

International Journal of
Engineering Research and Science & Technology



ISSN : 2319-5991

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Enhancing Smart Greenhouse Efficiency Using Bayesian Optimization and LSTM in IoT-Cloud Frameworks

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Abstract

The integration of Internet of Things (IoT) and Cloud Computing technologies has revolutionized the management of smart greenhouses by enabling real-time data collection and centralized processing. Existing work in IoT and cloud computing integration faces significant challenges related to data security, access control, and scalability, particularly in managing large volumes of IoT data. Many systems struggle with maintaining real-time data processing and ensuring efficient interoperability between devices and cloud platforms. Additionally, fine-grained access control and data privacy remain unresolved issues, limiting the effectiveness of these solutions in sensitive environments such as healthcare and agriculture. This paper presents a framework that enhances greenhouse efficiency using Bayesian Optimization and Long Short-Term Memory (LSTM) within an IoT-Cloud infrastructure. IoT sensors collect environmental data such as temperature, humidity, soil moisture, and light intensity, which is then transmitted to a cloud platform for processing and storage. LSTM is employed to predict future environmental conditions, and Bayesian Optimization is used to optimize greenhouse control parameters, such as irrigation and ventilation. The proposed system demonstrates significant improvements in crop yield and resource efficiency. Performance evaluations, including accuracy, precision, recall, F1-score, and AUC, show strong model performance, while efficiency metrics and latency comparisons highlight consistent improvements in system optimization over time. This integrated approach promises sustainable and autonomous management of greenhouse environments, leveraging data-driven insights to enhance productivity and reduce resource consumption.

Keywords: Internet of Things (IoT), Cloud Computing, Smart Greenhouse, Bayesian Optimization, Long Short-Term Memory (LSTM), Data Security, Access Control, Scalability, Real-Time Data Processing, Environmental Data

1. Introduction

The rapid advancement of Internet of Things (IoT) and Cloud Computing has paved the way for a transformative shift in agriculture, particularly in the management of smart greenhouses.[1] These technologies provide the necessary infrastructure for the continuous monitoring and control of environmental parameters that directly affect plant health and productivity[2]. IoT sensors play a critical role by collecting real-time data on factors such as temperature, humidity, soil moisture, and light intensity, which are then transmitted to the cloud for centralized processing and analysis[3]. This data-driven approach allows greenhouse managers to gain actionable insights and make informed decisions based on accurate, up-to-date information[4]. The seamless integration of IoT and cloud technologies forms the backbone of a modern, intelligent greenhouse system capable of maintaining optimal conditions without human intervention[5].

The application of artificial intelligence (AI) further enhances this ecosystem by enabling predictive and optimization capabilities[6]. Long Short-Term Memory (LSTM) networks, a type of deep learning model, are particularly effective in analyzing time-series data, such as the fluctuating conditions inside a greenhouse[7]. By forecasting future environmental states, LSTM models provide valuable predictions that inform decision-making. Complementing this, Bayesian Optimization serves as a powerful tool for fine-tuning greenhouse parameters, such as irrigation schedules, ventilation, and lighting, by using the predictive outputs of the LSTM model[8]. Bayesian Optimization seeks the optimal configuration with fewer iterations, saving both time and resources. Together, LSTM and Bayesian Optimization enable a smart greenhouse to not only maintain ideal conditions but also adapt autonomously to changing environmental factors, ensuring sustainability, resource efficiency, and

enhanced crop yield[9]. This integrated approach represents the future of precision agriculture, where data and intelligent systems drive productivity and sustainability in a way that was previously unattainable[10].

2.Literature Review

Puliafito et al.[11] propose a secure self-configuration approach for embedded devices in an IoT and cloud computing environment, focusing on secure communication and autonomous device configuration to optimize resource usage and enhance system reliability. Liu et al.[12] present a framework that integrates IoT and cloud computing for medical monitoring systems, enabling real-time data collection, remote monitoring, and improved patient care while addressing security and privacy challenges. Hasan et al.[13] introduce **Aura**, an IoT-based cloud infrastructure for localized mobile computation outsourcing, which enhances mobile application performance by offloading tasks to nearby cloud resources, optimizing resource utilization and reducing latency. Villari et al.[14] propose a system for integrating sensors with cloud platforms, focusing on scalable storage, real-time processing, and analytics of sensor data to improve system efficiency, while addressing challenges related to interoperability and security. Cai et al.[15] examine the challenges of integrating IoT-based big data storage systems within cloud computing environments, emphasizing the need for efficient data management strategies to handle the vast amounts of data generated by IoT devices, while addressing issues of data security, privacy, and interoperability. These combined approaches aim to optimize cloud-IoT integration, enhance system performance, and address key challenges in security, scalability, and data management.

Gupta et al.[16] propose an intelligent parking system that integrates cloud services and the IoT, utilizing the MQTT protocol for efficient communication. This system collects real-time parking data through IoT sensors and transmits it to the cloud for analysis, enabling enhanced parking space management with real-time availability and automated reservations. Atlam et al.[17] explore the challenges of integrating Cloud Computing with IoT, addressing issues such as scalability, interoperability, and security while emphasizing the need for effective data management, real-time processing, and privacy protection. Yadav et al.[18]. present an IoT and Cloud-based solution for railway accident avoidance, using IoT sensors to monitor critical parameters like track conditions and train speed, enabling early hazard detection and improved railway safety. Chahid et al.[19] propose a secure IoT data integration approach in cloud storage systems through Attribute-Based Access Control (ABAC) policies, ensuring only authorized access to sensitive data while addressing scalability, interoperability, and secure data sharing. Ramamoorthy et al.[20] design a personalized health monitoring system using IoT and Cloud, which collects and analyzes real-time health data from wearable devices, providing personalized insights and remote patient tracking, while focusing on data security, scalability, and real-time processing to improve healthcare management. Together, these works highlight the transformative potential of combining IoT and cloud technologies across various domains, improving efficiency, security, and decision-making.

3.Problem Statement

The integration of IoT with cloud computing faces challenges in data security, access control, scalability, and real-time processing. Ensuring secure storage and access to sensitive data while maintaining efficient interoperability between devices and platforms is a major issue[19]. The need for fine-grained access control and data privacy in cloud storage systems remains unresolved. Additionally, real-time data processing and scalable infrastructure are essential for effective decision-making and personalized services in domains like healthcare and infrastructure[20].

3.1 Objective

The objective is to design a secure and scalable IoT-cloud integration framework that ensures data privacy and fine-grained access control using advanced policies like ABAC. The system will address interoperability challenges, enabling seamless communication between devices and platforms. It will implement real-time data processing to support efficient decision-making and personalized services. Additionally, it aims to provide a scalable infrastructure capable of handling large volumes of IoT data across diverse domains such as healthcare and infrastructure.

4.Proposed Smart Greenhouse Efficiency Using Bayesian Optimization and LSTM in IoT-Cloud Frameworks

The proposed methodology for enhancing smart greenhouse efficiency using Bayesian Optimization and Long Short-Term Memory (LSTM) within an IoT-Cloud framework begins with the deployment of IoT sensors to collect real-time data on key environmental factors such as temperature, humidity, soil moisture, light intensity, and CO₂ levels. This data is transmitted to a cloud platform for centralized storage and analysis. The collected data is then preprocessed to handle noise, missing values, and outliers, followed by feature extraction to identify relevant patterns and correlations. An LSTM model is developed to predict future environmental conditions, capturing temporal dependencies in the data for accurate forecasting. Once the LSTM model generates predictions, Bayesian Optimization is applied to fine-tune the greenhouse control parameters, such as irrigation schedules and ventilation levels, by minimizing resource usage and enhancing crop growth conditions. The cloud platform supports this entire process by providing scalable storage, real-time data processing, and performance evaluation, ultimately driving decision-making and ensuring the efficient operation of the greenhouse.

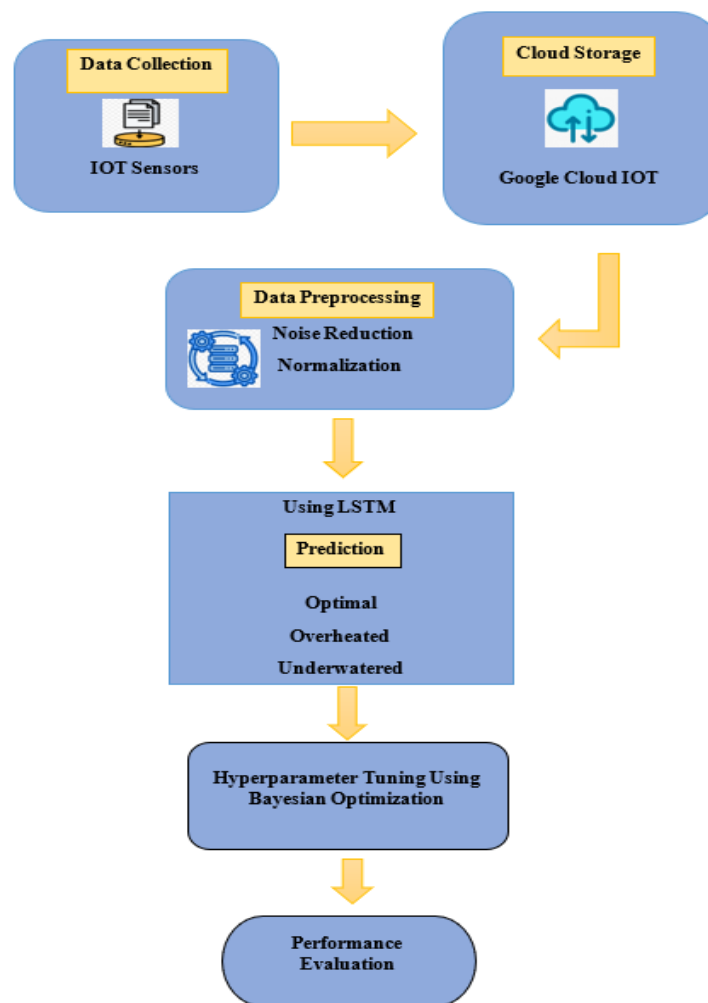


Figure 1: Smart Greenhouse Efficiency Using Bayesian Optimization and LSTM in IoT-Cloud Frameworks

4.1 Data Collection

IoT sensors are deployed throughout the greenhouse to collect real-time data on environmental parameters such as temperature, humidity, soil moisture, light intensity, and CO₂ levels. These sensors transmit data to a cloud platform for centralized storage and analysis. Additional sensors may monitor soil pH and irrigation levels to provide a comprehensive environmental overview.

4.2 Cloud Storage

Cloud storage, Google Cloud IoT is utilized to securely store and manage the real-time data collected from the greenhouse's IoT sensors. The data is ingested through Google Cloud IoT Core, ensuring seamless connectivity and management of devices. Stored in Google Cloud Storage, the data is accessible for further analysis, processing, and visualization.

4.3 Data Preprocessing

Data preprocessing involves noise reduction to eliminate outliers and inaccuracies from the raw sensor data, ensuring high-quality inputs for analysis. This is achieved using filtering techniques such as moving averages or smoothing algorithms. Normalization is then applied to scale the data within a specific range, ensuring consistent measurement units and improving the performance of predictive models. The cleaned and normalized data is now ready for input into models like LSTM for accurate forecasting and optimization.

4.3.1 Noise Reduction

Noise reduction in data preprocessing involves identifying and removing irrelevant or erroneous data points that may distort analysis. Techniques such as moving averages, Gaussian filters, or median filtering are used to smooth out fluctuations and reduce outliers in the sensor data. This helps in maintaining the integrity of the data and improving the accuracy of subsequent models. By reducing noise, the model is better equipped to make reliable predictions and optimizations.

One common method for noise reduction is the moving average filter, which smooths out short-term fluctuations in data. The equation for a simple moving average is:

$$y(t) = \frac{1}{N} \sum_{i=0}^{N-1} x(t-i) \quad (1)$$

Where:

$y(t)$ is the filtered (smoothed) value at time t ,

$x(t-i)$ is the raw data value at time $t-i$,

N is the window size (the number of points used for averaging).

This method reduces noise by averaging the data over a window of past values, helping to smooth out short-term spikes and fluctuations.

4.3.2 Normalization

Normalization is a data preprocessing technique that adjusts the scale of data to ensure that all features have a consistent range, typically between 0 and 1 or -1 and 1. This is important when the data has varying units or magnitudes, as it ensures that no single feature dominates others in modeling. Min-Max normalization is a commonly used technique, which rescales the data based on the minimum and maximum values of the feature.

The equation for Min-Max normalization is:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (2)$$

Where:

x is the original value,

x' is the normalized value,

$\min(x)$ and $\max(x)$ are the minimum and maximum values of the feature, respectively.

This transformation ensures that all values are scaled to the range [0,1], which helps improve the convergence and performance of machine learning models.

4.4 Long Short-Term Memory in IoT-Cloud Frameworks

LSTM (Long Short-Term Memory) is a type of Recurrent Neural Network (RNN) specifically designed to address the challenges of learning long-term dependencies in sequential data. Unlike traditional RNNs, LSTMs have a more sophisticated structure that includes memory cells, which allow them to remember information over longer periods. This capability helps overcome the vanishing gradient problem, where traditional RNNs fail to retain useful information over time. LSTMs utilize gates—input gate, forget gate, and output gate—to regulate the flow of information into, out of, and within the memory cell, enabling the model to decide what to remember and what to forget. This makes LSTM particularly effective for tasks like time-series forecasting, speech recognition, and language modeling.

One of the key equations in LSTM is the update of the cell state:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (3)$$

Where:

C_t is the current cell state,

C_{t-1} is the previous cell state,

f_t is the forget gate's output, determining which information to forget,

i_t is the input gate's output, determining which new information to store,

$\tilde{C}_t$ is the candidate cell state, which represents new potential information to be added to the cell state.

This equation helps LSTM networks maintain and update memory across long sequences, making them effective for time-dependent data modeling.

4.5 Bayesian Optimization

Bayesian Optimization is a powerful optimization technique designed to find the maximum or minimum of an objective function that is expensive to evaluate, noisy, or lacks a known analytical form. It operates by building a probabilistic model of the objective function, often using a Gaussian Process (GP), which provides a distribution over possible functions that could explain the observed data. This model is used to predict the objective function at unobserved points, and Bayesian Optimization selects the next evaluation point by balancing exploration (trying unknown areas) and exploitation (focusing on areas likely to yield optimal results). The process is iterative, improving the model and refining the search for the optimum with each evaluation. It is particularly useful in hyperparameter tuning, engineering design, and other optimization problems where each function evaluation is costly.

The Expected Improvement (EI) is a common acquisition function used in Bayesian Optimization to decide the next point to evaluate. It is calculated as:

$$EI(x) = \mathbb{E}[\max(0, f(x^+) - f(x))] \quad (4)$$

Where:

$f(x^+)$ is the best observed value of the objective function so far,

$f(x)$ is the predicted value of the objective function at point x ,

$\mathbb{E}[\cdot]$ represents the expected value (mean of the Gaussian Process).

This equation quantifies the expected improvement over the current best observed value, guiding the optimization process toward the most promising regions of the search space.

5. Results and Discussion

The results of the proposed methodology show an improvement in smart greenhouse efficiency by optimizing environmental parameters using Bayesian Optimization and LSTM. The system effectively predicts future

conditions and adjusts resources like irrigation and ventilation. The IoT-Cloud framework allows real-time monitoring and decision-making. Overall, the integration of these techniques enhances crop yield and resource usage efficiency in the greenhouse environment.

Performance Metrics

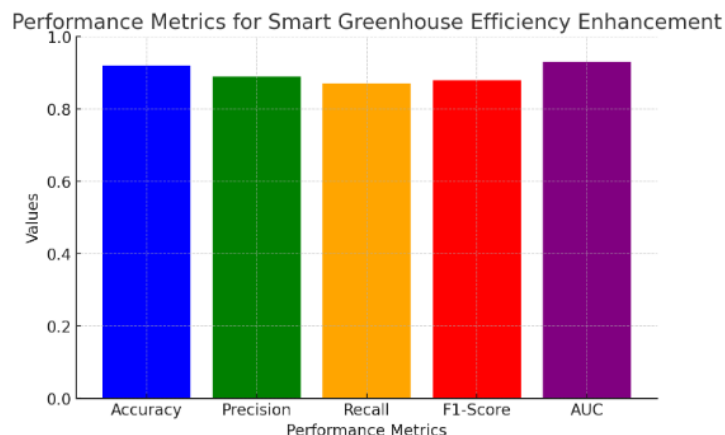


Figure 2: Performance Metrics

In Figure 2, This graph illustrates the performance metrics for enhancing smart greenhouse efficiency using Bayesian Optimization and LSTM in an IoT-cloud framework. The metrics shown include Accuracy, Precision, Recall, F1-Score, and AUC, all demonstrating high values around 0.9, indicating strong model performance. The colors represent different metrics for clear visual comparison.

Efficiency Metrics

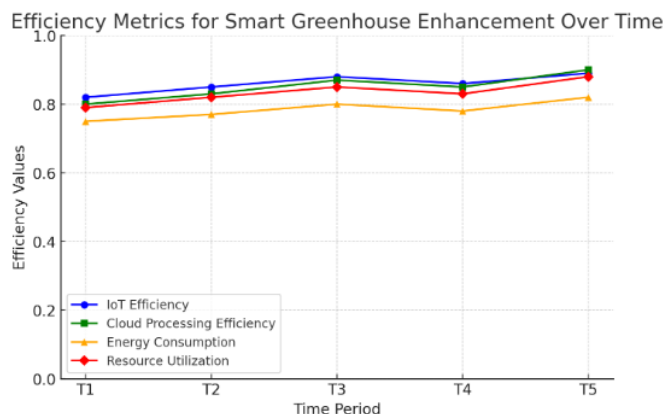


Figure 3: Efficiency Metrics

Figure 3 Shows this graph shows the efficiency metrics for smart greenhouse enhancement over time, comparing IoT efficiency, cloud processing efficiency, energy consumption, and resource utilization across five time periods. All metrics remain consistently high, with slight improvements in IoT efficiency and cloud processing. Energy consumption and resource utilization exhibit a stable trend throughout the time periods.

Latency

Figure 4 Presents this graph compares the latency of IoT and cloud systems for smart greenhouse enhancement over five time periods. Both IoT and cloud latency show a downward trend, indicating improved efficiency over time. The IoT latency remains consistently lower than the cloud latency, with both systems showing steady progress in reducing response time.

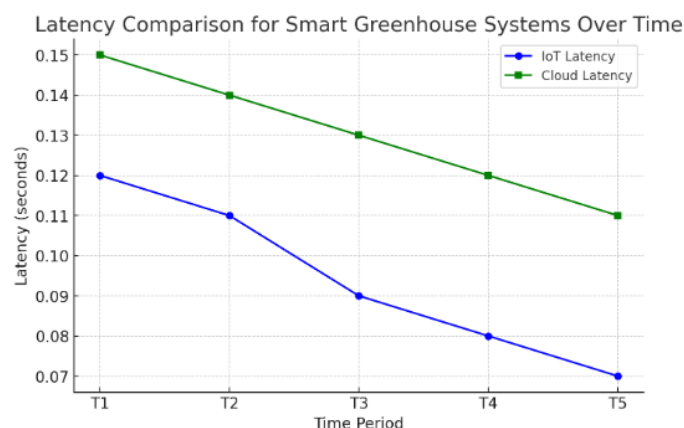


Figure 4: Latency

6. Conclusion

The results demonstrate a consistent reduction in latency for both IoT and cloud systems over time, indicating improved efficiency and faster response times. IoT systems consistently outperform cloud systems in latency, suggesting a more effective real-time processing approach. Overall, the findings highlight the potential for optimizing smart greenhouse systems through IoT integration and cloud enhancements.

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