which the enclosed poultry house was thoroughly cleaned and prepared for operation. The observed 100% litter moisture value resulted from the default threshold configuration of the moisture sensor. A decrease below this threshold indicates the beginning of litter dampness detection. During the maintenance process the removal of litter waste and improvements in ventilation significantly reduced ammonia concentration, while residual moisture from cleaning activities increased the measured litter moisture values. These environmental conditions represent a controlled maintenance state rather than normal production operation, demonstrating the capability of the proposed monitoring system to accurately capture real-time environmental fluctuations.

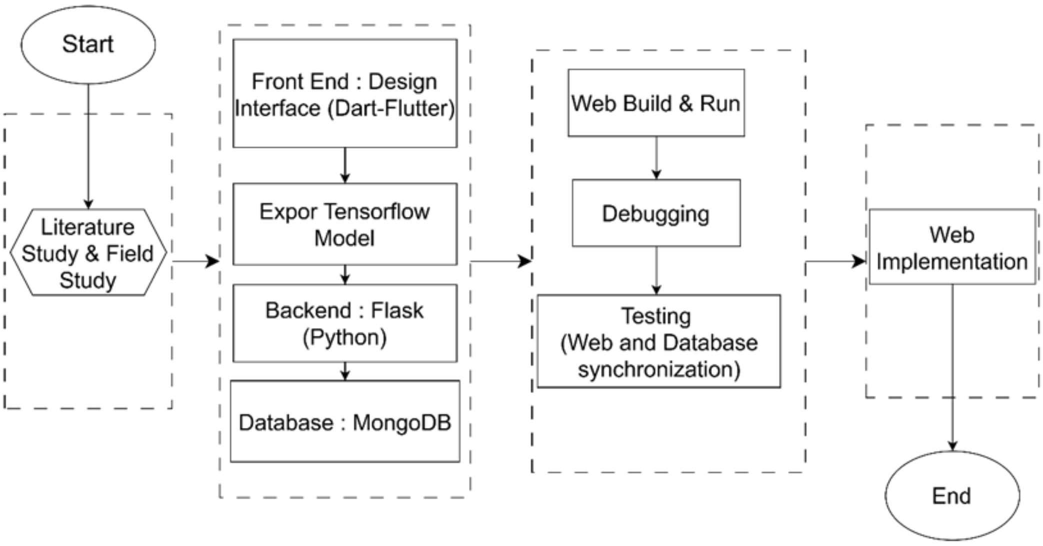


*Figure 4. Flowchart for Creating Web and Database*

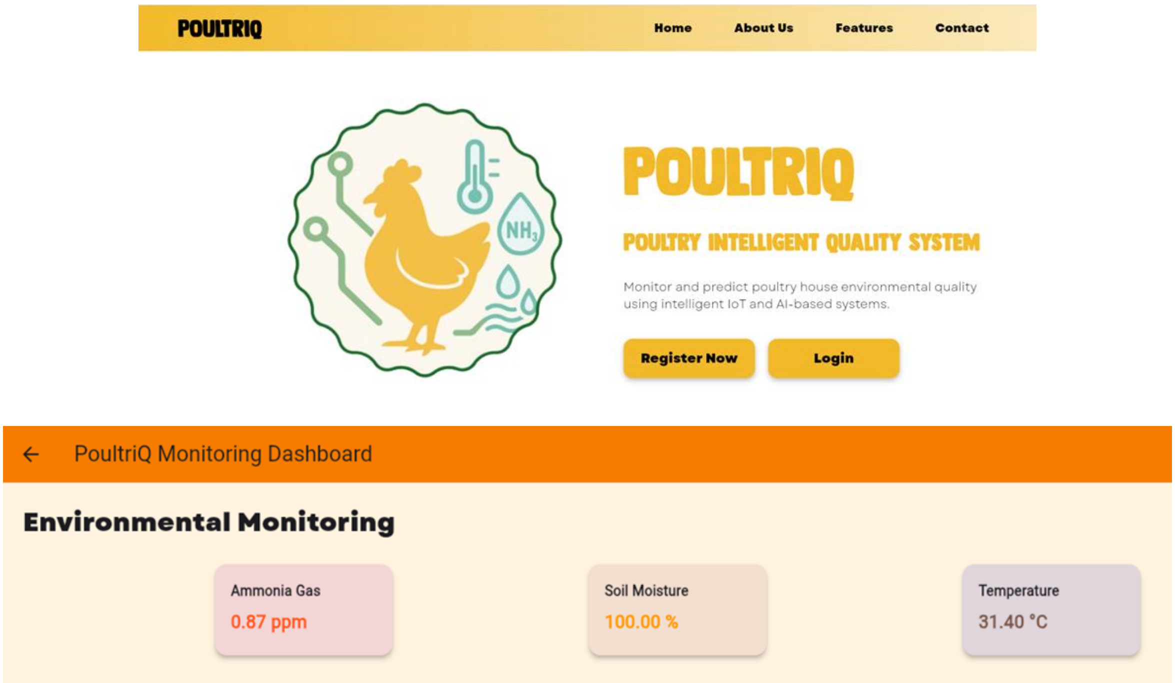


*Figure 5. Visualization of Homepage on Web Implementation and Evironmental Monitoring*

## 3. Results and Discussion

### 3.1 Comparison between the proposed Model and the RF-SARIMA hybrid Model

This study evaluates the performance of two residual-based hybrid forecasting models: LSTM-SARIMA and RF-SARIMA. Both approaches utilize SARIMA to model linear and seasonal trends, while a secondary learning model is employed to capture the remaining nonlinear residual patterns. As presented in Table 1, the LSTM-SARIMA model outperforms the RF-SARIMA model across all evaluation metrics. These results indicate that LSTM is more effective in learning residual temporal patterns from environmental time-series data [4], [5]. The primary advantage of LSTM-SARIMA framework lies in its ability to capture temporal dependencies and preserve sequential information, which are essential for modeling dynamically changing microclimate conditions within poultry houses.

In contrast, although RF-SARIMA can identify nonlinear relationships through tree-based learning mechanisms, the absence of temporal memory limits its effectiveness in performing time-dependent residual correction. Consequently, RF-SARIMA exhibits lower forecasting accuracy and reduced prediction stability compared to the proposed LSTM-SARIMA framework.

The findings demonstrate that integrating LSTM within the residual learning framework provides a substantial improvement in forecasting performance. Therefore, the proposed LSTM-SARIMA model is more suitable for short-term forecasting and early warning applications in enclosed poultry housing systems.

*Table 1. Comparison Model*

| Model | Parameter Metric | | | | |
|---|---|---|---|---|---|
| | MAE | MSE | RMSE | MAPE | $R^2$ |
| LSTM-SARIMA | 0.62 | 0.55 | 0.58 | 7.89 | 0.86 |
| RF-SARIMA | 0.67 | 0.73 | 0.82 | 9.33 | 0.74 |

Table 1 indicates that the LSTM-SARIMA model achieves superior performance with lower error values compared to the RF-SARIMA model across all error-based evaluation metrics. The lower MAE value indicates smaller average deviations between predicted and actual observations, enbaling more accurate short-term environmental forecasting.

Similarly, the lower MSE and RMSE values demonstrate that LSTM-SARIMA model is more robust against large prediction errors, particularly during sudden environmental fluctuations such as rapid increases in ammonia concentration. Moreover, the lower MAPE value reflects more consistent predictive performance under varying environmental conditions, thereby reducing relative forecasting uncertainty.

These findings confirm that the LSTM-SARIMA framework provides more accurate and stable predictions than RF-SARIMA for environmental time-series forecasting tasks. The consistent reduction across all error metrics highlights the effectiveness of LSTM in correcting residual forecasting errors and improving the overall reliability of hybrid forecasting within closed-type poultry housing systems [30].

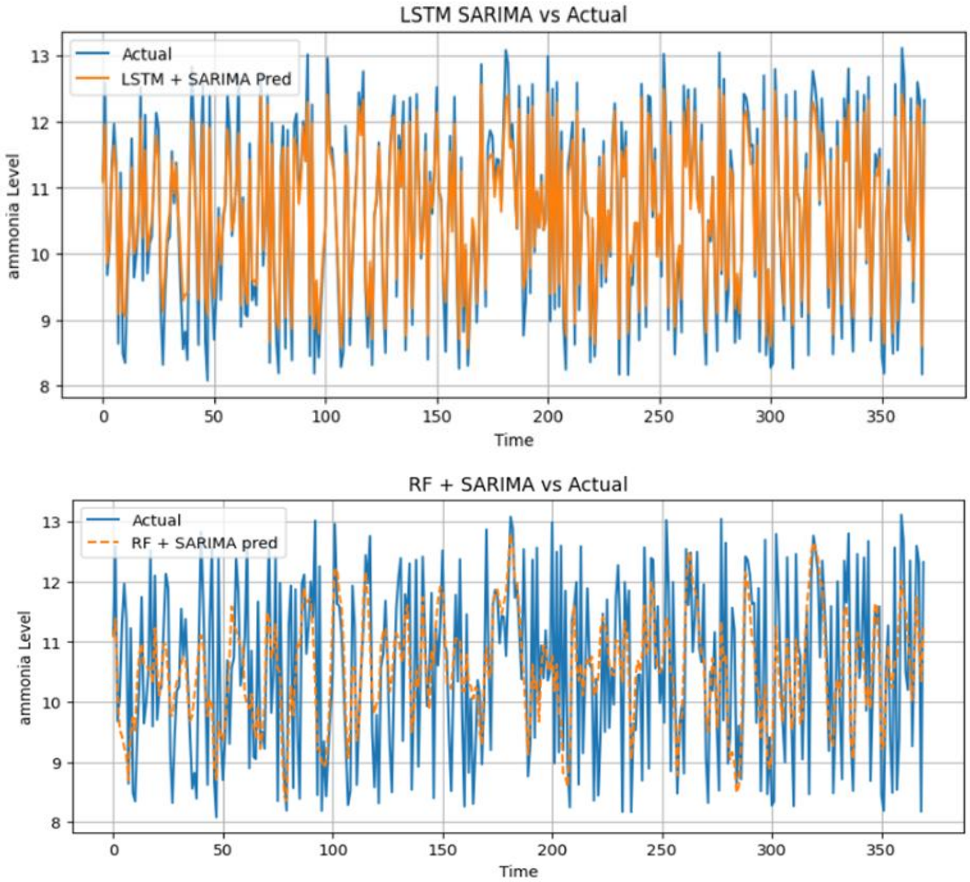


*Figure 6. Model Hybrid LSTM-SARIMA vs RF-SARIMA Comparison*

Figure 6 presents a visual comparison between the actual ammonia concentration values and forecasts generated by the LSTM-SARIMA and RF-SARIMA models. The LSTM-SARIMA model closely follows the actual time-series pattern, producing smoother and more continuous predictions with smaller deviations from the observed values.

This strong visual correspondence supports the lower MAE, MSE, and RMSE values reported in Table 1, indicating reduced average and extreme prediction errors.

In contrast, the RF-SARIMA model exhibits greater variability and more frequent deviations from the actual data, particularly during sudden fluctuations in ammonia concentration. These visual inconsistencies correspond to the higher error metrics obtained by RF-SARIMA, reflecting lower forecasting stability and reduced prediction reliability. Overall, the results demonstrate that the LSTM-SARIMA framework provides more accurate and consistent forecasting performance, especially under rapidly changing environmental conditions. The graphical analysis further validates the quantitative error evaluation and confirms the effectiveness of LSTM-SARIMA for short-term ammonia forecasting in closed-type poultry housing systems.

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### 3.2 Comparison between the proposed Model to Prior Research

This study evaluates the proposed hybrid forecasting model against several machine learning hybrid approaches, including RF-SARIMA, and compares its performance with previous LSTM-SARIMA implementations reported in prior studies. This comparison is important for assessing the generalization capability and robustness of the proposed hybrid framework across different datasets, application domains, and forecasting environments. By comparing forecasting accuracy, dataset characteristics, and methodological approaches from previous studies, this research highlights the improved learning stability and predictive reliability achieved by the proposed LSTM–SARIMA model, particularly in the context of time-series forecasting in poultry farming applications.

*Table 2. Comparison Model to Prior Research*

| Author | Year | Dataset | RMSE |
|---|---|---|---|
| Naumi Krishna K. Panicker, et al [4] | 2024 | Monthly Aerosol Optical Deph | 0.1508 |
| Diwakar Naidu, et al [5] | 2025 | Rainfall Forecasting Zone | 41.7 |
| Azhar Aiman Dzulfiqar, et al [23] | 2025 | Butterfly Valve erosion | 0.936 |
| J. S. Adeyeye, et al [29] | 2023 | Malaria Incidentt | 11234.2 |
| Yongxin Dai, et al [10] | 2025 | Rock Slope Slide | 1.644 |
| Proposed Model | 2025 | Enclosed Poultry Environmental | 0.58 |

Table 2 compares the RMSE values of the proposed LSTM-SARIMA model with those reported in previous studies employing similar hybrid forecasting approaches across multiple domains. The proposed model achieved an RMSE value of 0.58 when applied to enclosed poultry house environmental data, indicating strong forecasting accuracy under dynamically changing microclimate conditions.

Previous work by Naumi Krishna reported a lower RMSE value of 0.1508 for monthly Aerosol Optical Depth forecasting, which was derived from relatively smooth and aggregated time-series data characterized by stable temporal trends. In contrast, Diwakar Naidu achieved an RMSE of 41.7 in rainfall forecasting, while J. S. Adeyeye reported an RMSE of 11234.2 for malaria incidence prediction.

The substantially different RMSE values across studies are influenced by variations in dataset scales, temporal frequency, environmental variability, and data collection methodologies, which often involve significantly larger numerical ranges and extensive historical records.

Furthermore, several previous studies primarily relied on offline historical datasets rather than real-time environmental monitoring systems. Therefore, the RMSE value of 0.58 achieved by the proposed framework demonstrates that the model performs reliably within a dynamic and high-variability poultry environmental monitoring context.

## 4. Conclusion

### 4.1 Evaluation Results of Proposed Model

The evaluation results confirm that the proposed LSTM–SARIMA hybrid model effectively captures poultry house environmental conditions by simultaneously learning nonlinear temporal dependencies and linear seasonal patterns. The achieved reductions in MAE and RMSE, together with a high $R^2$ value, indicate improved forecasting stability and smaller deviations from actual ammonia concentration, temperature, and litter moisture measurements. This performance enables early detection of microclimate anomalies and supports responsive environmental management within enclosed poultry houses, thereby reducing prolonged livestock exposure to unfavorable environmental conditions.

Nevertheless, several limitations should be acknowledged. The LSTM component requires a sufficient amount of historical data and higher computational resources compared to purely statistical models, which may limit deployment on low-power edge devices. In addition, the current implementation still relies on offline training and does not yet incorporate continuous online learning, making the model potentially sensitive to long-term shifts in environmental patterns or changes in poultry management practices.

For practical deployment, real-time adaptive learning could be implemented through periodic LSTM model updates using sliding-window retraining or incremental learning approaches. Furthermore, deploying inference processes on edge computing devices would enable low-latency forecasting directly at the poultry house level, while centralized servers could manage scheduled model updates and parameter synchronization. This architecture also support scalability across multiple farms, as the modular IoT sensor integration together with the Flask–MongoDB backend facilitates distributed data collection and centralized model management. Supported by this infrastructure, the proposed LSTM-SARIMA framework can be extended to larger datasets and geographically distributed poultry farming environments without significant degradation in forecasting performance. Overall, the proposed hybrid framework provides a robust and scalable foundation for intelligent, real-time microclimate monitoring and proactive environmental management in precision poultry farming systems.

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