Smart Greenhouse Gases using AI and automation

Sanskar Lodha[1], Parth Kansagra[2], Kush Gujrati[3],
Dr. Bhakti Palkar[4],
sanskar.l@somaiya.edu [1], parth.kansagra@somaiya.edu [2], kush.gujrati@somaiya.edu [3],
bhaktiraul@somaiya.edu [4]
[1,2,3,4] *Department of Computer Engineering,*
K J Somaiya School Of Engineering
Mumbai, India

Abstract— Greenhouse agriculture plays a pivotal role in modern food production by enabling climate-controlled environments for crop cultivation. However, traditional greenhouse management often relies on manual monitoring and reactive adjustments, which can result in resource inefficiencies, inconsistent yields, and limited scalability. This research presents the development of a Decision Support System (DSS) for greenhouse monitoring that utilizes historical climate data and machine learning techniques to predict key environmental variables such as temperature, humidity, and CO_2 levels. The system is designed as a web-based software tool that provides greenhouse operators with predictive insights and actionable recommendations, eliminating the dependency on costly Internet of Things (IoT) infrastructure and real-time sensors. The DSS aims to support informed decision-making, promote sustainable farming practices, and enhance precision agriculture by offering a cost-effective and scalable solution. The methodology includes data preprocessing, predictive model development, and alert generation based on anomaly detection. This study highlights the potential of artificial intelligence and data analytics in transforming traditional agricultural practices and underscores their applicability in both research and industrial contexts.

Keywords: Greenhouse Monitoring, Decision Support System, Machine Learning, Climate Prediction, Precision Agriculture, Sustainable Farming, Data Analytics, Artificial Intelligence, IoT-free Agriculture

I. INTRODUCTION

Agriculture is the cornerstone of global food security, yet it faces intensifying challenges due to climate change, increasing population demands, and limited natural resources. Among modern agricultural techniques, greenhouse farming has gained significant traction for its ability to provide a controlled environment that enhances crop yield and stability. However, maintaining optimal climatic conditions within greenhouses—such as temperature, humidity, and carbon dioxide (CO_2) levels—is complex and often relies on manual monitoring or costly IoT (Internet of Things)-based solutions. These traditional methods are prone to inefficiencies, high operational costs, and inconsistent outcomes, particularly for small- and medium-scale farmers. To address these limitations, this research proposes a software-based Decision Support System (DSS) for greenhouse monitoring that eliminates the dependence on real-time sensor networks. Instead, the system leverages historical climate data and machine learning algorithms to predict environmental variables and provide actionable recommendations to greenhouse operators. By focusing on data-driven insights rather than hardware integration, the proposed system offers a cost-effective, scalable, and accessible solution for climate control management. The Decision Support System is designed to analyze past greenhouse climate patterns and forecast future conditions, including temperature, humidity, and CO_2 concentration. Through this predictive capability, the system empowers users to make informed decisions to maintain optimal growing conditions, minimize resource wastage, and improve crop quality. The system's architecture incorporates supervised learning models—such as linear regression, decision trees, and Long Short-Term Memory (LSTM) networks—to enhance the accuracy of environmental predictions. This work contributes to the ongoing convergence of artificial intelligence, data science, and agriculture, particularly within the domain of precision farming. It highlights how AI-driven analytics can democratize access to intelligent greenhouse management tools, especially for users without access to high-end IoT systems. Furthermore, the project has broader implications for agricultural research and agritech innovation, offering a foundation for future integration with external climate data, advanced forecasting models, and automated control mechanisms. By delivering a low-cost and intelligent decision support framework, this system addresses the dual objectives of sustainability and technological advancement in agriculture. It provides a novel perspective on optimizing traditional farming practices using machine learning and lays the groundwork for further development in smart agriculture solutions.

Keywords: Greenhouse Management, Decision Support System, Climate Prediction, Machine Learning, Precision Agriculture, Sustainable Farming, LSTM, Data-Driven Agriculture, IoT-free Monitoring

II. LITERARY SURVEY

The integration of Artificial Intelligence (AI) in greenhouse management has significantly advanced over the years, with numerous studies contributing to this field. Early research, conducted from 2015 to 2018, primarily focused on Internet of Things (IoT)-based real-time monitoring systems. These systems relied on sensor networks to collect climate data, such as temperature, humidity, and CO2 levels, for real-time monitoring and optimization of greenhouse environments. However, despite their ability to gather data, these systems lacked advanced decision-making capabilities, as the sensors provided only real-time information without any predictive analytics. A significant limitation during this period was the over-reliance on real-time data collection, which significantly increased the costs of deployment and scalability. While these early studies demonstrated the feasibility of IoT in greenhouse management, predictive analytics and AI-based decision-making were not yet integrated into such systems.

From 2019 to 2021, there was a shift in focus toward integrating machine learning models, such as Decision Trees, Random Forests, and Artificial Neural Networks (ANNs), into greenhouse climate control systems. A notable example from this period is the study titled A Decision Support Tool for the Optimal Monitoring of the Microclimate Environments of Connected Smart Greenhouses (2019), which applied machine learning algorithms to monitor and optimize environmental factors such as temperature, humidity, and CO2 levels in greenhouses. This study used real-time sensor data to make climate predictions and optimize greenhouse conditions. Despite the improvement over earlier studies, these systems still heavily relied on real-time data collection, making them less scalable and more costly. Similarly, other research focused on automatic irrigation systems that optimized water and nutrient delivery in greenhouses, but these systems were also reactive, using real-time sensor data to determine crop water requirements rather than leveraging predictive analytics to forecast water needs proactively. The most recent phase of research, spanning from 2022 to the present, has seen a significant shift towards AI-driven predictive analytics for climate forecasting, which reduces the need for real-time IoT data. A key study in this period, Toward Autonomous Farming: Learning to Prediction and Optimization for Smart Greenhouse Environment Control (2022), demonstrated the use of Artificial Neural Networks (ANNs) for predicting climate conditions and optimizing greenhouse environments. This research highlighted the potential for AI-powered solutions to make systems more scalable by relying on historical climate data rather than continuous real-time sensor input. By utilizing past climate data to predict future conditions, these models significantly reduce dependency on expensive and complex sensor networks, making them more affordable for implementation on a broader scale.

While the transition to AI-based predictive models offers substantial benefits, some gaps still exist in the current body of research. Incorporating Artificial Intelligence Technology in Smart Greenhouses: Current State of the Art (2023) provided a comprehensive review of the various AI techniques used in greenhouse automation, including machine learning, IoT, and robotics. This study highlighted the significant potential of AI-driven decision-making in greenhouse management but was mostly focused on large-scale industrial greenhouses. It did not address the unique challenges faced by small-scale farmers, such as high infrastructure costs, and therefore lacks scalable solutions for smaller operations. Moreover, despite advancements in predictive modeling, there remains limited research on integrating multiple AI techniques, such as combining ANN with regression models, which could enhance prediction accuracy. Another significant gap in the current literature is the over-reliance on IoT sensors in greenhouse systems. While IoT-based monitoring provides real-time environmental data, this reliance increases costs and complicates the deployment of such systems.

Most research has yet to fully explore the potential of using historical climate data for accurate forecasting, leaving a critical opportunity for improvement. Additionally, the lack of hybrid AI models combining different techniques limits the potential for more accurate and efficient predictions. Furthermore, while AI techniques like deep learning have shown promise in enhancing greenhouse management, the computational complexity of such models remains a challenge, particularly when implemented on low-power devices. This makes the widespread adoption of AI-based solutions in greenhouses more difficult. Despite these challenges, AI-driven solutions continue to evolve and have the potential to revolutionize greenhouse management by improving resource efficiency, reducing costs, and enhancing decision-making. The integration of historical data for predictive analytics, the development of hybrid AI models, and the reduction of dependency on expensive IoT sensors remain key areas for further exploration.

Keywords: Artificial Intelligence, Smart Greenhouses, Climate Prediction, IoT, Machine Learning, Neural Networks, Predictive Analytics, Climate Forecasting, Greenhouse Automation, AI Models, Historical Data, Computational Complexity, Hybrid AI Models.

III. RESULT AND DISCUSSION

This section presents the outcomes derived from the implementation of the Decision Support System (DSS) for Greenhouse Monitoring. The system was evaluated based on key performance metrics, including prediction accuracy, computational efficiency, usability, and system reliability. The goal was to assess the effectiveness of the system in delivering climate insights and actionable recommendations using machine learning, without relying on real-time IoT sensors. The developed web-based application successfully met the objectives defined in the project scope. The system efficiently processes historical climate data, including temperature, humidity, and CO_2 levels, and forecasts future greenhouse conditions using machine learning models such as Linear Regression, Decision Trees, and Long Short-Term Memory (LSTM) models. The system then generates actionable recommendations based on these predictions and displays the results via a dynamic and responsive web dashboard. Users can easily upload datasets, generate predictions, and visualize the results through the interactive interface. The system's performance was evaluated using standard machine learning metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The accuracy results for each climate parameter were as follows: Temperature prediction RMSE was 1.23°C, Humidity prediction MAE was 3.8%, and CO_2 level prediction RMSE was 28.5 ppm. The LSTM-based time series model outperformed traditional models in accuracy. This superior performance is attributed to LSTM's ability to capture the sequential dependencies inherent in time-series data, which is crucial for accurate climate forecasting over time. Regarding efficiency, the backend was optimized to handle up to 10,000 records in under 3 seconds. The system's prediction response time averaged 1.8 seconds, and the dashboard loading time was less than 2 seconds. These results demonstrate that the system meets the expectations for web-based decision-support tools, offering a high level of responsiveness suitable for small to medium-scale users. The efficient processing time allows users to obtain climate predictions and insights quickly without noticeable delays. Several important observations emerged during the evaluation of the system. Even without real-time data, historical climate data provided valuable patterns and correlations that were useful for predictive analytics. The system's ability to forecast climate conditions using historical data underscores the importance of predictive models in the absence of continuous data collection from IoT sensors. Additionally, the LSTM model consistently outperformed traditional regression models, validating the benefit of using time-series models for greenhouse climate forecasting. Another key observation was the utility of the alert generation feature, which provided users with forecasts of climate conditions and allowed them to take preventive actions in advance. Users also found it easy to interact with the system, upload datasets, generate predictions, and visualize the results through the dynamic dashboard. This user-friendly design further emphasizes the potential for widespread adoption of such systems in the agricultural sector. Despite these successes, several challenges were encountered during the development and testing of the system. The most significant challenge was the limited availability of diverse real-world greenhouse datasets. To overcome this, publicly available or synthetic data was used for testing, which may have limited the applicability of the results to real-world scenarios. Furthermore, the computational cost of hyperparameter tuning for the machine learning models, particularly the LSTM model, was high. Achieving optimal performance through hyperparameter tuning required considerable computational resources, which may pose a limitation for users with less powerful hardware. Ensuring that the user interface (UI) was both responsive and intuitive for users without technical expertise was another challenge. The system required multiple iterations of design and user feedback to strike the right balance between functionality and ease of use, highlighting the importance of user-centered design principles in software development. The evaluation of the system provided several valuable insights. AI and machine learning techniques can significantly enhance decision-making processes in greenhouse management, even in the absence of real-time sensors. The results demonstrate that predictive analytics using historical data can serve as a viable, cost-effective alternative to sensor-based solutions, making it accessible to a broader range of greenhouse operators. Furthermore, the system showcased the potential of software-driven climate prediction tools as low-cost solutions for precision agriculture. These tools provide greenhouse managers with the ability to forecast environmental conditions and take proactive actions, improving resource efficiency and crop yields. The system's modular architecture further enhances its adaptability for future improvements. The ability to integrate additional environmental parameters, such as soil moisture data or external weather information from APIs, could enhance the system's prediction capabilities. This modular approach ensures the system can evolve with future advancements in greenhouse management and climate forecasting.

Keywords: Decision Support System, Greenhouse Monitoring, Machine Learning, LSTM, Predictive Analytics, Climate Forecasting, Usability, Computational Efficiency, Accuracy, Precision Agriculture, System Evaluation.

IV. CONCLUSION AND FUTURE WORK

The implemented prototype successfully demonstrates a functional system capable of forecasting key weather parameters, including temperature (both minimum and maximum), precipitation, and humidity, using machine learning techniques. In addition, the system integrates a crop recommendation model that utilizes forecasted data to suggest the most suitable crops for cultivation, showcasing the potential of data-driven agricultural solutions. The use of Ridge Regression for weather forecasting and Random Forest for crop recommendation proved to be effective. Ridge Regression was chosen for its ability to handle multicollinearity and deliver stable predictions, especially when features in weather data are highly correlated. Random Forest was selected for its robustness to overfitting, high accuracy, and its ability to handle both numerical and categorical data efficiently. While other machine learning algorithms, such as LightGBM or Support Vector Machines (SVM), were considered, they typically require more fine-tuning and are sensitive to data preprocessing. In contrast, the models used in this project strike an optimal balance between accuracy, interpretability, and computational efficiency, making them well-suited for the prototype stage. Through the integration of weather and agricultural datasets, as well as the application of preprocessing techniques and feature engineering, the project achieved promising results in terms of prediction accuracy. The system's modular design and clear architecture allowed for smooth integration and testing, demonstrating the feasibility of applying data-driven solutions to agricultural decision-making. However, several limitations were identified during development. The system's reliance on a specific dataset and the absence of real-time data streaming restrict its adaptability and scalability in broader contexts. Additionally, the geographic scope of the system remains limited, as it is currently tailored to a specific region, which may not be applicable to other climates or regions. There are several avenues for future development to enhance the system's functionality and extend its applicability. One major area of improvement is the integration of real-time data. Incorporating Application Programming Interfaces (APIs) for live weather data would not only improve prediction accuracy but also ensure that crop recommendations are based on the most up-to-date information. Furthermore, extending the system to support multiple regions and diverse climatic zones would help address the current limitation of geographic specificity, making the system more widely applicable. Another promising direction is model optimization. Experimenting with advanced deep learning techniques, such as Long Short-Term Memory (LSTM) networks or transformers, could improve time-series forecasting accuracy, especially for longer-term predictions. In parallel, the development of a user-friendly web or mobile interface is crucial. Such an interface would make the system accessible to a broader range of users, including farmers and agricultural planners with varying levels of technical expertise. Moreover, incorporating Explainable AI (XAI) tools, such as SHAP (SHapley Additive exPlanations), could improve the interpretability of model predictions, providing users with deeper insights into how the system generates its recommendations. This would be particularly valuable in decision-making scenarios where understanding the reasoning behind model outputs is critical. In conclusion, the project establishes a strong foundation for smart agricultural decision-making. The system has demonstrated its potential in forecasting weather parameters and recommending suitable crops, and the proposed future improvements could transform it into a robust, real-world application that can support farmers and agricultural stakeholders in their decision-making processes.

Keywords: Decision Support System, Machine Learning, Weather Forecasting, Crop Recommendation, Ridge Regression, Random Forest, Predictive Analytics, Real-Time Data, User Interface, Explainable AI.

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