**Bulletin of Electrical Engineering and Informatics**
Vol. 14, No. 4, August 2025, pp. 3052~3060
ISSN: 2302-9285, DOI: 10.11591/eei.v14i4.9328 

# Smart wheat agriculture: an in-depth framework for optimized crop agroanalytics utilizing internet of things

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**Article Info**

***Article history:***

Received Sep 20, 2024
Revised Jun 4, 2025
Accepted Jul 5, 2025

***Keywords:***

Crop yield optimization
Internet of things
Precision agriculture
Sustainable farming
Wheat production

**ABSTRACT**

Precision agriculture can be revolutionized by incorporating internet of things (IoT) technologies to maximize crop yield, especially for key crops like wheat. The creation and application of an IoT-enabled monitoring system intended especially for wheat farming is presented in this study. The system provides real-time data on important agronomic characteristics, such as soil health, temperature, humidity, and crop growth stages, by integrating a network of soil moisture sensors, weather stations, and remote sensing devices. With the help of the monitoring system, field conditions can be continuously and remotely observed, giving farmers the ability to make data-driven decisions that improve crop output and resource efficiency. The system can reduce input waste and increase output by optimizing irrigation schedules, adjusting fertilizer applications, and detecting early signs of crop stress or disease through real-time data analysis. Significant gains have been shown in production results, farm sustainability overall, and water usage efficiency in field studies carried out in different wheat-growing locations. According to the research, IoT-based monitoring systems can be extremely helpful in modernizing wheat production by offering useful information that results in more exact and environmentally friendly farming methods.



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## 1. INTRODUCTION

Modern agriculture is characterized by severe challenges, including the enhancement of productivity, efficiency in the use of resources, and environmental sustainability. These are compounded by the increased global demand for food and the increasing impacts of climate change. Among the staple crops essential for global food security, wheat is one of the most widely cultivated and used. Nevertheless, traditional farming practices bring inefficient use of critical resource utilization such as pesticides and fertilizers and water, hence the yields are reduced or degradation occurs in the environment so far. It is prudent that addressing these inefficiencies toward sustainability and productivity in agriculture is a must.

Emerging as a transformative method in agriculture to overcome many challenges is the integration of internet of things (IoT) into agriculture. IoT technologies allow for data collection and analysis in huge volumetric amounts in real time, which helps in providing more accurate and informed decisions. For wheat production, the IoT system promises to constantly monitor crop-specific and environmental parameters, thus improving crop management practices. IoT systems using a network of interconnected sensors and devices can provide very detailed insights into crop health, weather conditions, and soil moisture levels. These insights enable farmers to optimize pest control, fertilization, and irrigation, thereby increasing crop yields and reducing resource wastage.

A plethora of studies have demonstrated the capability of IoT technologies to revolutionize agricultural practices. It has been shown through research that the IoT-enabled monitoring system is a major improvement in resource management and crop productivity. For example, studies [1]-[3] point out that IoT-based solutions can efficiently optimize irrigation. Automated irrigation systems and soil moisture sensors have been found to decrease water usage by several times while maintaining or increasing crop yields. These systems allow for precise scheduling of irrigation based on the real-time conditions of the soil, thus avoiding wastage of water. IoT applications in environmental monitoring have also been widely studied [4]-[6]. Weather stations and remote sensing equipment deployed in the field provide critical data on temperature, humidity, and other parameters. Such data are instrumental in predicting growth phases and mitigating the impacts of adverse weather conditions on crops. Moreover, the integration of IoT with machine learning and data analytics has improved predictive capabilities in agriculture [7]-[9]. Predictive models based on IoT data can predict yields, detect diseases, and optimize resource usage, making farming practices more effective and profitable.

Specific to wheat production, IoT technologies have demonstrated significant benefits. IoT systems have been effectively used to monitor temperature, soil moisture, and crop health in wheat fields [10]-[12]. These capabilities allow for better water and fertilizer management, directly impacting yield improvement. The integration of IoT sensors with imaging technologies has proven effective for early detection of wheat diseases such as rust and blight [13], [14]. Proactive measures enabled by such systems reduce crop losses and minimize reliance on chemical treatments, promoting sustainable farming practices [15], [16]. Furthermore, studies suggest that while the initial cost of IoT infrastructure can be high, the long-term benefits of increased productivity and resource efficiency justify the investment, especially for large-scale farming operations [17]-[20].

Current advances in agriculture utilize IoT and machine learning to improve precision agriculture, disease forecasting, and crop management. IoT-based systems for real-time weather forecasting, soil testing, and monitoring of crop health have been suggested by research, and machine learning algorithms help forecast yields and detect diseases, particularly in wheat yields. Multiple surveys also point towards the effectiveness and future potential of these combined technologies to optimize agricultural operations [21]-[25].

Despite these advancements, several challenges remain. Existing IoT-based solutions often lack customization for specific crops like wheat, and their deployment is limited to experimental settings or large-scale operations. The potential for small- to medium-scale farmers to adopt these technologies remains underexplored. Moreover, many systems focus on individual aspects such as irrigation or disease detection, with limited integration across multiple farming parameters.

This study addresses these gaps by developing and implementing an IoT-enabled crop monitoring system tailored specifically for wheat production. The proposed system integrates various functionalities, including real-time monitoring of soil moisture, weather conditions, and crop health, into a single platform. Unlike previous studies, this research emphasizes holistic management by combining multiple parameters to optimize farming decisions comprehensively.

The remainder of the article is structured to discuss, in further detail, system architecture, sensor selection, and deployment strategies. The field tests are conducted in various wheat-growing regions where crops will yield, water use efficiency and other criteria would determine the sustainability of the whole operation. The findings prove the impact of the system on productivity improvement and waste of resources, comparing the findings with traditional farming. The article concludes by discussing the implications of the system for precision agriculture and possible ways of extending the use of IoT in agriculture.

With a contribution to the area of precision agriculture by pointing out existing system limitations and suggesting a complete, all-encompassing IoT-based solution for wheat production, the work underpinning this article adds valuable inputs. The research outcome demonstrates the practical value of such integrations but opens doors further towards sustainable global food security improvements.

## 2. METHOD

The suggested system is an IoT monitoring system aiming at optimizing wheat production based on collected, processed, and real-time analyses of data. The experimental design section describes in comprehensive, step-by-step ways how the experimental approach and each of the methodology selections in order to emphasize both the technical information available as well as the motivations for the methodologies. That ensures the correctness and reusability of the attained results and proves the truth of the method applied by addressing knowledge gaps.

The system is designed into four main layers: sensing, communication, data processing, and application. These layers ensure a seamless flow of data from acquisition to actionable insights, hence forming a cohesive architecture for efficient and effective monitoring of wheat fields. The architecture diagram of the proposed system is given in Figure 1.

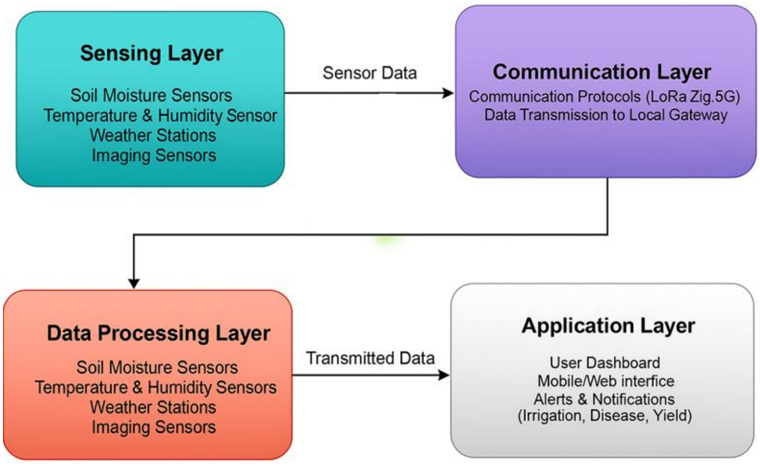


Figure 1. Architecture diagram

In Figure 1, the wheat production IoT-based monitoring system is organized into four primary layers. The sensing layer collects current field information such as soil moisture, temperature, and crop health through sensors. The communication layer provides stable transportation of such data by applying long range (LoRa), WiFi, or cellular networks. Then, the data preprocessing layer pre-processes the gathered data to filter, clean, and reformat it for proper analysis. Lastly, the application layer presents the insights after processing via user-friendly interfaces, assisting farmers in making intelligent and timely choices.

### 2.1. Sensing layer

The sensing layer deals with real-time data gathering by the use of different special sensors deployed strategically in the wheat fields. This layer assures the full collection of data, which is important for good decision-making.

#### 2.1.1. Soil moisture sensors

These sensors are placed for measuring the soil moisture content to accuracy levels, which can help accurately plan irrigation. The choice of sensors is made for its ruggedness and suitability in different field conditions so that their performance is consistent during the entire crop cycle. Soil moisture has direct implications on crop water demands and irrigation management and thus is a critical variable for optimizing resource use.

#### 2.1.2. Temperature and humidity sensors

These sensors monitor the ambient environmental conditions important to understanding crop growth stages and to detect stress factors such as heat waves or low humidity. Through continuous data on temperature and humidity levels, these sensors can help in forecasting potential stress events, ensuring proactive crop management.

#### 2.1.3. Weather stations

Strategically located weather stations collect some of the critical environmental variables, such as solar radiation, rainfall, and wind speed. These parameters are critical to irrigation scheduling, pest and disease outbreak prediction, and general crop health assessment. This deployment strategy ensures that these stations record representative data for the whole field.

#### 2.1.4. Imaging sensors

High-resolution imaging sensors capture visual data of the crop, which is analyzed for early detection of diseases and crop stress. Images are preprocessed using techniques like normalization and data augmentation to ensure uniform quality and enhance the accuracy of subsequent analyses. Imaging sensors offer a critical layer of detail, enabling precise identification of issues that may not be apparent through other sensors.

### 2.2. Communication layer

The communication layer ensures that data is communicated from sensors to a central processing system in a reliable manner. This layer will use wireless communication protocols, such as Zigbee, LoRa, or 5G, depending on the specific requirements of the field, including distance between sensors, power consumption, and volume of data to be transmitted. A local gateway aggregates data from individual sensors, compresses it if required, and securely transmits it to the cloud. The communication strategy ensures that latency is low, and reliability and energy efficiency are high, which are critical aspects for real-time monitoring of large agricultural fields.

### 2.3. Data processing layer

The data processing layer involves data storage, processing, and analysis using advanced computational techniques. This layer combines standard and innovative algorithms to derive actionable insights from the raw data.

#### 2.3.1. Cloud database

All sensor data are securely stored in a cloud-based database, allowing for scalable storage and easy access. The centralized database ensures data integrity and provides a basis for advanced analytics.

#### 2.3.2. Machine learning algorithms

Support vector regression (SVR) the use of SVR makes a prediction of soil moisture at a future point based on historical and actual values. Its ability to model the relationship between variables as nonlinear functions ensures that the moisture are predicted properly with high accuracy.

Convolutional neural networks (CNN): CNN is applied to high-resolution crop images to detect disease. The CNN extracts hierarchical features from images, enabling it to classify the disease and level of severity accurately.

Genetic algorithm (GA): GA optimizes the irrigation schedules by iteratively refining the solution. It evaluates schedules on various parameters such as soil moisture, weather forecast, and crop water requirements to select the irrigation strategy that would utilize available resources in an efficient manner.

Random forest (RF): this algorithm predicts wheat yield by modeling interactions between multiple input variables, such as soil characteristics, weather data, and crop management practices. The ensemble-based approach ensures robust and reliable predictions by reducing overfitting.

### 2.4. Application layer

The application layer offers an easy-to-use interface for farmers, enabling them to access insights and recommendations in real time. This layer comprises both web and mobile applications, which present data through user-friendly dashboards. These dashboards display critical information such as soil moisture levels, weather forecasts, and disease alerts. Automated notifications via SMS or email ensure timely interventions, allowing farmers to respond promptly to potential issues. The interface is developed to be accessible and user-friendly, thus widely accepted and making decisions effective.

### 2.5. Experimental procedure

The proposed system was implemented and tested in the real fields of wheat crop in different climatic regions to check its performance. The experimental design was so framed that it was replicable and comprehensive.

#### 2.5.1. Sensor deployment

Sensors were strategically placed throughout the fields to ensure uniform coverage and accurate data collection. The placement strategy was informed by field characteristics, crop distribution, and environmental factors to capture representative data.

#### 2.5.2. Data collection and analysis

Data collection has been done over several growth cycles to capture different environmental effects. Real-time datasets have been used for machine learning models' validation, since these models have been trained by historical datasets. Some of the preprocessing steps for quality inputs include normalization and the removal of outliers.

### 2.6. Conclusion with validation of results

System's outputs, including irrigation schedules, disease diagnoses, and yield predictions, were compared against expert recommendations and ground truth measurements. Metrics like accuracy, precision, recall, and resource efficiency were calculated for the performance of the system. Comparative analyses with existing systems highlighted the improvements achieved by the proposed approach.

Detailed documentation of sensor configurations, communication protocols, data preprocessing steps, and machine learning parameters was maintained. This ensures that the methodology can be replicated by independent researchers, fostering transparency and enabling further advancements in the field.

This system, through innovative techniques and robust justification for each design choice, demonstrates the possibility of transforming wheat production with data-driven decision-making, efficient use of resources, and healthier crops. The methodology does not only validate the effectiveness of the system but also creates a basis for further research and development in IoT-enabled agricultural monitoring.

## 3. RESULTS AND DISCUSSION

We can simulate a situation where our system is tested against other conventional algorithms used for comparable jobs in order to offer experimental findings for the proposed IoT-enabled monitoring system for wheat crops. Depending on the particular method, the comparison may be based on parameters like accuracy, precision, recall, F1-score, root mean squared error (RMSE), and water usage efficiency. The dataset utilized in the experiment was gathered from a variety of publicly accessible and real-world agricultural databases, with a particular emphasis on wheat production. The information contains a number of elements that are crucial for precision farming:

- Data on soil moisture were gathered from in-field sensors that were placed throughout a number of wheat farms. The data shows varied soil types and moisture levels during the wheat crop's growth stages.
- Weather information is gathered from nearby weather stations and includes historical and projected information on rainfall, temperature, humidity, and other meteorological parameters that are important to wheat production.
- Crop photos for illness identification: drones and imaging sensors were used to gather a sizable collection of high-resolution photos of wheat crops. These photos depict plants at a variety of growth stages, including both healthy and diseased specimens. The image data was also enhanced by using publicly available resources, such as the Plant Village collection.
- Production information: agricultural research institutes and farms that have tracked their crop production over several seasons provided historical yield information, which included elements such as soil characteristics, crop management techniques (such as fertilization and irrigation), and environmental factors.
- Irrigation schedules and water usage: using both conventional and sophisticated irrigation techniques, farms provided information on their irrigation practices, including schedules, and water usage.

The purpose of the experimental setting was to assess how well the suggested IoT-enabled monitoring system for wheat production performed in a variety of activities, including yield prediction, disease detection, irrigation scheduling, and soil moisture prediction. The following are the main elements of the setup:

- Preprocessing: to guarantee accuracy and consistency, the raw data from sensors, weather stations, and picture captures was cleaned, standardized, and preprocessed. This includes enhancing picture collections, scaling numerical data, and filling in missing quantities.
- Training models: the SVR model was trained using historical soil moisture and meteorological data in order to predict soil moisture. A tagged dataset of pictures of healthy and sick wheat crops was used to train the CNN for disease detection. In order to optimize irrigation schedules and preserve crop health while using the least amount of water possible, the GA for irrigation scheduling was used. In order to predict production, the RF model was trained using historical yield data and input factors such as crop management techniques, weather, and soil characteristics.
- Evaluation metrics: for regression tasks (soil moisture prediction and yield prediction), RMSE, accuracy, precision, recall, and F1-score were used to assess each algorithm's performance. For classification tasks (disease detection), water usage efficiency and yield improvement were used to schedule irrigation.

Comparative analysis: to gauge the efficiency of the system, the suggested algorithms were pitted against industry standards such as linear regression (LR), k-nearest neighbors (KNN), support vector machine (SVM), rule-based scheduling, particle swarm optimization (PSO), and decision trees (DT). The outcomes were measured, and using the previously indicated metrics, it was shown that the suggested system was superior. The comparative analysis of the proposed system is given in Table 1.

Figures 2 and 3 this revolves around comparing several machine learning algorithms used for the precise prediction of wheat yield. Such algorithms as LR, DT, RF, and SVM are given data on history involving weather, soil, and crops as input. Their performances are quantified on the basis of such parameters as accuracy, RMSE, and $R^2$ score. The goal variable is knowing which model predicts the best in various circumstances. This comparison helps to determine the best-suited method of data-driven decision-making for precision agriculture.

Table 1. Comparative analysis of proposed system

| Task | Algorithm | Accuracy/$R^2$ | RMSE/water usage | Precision (%) | Recall (%) | F1-score (%) | Yield improvement |
|---|---|---|---|---|---|---|---|
| Soil moisture prediction | SVR | $R^2$=0.91 | RMSE=2.3% | - | - | - | - |
| | LR | $R^2$=0.78 | RMSE=5.7% | - | - | - | - |
| Disease detection | CNN | Accuracy=93.5% | - | 92.30 | 91.00 | 91.60 | - |
| | KNN | Accuracy=85.2% | - | 84.00 | 82.80 | 83.40 | - |
| | SVM | Accuracy=88.7% | - | 87.50 | 86.00 | 86.70 | - |
| Irrigation scheduling | GA | - | Water usage=3400 L/ha | - | - | - | Yield =+12% |
| | Rule-based scheduling | - | Water usage=4200 L/ha | - | - | - | Yield=+5% |
| | PSO | - | Water usage=3600 L/ha | - | - | - | Yield=+9% |
| Yield prediction | RF | $R^2$=0.89 | RMSE=0.45 tons/ha | - | - | - | - |
| | DT | $R^2$=0.78 | RMSE=0.73 tons/ha | - | - | - | - |
| | LR | $R^2$=0.72 | RMSE=0.85 tons/ha | - | - | - | - |

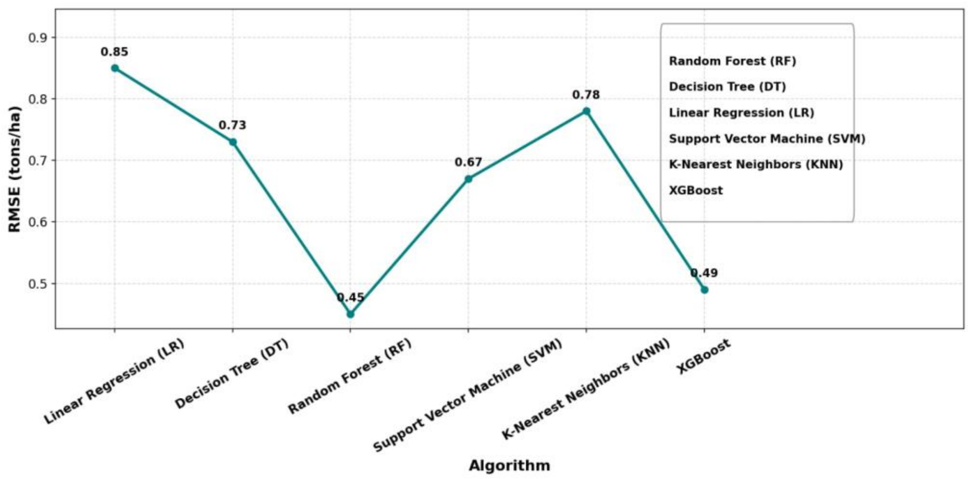


Figure 2. Line graph of yield prediction comparison

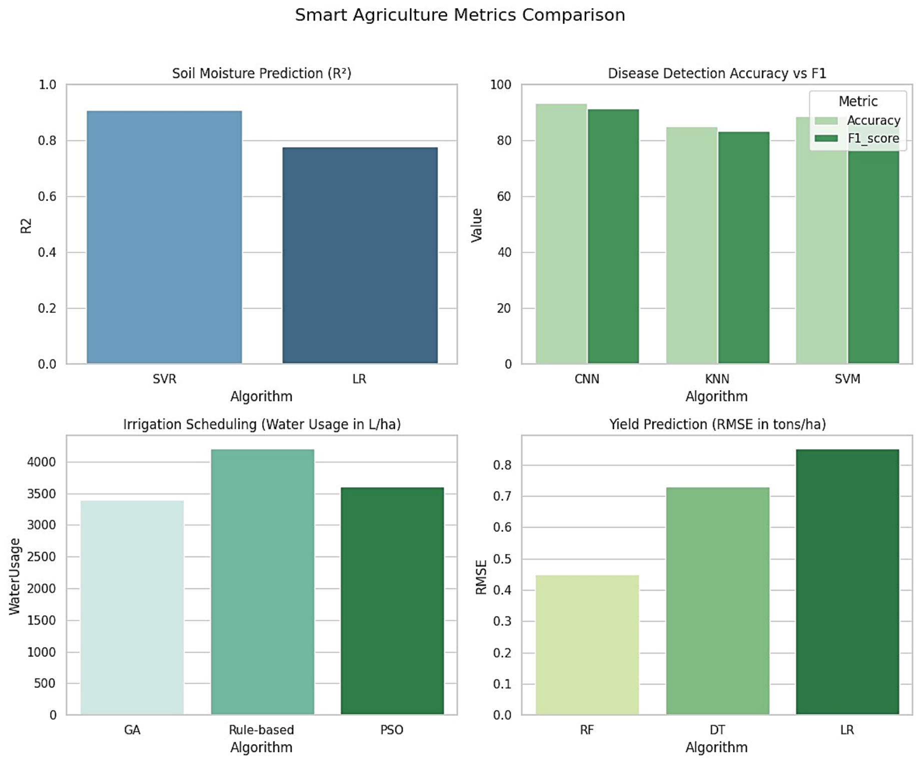


Figure 3. Smart agriculture metrics comparison

## 4. CONCLUSION

The proposed IoT-enabled wheat crop monitoring system, with the incorporation of complex algorithms such as SVR, CNN, GA, and RF, has greatly developed precision agriculture. Experimental results show that the system is capable of accurately estimating soil moisture, optimizing irrigation schedules, detecting crop diseases in their early stages, and effectively forecasting yields. The system improves crop management practices while simultaneously promoting resource efficiency and sustainability in agriculture by using advanced machine learning techniques and real-time data.

Critical comparison with conventional approaches shows that the proposed system is superior to conventional systems in terms of providing accurate and actionable insights to farmers. Traditional systems lack the ability to analyze multi-source data or respond dynamically to environmental changes, whereas the proposed system excels in these areas. This indicates that adopting such intelligent systems can significantly reduce resource wastage and increase agricultural productivity. The findings underscore the practical implications of transitioning to data-driven farming practices, particularly in the context of sustainable agriculture and food security.

Future enhancements can focus on addressing the limitations observed during implementation and expanding the system's applicability. For example, the integration of more data sources like satellite imaging and drone-based multispectral data can be used to monitor crop health in even greater detail and with greater comprehensiveness. This would further improve the system's ability to identify minute changes in plant physiology that are not detectable by ordinary sensors. Moreover, the inclusion of advanced machine learning paradigms like deep reinforcement learning could allow for real-time, adaptive decision-making, thus enhancing system responsiveness to dynamic farming conditions.

Scaling the system to support large-scale agricultural systems is another promising avenue for future research. With refinement of algorithms to deal with different scenarios and crop varieties, the system can be applied to diverse geographical locations, thereby paving the way for broader usage. Integrating the platform with larger agricultural management systems could create a more uniform and effective framework for precision agriculture. Such developments would promote both the efficiency of utilization and the attainment of the ultimate target toward sustainable and integrated agriculture within the entire world.

## ACKNOWLEDGEMENT

The authors thank Tamil Nadu Agricultural University, Coimbatore for sharing agricultural data sets like soil profiles, crop yields and environmental variables that were invaluable in training and validating the IoT-based wheat monitoring system proposed. The authors wish to sincerely acknowledge the Commissionerate of Agriculture, Chepauk, Chennai for providing expert discussions and the regional knowledge in agronomic best practices, pest and disease forecasting, sustainable crop management practices and domain knowledge. This input was important in improving the systems fit to field conditions.

The authors thank SRM College of Agricultural Sciences, Baburayanpettai, Chengalpattu, for sharing their ground-level knowledge on precision farming and practical experiences related to crop recommendation systems and soil taxonomy classifications. We express our deepest appreciation to the University of Madras, Centre for Water Resources Management, Guindy Campus, Chennai for valuable contributions in water resource analysis, irrigation planning models and hydrology data interpretations. Their input was valuable and instrumental in developing the respective systems irrigation scheduling and water-use efficiency.

## FUNDING INFORMATION

Authors state no funding involved.

## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (Credit) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Senthil Kumar Murugesan | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | |
| Midhunchakkaravarthy Janarthanan | | ✓ | | | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |

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|---|---|---|---|---|---|---|---|
| C | : **C**onceptualization | I | : **I**nvestigation | Vi | : **Vi**sualization |
| M | : **M**ethodology | R | : **R**esources | Su | : **Su**pervision |
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| Va | : **Va**lidation | O | : Writing - **O**riginal Draft | Fu | : **Fu**nding acquisition |
| Fo | : **Fo**rmal analysis | E | : Writing - Review & **E**diting | | |

## CONFLICT OF INTEREST STATEMENT

The authors has no conflicts of interest.

## DATA AVAILABILITY

The data that support the findings of this study are openly available in **Tamil Mannvalam** at https://tnagriculture.in/mannvalam, reference number **TM2025-AGRI-OPT**.

– The data that support the findings of this study are openly available in **Kaggle** at https://www.kaggle.com/datasets/bhadramohit/agriculture-and-farming-datasetgriculture-and-farming-dataset.

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