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PREDICTIVE ANALYTICS FOR PLANT HEALTH USING MACHINE LEARNING TECHNIQUES AND SMART FARMING TECHNOLOGIES

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Abstract –
An innovative approach to improving plant health management have emerged in response to the growing need for sustainable farming methods and the widespread use of smart farming technology. There is an emergency need for systems that can assist in the effective and sustainable management of plant health due to the increasing global population and increasing impact of climate change on agriculture. Essential for real-time monitoring and decision-making, this study proposes a framework for predictive analytics for plant health using machine learning (ML) approaches. The system utilizes instrumentation used in agriculture. In particular, we focus on Agricultural Sensor Data, which consists of characteristics collected from sensors deployed in diverse agricultural environments, inclusive of soil moisture, temperature, pH, light, and humidity. Within such data, one can ascertain which gaps in multi-factor environmental imbalances, nutrients, and water are most harmful to plants. In enhancing proactive management, this research utilizes ML models, including k-nearest neighbor (kNN), decision tree (DT), random forest (RF), and Gradient boosting (GB), to predict and forestall critical levels of responsive concerns. The algorithms developed in this framework predict stress indicators and overall plant health with remarkable accuracy. Both RF and GB facilitate 98.75% of accuracy compared to other classifiers. Such predictive data can substantially advance monitoring of plant health. This enables timely and precise intervention. Further the implementation of smart farming techniques, such as IoT sensors for real-time data collection, enables optimization of resource use, reduction of pesticide application, and increased crop productivity.

Keywords - Agricultural sensor data, Crop monitoring, Plant health, Predictive analytics, Smart farming, Sustainable agriculture.

1. Introduction

For centuries, agriculture has been the backbone of humans, shifting from straighter methods to more intricate technologies. Planting, irrigation, pest control, and harvesting, were historically reliant on personal observation and experience, more on the farmer's skill and insight [1]. While useful in a mono-crop environment, these methods are totally inadequate

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for contemporary agriculture, which has to deal with the rapidly increasing demand for food and the dwindling of land and other resources, climate change, and all that new-age woes. The twentieth century revolution in agriculture has been a result of the mechanization of the farming system and the introduction of chemical agro inputs. Technologies like tractors, irrigation devices, and super-phosphate fertilizers, revolutionized production and the level of farming [2]. There are the flip sides of these technological breakthroughs, like lowering of the water table, soil erosion, the chemical pesticide and its overuse, and the attendant ecological problems. They were also too broad and lacked the nuance to deal with regional and crop level variability of the agricultural systems [3].

Farmers have utilized the steep the technological wave in farming by embracing techniques offered by precision agriculture and its consequent changes in farming. The use of information and communications technology or ICT in diverse farming applications has since, and IoT devices, satellites, and the farming ecosystem, farmers are able, for instance, to obtain real time soil temperature, pH, and moisture levels. The volume and complexity of this data usually overwhelm the use of traditional methods of analytics. Tools and methodologies that are sophisticated and complex are needed to obtain meaningful information and insights [4].

ML in agriculture has carved out its critical and center piece in analytics of agriculture and every precision farming technique due to its unlimited potential [5]. Agricultural ML systems are sophisticated enough to predict, assess, and respond to plant/ crop diseases, deficiencies and challenges, in a way, that they use 'real-time' data as opposed to static data. Integration of algorithms and farming activities goes a step ahead in enabling a farming technique called predictive farming [6]. ML algorithms are able to automatically assess farming data and pinpoint crop problematic regions with predictive assessment of farming data.

The provided text focuses on measuring plant health using Machine Learning techniques on datasets from agricultural sensors. The goal is to overcome the challenges posed by current methodologies by constructing prediction models using real-time data from sensors measuring soil moisture, temperature, pH, luminosity, and humidity [7]. The paper illustrates the advantages of employing ML on plant health prognostics and the responsible optimization of agricultural resources through DT, support vector machine (SVM), and RF models. The shift from traditional farming to farming infused with ML techniques has marked a huge step in the resolution of current challenges in agriculture [8]. The study emphasizes the importance of ML in the adoption of more advanced and refined methodologies in agriculture, paving the path for a new era in the field.

2. Literature Survey

Traditionally the study and analysis of leaves in agriculture has been done through manual labour. While there are cases in which these methods are applicable, more often than not, these methods are highly expensive, time-consuming, manual-heavy and biased which all these factors in turn lead to a loss [9]. With the help of technology, researchers are focusing more and more on the automation of the diagnostics in order to improve the speed and accuracy of the diagnoses. Recently developed techniques for the identification and characterization of plant diseases, computer vision, image processing, pattern recognition, and ML have been incorporated [10]. To extract thirty parameters which are considered to be crucial and important in determining and highlighting particular plant abnormalities, the methods scrutinize parameters such as the pictures produced, and their size, colour, shape, and texture. The development of these models have decreased the reliance on human processes for automatic assessment of plant health and have produced more reliable results [11]. These techniques have proven to be more reliable and pragmatic, offering a possible solution to the challenges posed by archaic methods.

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The ML and deep learning (DL) techniques are becoming very popular when it comes to diagnosing plant diseases, compared to older and more tedious techniques [12]. These techniques are of utmost importance in preventing disease outbreaks and related epidemics because as Akbar et al. [13] pointed out, they help in early disease pattern recognition. In research, it has been found out that ML techniques can classify and segment digital images of plant lesions efficiently. Applying conventional ML techniques such as C4.5 classifiers, tree bagger, and SVM to identification of plant diseases and predicting crop yields and optimally developing plants is numerous [14]. The tree bagger and C4.5 classifiers are capable of pest and disease recognition, which in turn maximizes crop yields for farmers as shown by Yoosefzadeh-Najafabadi et al. [15] and Cedric et al. [16].

To tell the difference between healthy and diseased cucumber leaves Jeny et al. [17] fitted an SVM-based model using statistical pattern recognition. In a different work, Lu et al. [18] and other researchers developed an analogous SVM model for rice plants. To segregate the sick parts from the healthy, the authors applied a colour transformation technique. The algorithm achieved good results in classifying the sick areas by determining the properties of colour, texture, and shape of the diseased polygons. In the model introduced by Sharma et al. [19] for the identification of plant diseases, the image quality was improved by combining the multi-layer perception technique with a pre-processing module which followed the segmentation, using K-means clustering, of the diseased leaf parts.

The authors performed a thorough examination of plant health by analyzing data on texture and color for each cluster. The stated accuracy rates demonstrate the efficiency of the ML algorithms in identifying plant diseases. For instance, Support vector machines managed to reach a staggering 87.6% accuracy when trained on form, texture, and color data [20]. Similarly, Kavitha et al. [21] derived an instance segmentation technique to detect plant diseases. Likewise, DT and kNN models have shown significant improvements in accuracy, with DT reaching 85.26% and kNN 87.00% [22]. Furthermore, NB classifiers have attained an accuracy of 87% when applied to the texture and color features [23]. While there has been some success with classic ML methods, these approaches have several drawbacks when it comes to scalability and feature representation. The intricate patterns and changes shown in photographs of leaves could be difficult for handcrafted features to capture, which could result in less-than-ideal performance [24]. The high level of feature engineering and domain knowledge needed by these approaches also limits their applicability to novel plant diseases or species [25]. In spite of DL models, still ML conforms its efficiency smart farming techniques [26].

3. Proposed Methodologies

Using ML approaches, the proposed methodology seeks to provide a complete framework for predictive analytics in plant health management. This method addresses the pressing issue of sustainable farming techniques in light of the growing world need for food and the negative impact of climate change on the agricultural sector. Here are the steps that make up the suggested plant health prediction systems, as illustrated in Figure 1.

- Preparation of Dataset
- Processing the Dataset
- Exploratory Data Analysis
- Build and Train ML Model
- Model Testing

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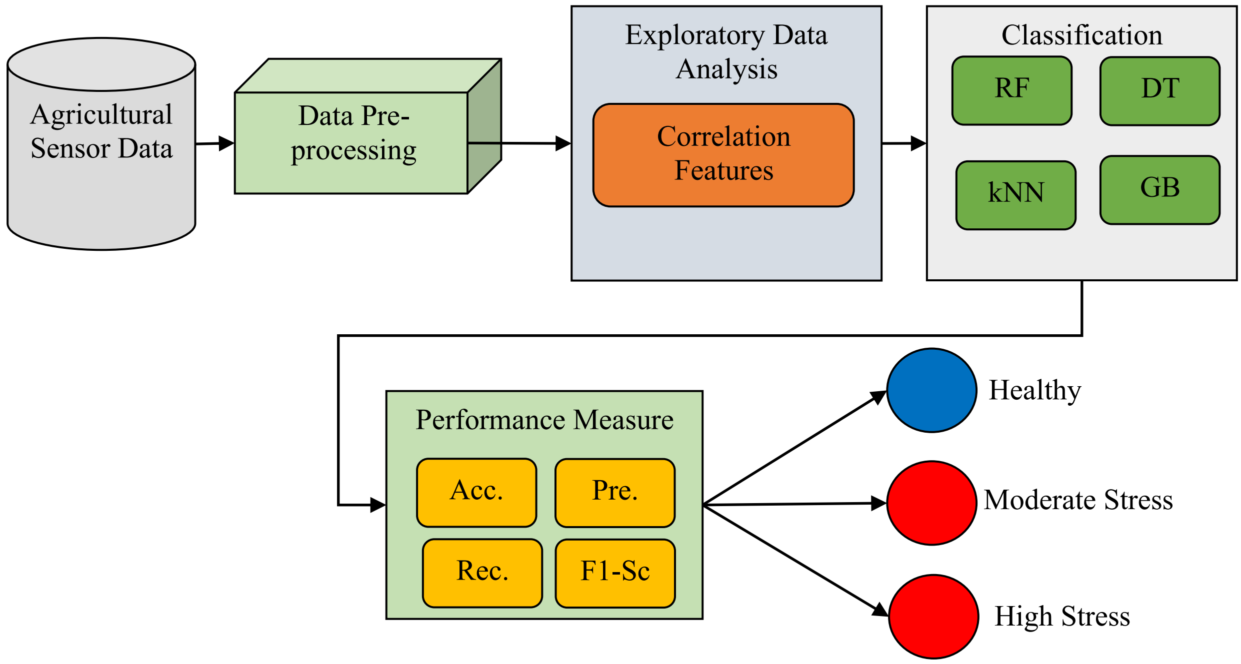

Fig. 1 Architecture of Plant Health Prediction Systems

3.1. Preparation of Dataset

The plant health dataset is an extensive archive of data collected from agricultural IoT sensors used in a variety of farming circumstances [27]. It is freely accessible from a number of places, including agricultural IoT platforms and Kaggle. Soil moisture, pH, nutrient concentrations (N, P, K), temperature, humidity, rainfall, wind speed, light intensity, solar radiation, air pressure, CO2 levels, and wind speed are only a few of the important environmental and soil variables captured in around 12,000 recordings. To further understand how plant health changes in response to different environmental factors, the collection also contains time-related variables including day-of-the-week and seasonal data. The data cover a wide range of crops, from wheat and maize to rice and fruits, and they cover a wide range of geographical locations with diverse climates. We use a two-part dataset for training and testing machine learning models: 80% for training and 20% for testing. This helps evaluate the models' generalizability by testing them on a broad and unexplored subset of the data. In Figure 2 we can see the spread of the plant health condition.

3.2. Dataset Pre-processing

To make sure the plant health dataset is ready for ML models, there are a number of important stages in processing it. Duplicate records are removed and missing data is dealt with via imputation, interpolation, or elimination. Time stamps are used to extract seasonal and time-of-day information, while crop kinds and other categorical variables are encoded to ensure model compliance. To make sure all the characteristics have the same scale, feature scaling is used, which includes normalization and standardization. To avoid biased analysis, outliers are identified using statistical approaches, and they are either eliminated or substituted. To rectify class imbalance and guarantee a more balanced dataset, methods such as SMOTE are employed for synthetic data creation and resampling.

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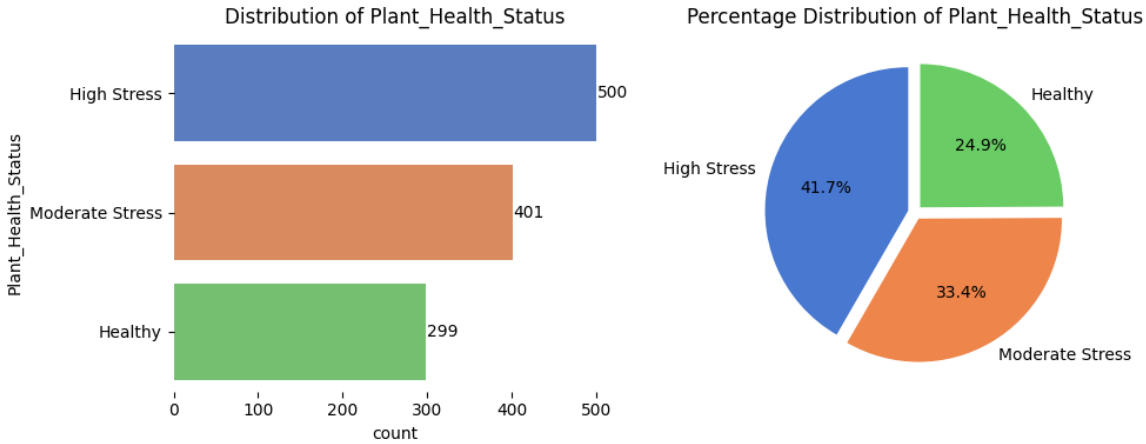

Fig. 2 Distribution of plant health status

3.3. Exploratory Data Analysis

The agricultural sensor dataset is analyzed using feature distribution plots to identify patterns and outliers, correlation matrix analysis to understand relationships between features like soil moisture, temperature, and pH levels, temporal and geospatial analysis to identify trends and hotspots, and classification analysis and dimensionality reduction to differentiate. Figure 3 displays the correlation heat map of the data collected by agricultural sensors.

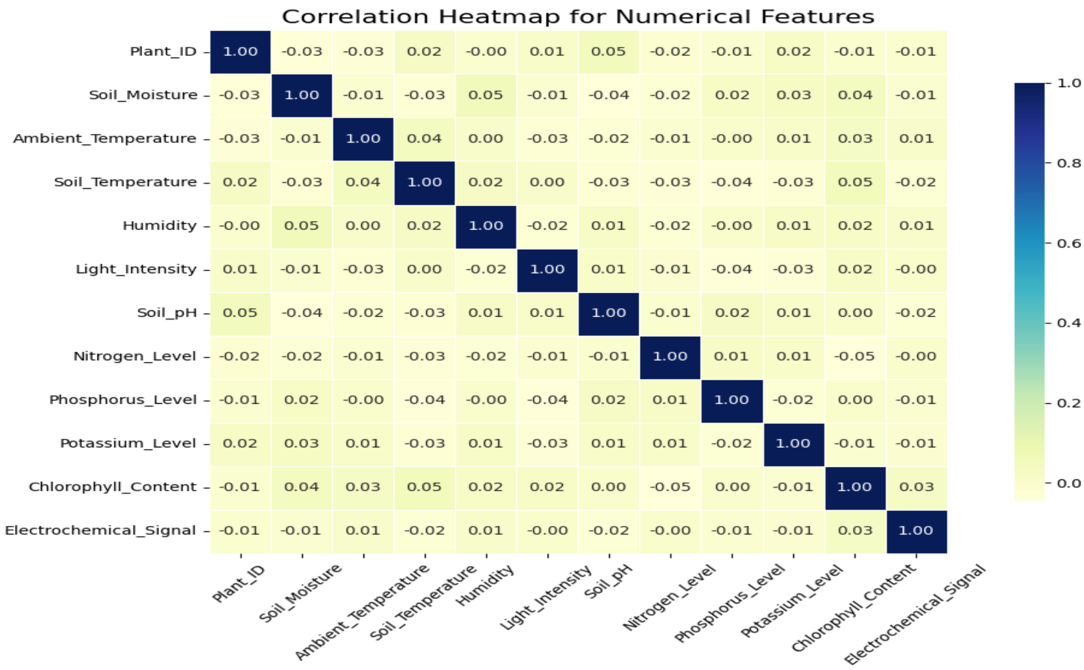

Fig. 3 Correlation Heat map of plant health data

3.4. Build and Train the Model

In order to accurately predict and monitor plant health, ML models such as kNN, DT, RF, and Gradient Boosting algorithms are crucial for interpreting data from agricultural sensors. Soil moisture, pH levels, temperature, light intensity, and humidity are some of the features used by these models. As shown in Figure 4, data is collected by agricultural sensors that are enabled by the IoT.

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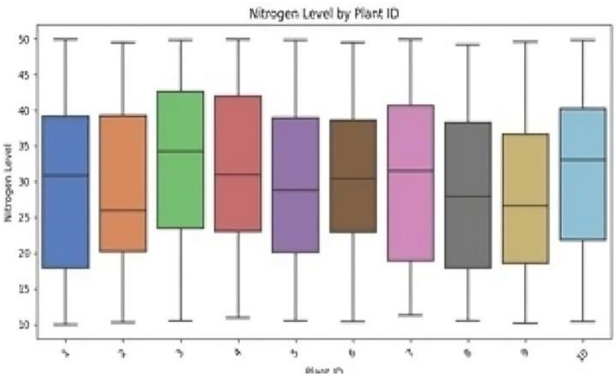
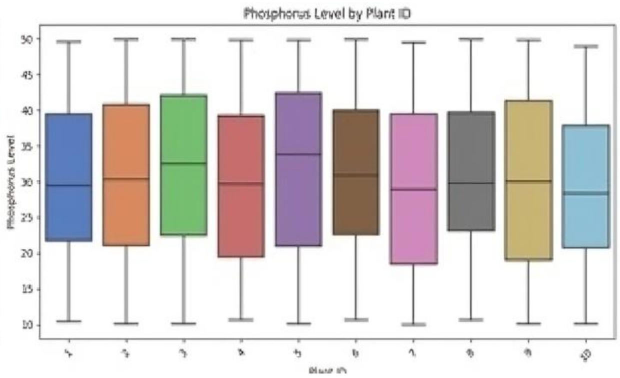
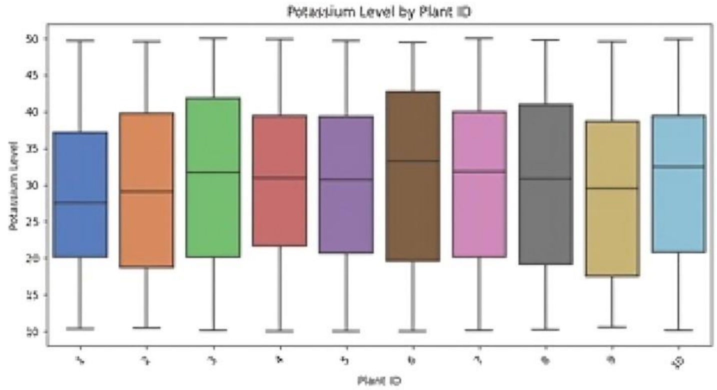




(a) (b)



(c)

Fig. 4 Nutrient levels of plant health representing (a) Nitrogen level (b) Phosphorous level and (c) Potassium level

This ML models produce useful results by using methods like feature significance analysis and hyper parameter optimization, which allow for strong model generalization. Optimizing environmental conditions for crop development, detecting stress signs, predicting nutrient shortages, and identifying water scarcity challenges are all within their capabilities. Improved agricultural yields, less reliance on pesticides, and sustainable use of resources are all possible outcomes of combining predictive analytics models with IoT devices, which allow for real-time monitoring, early alarms, and targeted interventions.

3.5. Model Testing

By applying various performance measures on a specified test dataset, model testing determines how well and reliably machine learning models work. To ensure accurate predictions and error detection, methods such as train-test split and confusion matrix analysis are used. To enhance the model accuracy and usefulness for long-term plant health management, hyper parameter tuning and real-time testing with data from IoT sensors are implemented.

Accuracy (A): The ratio of correctly predicted instances (both healthy and stressed plants) to the total number of predictions as N.

$$A = \frac{PTrue + NTrue}{N} \tag{1}$$

Precision (P): The proportion of correctly predicted positive instances (e.g., stressed plants) out of all predicted positives.

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$$P = \frac{PTrue}{PTrue + PFalse} \qquad (2)$$

Recall (R): The proportion of correctly predicted positive instances (e.g., stressed plants) out of all actual positives.

$$R = \frac{PTrue}{PTrue + NFalse} \qquad (3)$$

F1-Score (F_1): The harmonic mean of precision and recall, balancing the trade-off between them.

$$F_1 = 2 \times \frac{P \times R}{P + R} \qquad (4)$$

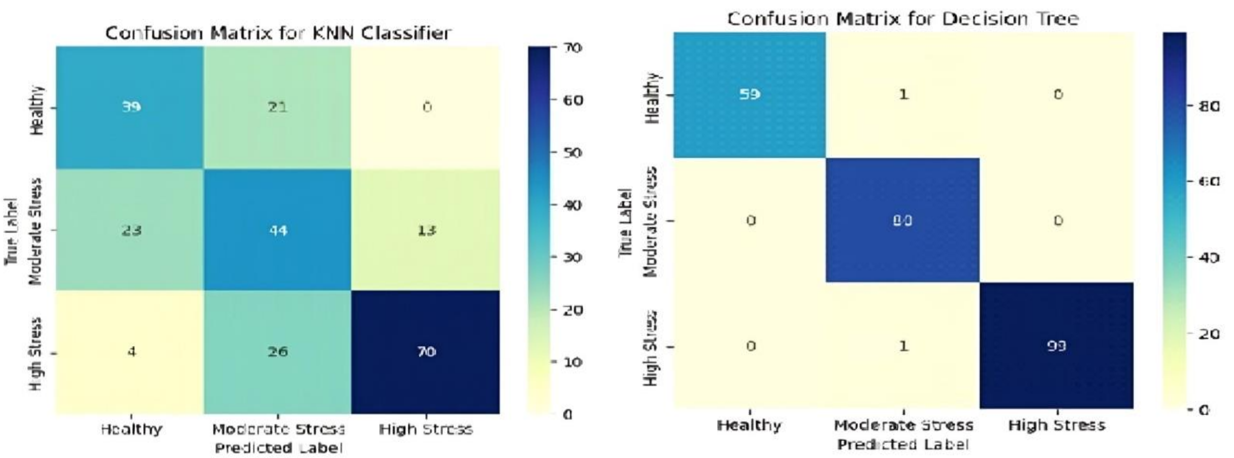
4. Results and Discussion

4.1. Experimental Setup

The plant health prediction framework efficiently monitors and manages plant health by combining ML with IoT sensors. Data integration in real-time is made possible by databases like MySQL and IoT systems, as well as Python with libraries like NumPy, scikit-learn, and Pandas. Along with Raspberry Pi microcontrollers, the hardware includes sensors for soil moisture, pH, temperature, light, and humidity. Model training is supported by a workstation with Intel i5/AMD Ryzen 5, 16 GB RAM, and an NVIDIA GPU. By maximizing resources, minimizing pesticide usage, increasing agricultural yields, and accurately anticipating water stress, nutritional deficits, and environmental imbalances, this system enables exact interventions.

4.2. Evaluation Results

The findings of this study indicate that the ML models employed for plant health prediction achieved significant accuracy, with Gradient boosting and RF exhibiting the highest performance, followed by DT and k-NN at less accuracy. As shown in Figure 5, the confusion matrix findings demonstrate that gradient boosting and RF had superior performance in reducing both false positives and false negatives, with an accuracy of 98.75%, a precision of 98.50% and a recall of 98.25%, finishing in an F1-score of 98.4%. This indicates that the gradient boosting and RF model was notably proficient in early detection of plant health problems while sustaining a minimal misclassification rate.



(a) (b)

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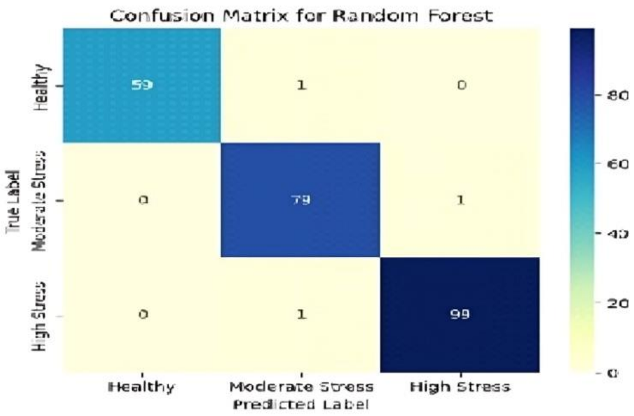
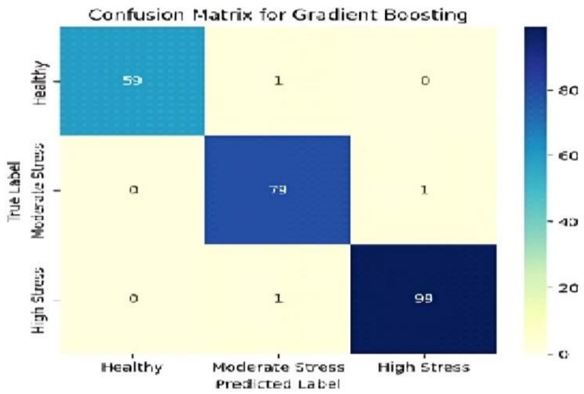


(c)



(d)

Fig. 5 Confusion matrices of classifiers showing (a) kNN (b) DT (c) RF and (d) G-Boost

As shown in Table 1 and Figure 6, DT performed similarly well, achieving 97.15% of high accuracy with a balanced precision of 97.40% and recall of 97.25%, showing that it was also effective in identifying plant health predictions. The kNN model demonstrated less performance with 63.75% of accuracy. The model showed the least ability to handle complex relationships between features, but it still provided valuable insights with reasonable.

Table 1. Performance analysis of plant health prediction systems

Classifier	A	P	R	F_1
kNN	63.75	64.25	64.10	64.35
DT	97.15	97.40	97.25	97.20
RF	98.75	98.50	98.25	98.40
Gradient Boost	98.75	98.50	98.25	98.40

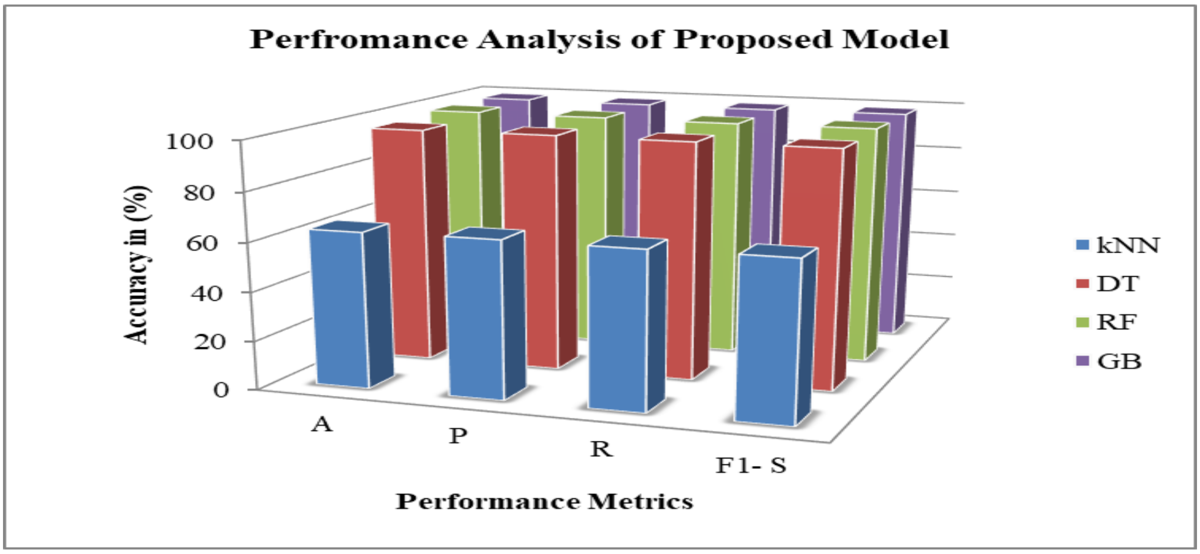


Fig. 6 Analysis chart of classifiers utilized in proposed system

In terms of overall performance, the ensemble model gradient boosting model outperformed the simpler models RF, kNN and DT, which aligns with the hypothesis that more complex models can handle feature interactions better and provide more accurate predictions in real-world agricultural.

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5. Conclusion

This work highlights the transformative potential of predictive analytics and ML in optimizing plant health management within modern agriculture. By utilizing real-time agricultural sensor data, including soil moisture, temperature, pH levels, and humidity, this research demonstrates how machine learning models can proactively predict plant health issues and identify stress factors with high accuracy. The ability to predict and address potential health risks before they escalate enables farmers to take timely, targeted actions that not only safeguard crops but also optimize resource usage, minimize pesticide reliance, and enhance overall sustainability.

The findings emphasize the critical role of integrating smart farming technologies, such as IoT sensors, with ML algorithms. Ultimately, the results affirm that leveraging predictive analytics for plant health is a crucial step toward advancing smart farming, ensuring food security, and fostering a more sustainable future for agriculture.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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All authors are equally contributed.

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