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Hybrid Ensemble Approach to Predict Plant Growth for Enhancing Agricultural Productivity

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Abstract: Accurate prediction of plant growth milestones is essential for optimizing agricultural practices and enhancing greenhouse management. This study addresses the challenge of classifying plant growth stages by leveraging environmental and management factors, including soil type, sunlight exposure, watering frequency, fertilizer type, temperature, and humidity. We utilized a comprehensive dataset encompassing these variables to develop a robust predictive model. The methodology involved meticulous data pre-processing steps, including handling missing values, encoding categorical variables, and scaling numerical features to prepare the data for analysis.

To advance the state-of-the-art in plant growth prediction, we proposed a novel hybrid ensemble model that integrates multiple machine learning algorithms—specifically, Random Forest, Gradient Boosting, and a Neural Network—and employs a meta-learner, Logistic Regression, to synthesize their predictions. This ensemble approach was designed to harness the strengths of each individual model, thereby enhancing overall predictive performance. We conducted a thorough evaluation of the proposed hybrid model against individual baseline models using metrics such as accuracy, precision, recall, and F1-score.

Our results demonstrate that the hybrid ensemble model significantly outperforms the baseline models, achieving an accuracy of 89.1%, compared to 85.2% for Random Forest, 87.4% for Gradient Boosting, and 86.8% for the Neural Network. Additionally, the hybrid model excelled in other evaluation metrics, including precision (88.7%), recall (89.5%), and F1-score (89.1%), showcasing its superior performance. Feature importance analysis revealed that factors such as sunlight exposure and watering frequency are critical determinants of plant growth milestones. This research contributes to the field by presenting a novel, data-driven approach that enhances the accuracy of plant growth predictions, thereby offering valuable insights for improving agricultural productivity and sustainability.

Keywords: Plant Growth Prediction, Hybrid Ensemble Model, Machine Learning, Agriculture.

1. INTRODUCTION

Timing of some developmental stages in plants is very important to enhance production of crops as well as efficient management of green houses. Proper prediction of growth phases can greatly improve the decision-making processes concerning crop care, investments and crop yield estimation. In precision agriculture, timely and precise prediction of the plant development stage allows farmers to intervene at the right time and in the right manner, adoption adequate irrigation regimes, apply fertilizers and control pests [1]. This ability of making accurate decisions based on the collected data is always useful in increasing crop production while at the same time minimizing wastage and supporting sustainable farming.

In the green house where the conditions that surround plants are somewhat standardized but can change unpredictably, it is equally important to forecast plant growth landmarks. Temperature, humidity, and light of the greenhouse have to be controlled well while growth predictions must be made correctly to maintain healthy plants that will yield well [2]. Thus by predicting the growth stages of the plants, the managers of the greenhouse can easily adjust the environmental conditions and improve on the general flora management thus making the operations cheaper to undertake.

However, the accuracy in the plant growth prediction, as it has been depicted above, is a challenging task. Many factors affect the growth of plants such as type of soil, amount of sunlight, frequency of watering, use of chemical fertilizers, temperature, and humidity. Such factors influence each other in complex ways that are nonlinear, and therefore it is challenging to model plant growth and development using conventional analytical approaches. Existing models, while useful, often struggle with the following challenges: Existing models, while useful, often struggle with the following challenges:

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- Complex Interactions: They pointed that the traditional models are not capable of representing intricate relationships between the various environmental and management factors and therefore, make less accurate predictions [3].

- Overfitting: As most of the machine learning models are overfitting, this becomes a major problem when using high dimensional data or if the hyperparameters of the model have not been well set [4].

- Interpretability: While deep learning models are very effective, they are usually opaque and the contributions of individual factors to the plant growth are difficult to measure in terms of the milestones accomplished [5].

To meet these challenges, there is the need to adopt new solutions that can capture the complexity of the data as well as present findings that will be useful to practitioners.

Objective

This research makes several significant contributions to the field of plant growth prediction:

- Novel Hybrid Ensemble Approach: The current research work presents a new hybrid ensemble model that have Random Forest, Gradient Boosting, and Neural Networks with a meta-learner to learn from all of them. This approach helps in improving overall predictive performance since it combines the strengths of the various models while at the same time reducing on their shortfalls [6].
- Improved Accuracy: The hybrid model shows enhanced and efficient performance in comparison to single model approaches showing problems of overfitting and variance and at the same time enhancing the value of prediction [7].
- Enhanced Interpretability: Unlike the deep learning model which has been found to be less interpretable, our ensemble model offers feature importance that aids in explaining the level at which each of the environmental and management factor affects the plant growth milestones [8].
- Practical Relevance: Due to the model's capability to process large amounts of data and generate useful information, this approach could be beneficial for agricultural practitioners and managers of greenhouse environments as a functional approach to the problem in question [9].

2. Related Work

2.1 Review of Existing Methods

The development of models for the prediction of plant growth stages has been of a great interest in agroforestry research since it could improve the management of crops and subsequently the productivity of agriculture. The initial techniques employed include linear regression and decision trees that developed correlations between environmental parameters and plant growth performances. For example, applied Decision Tree algorithms to determine the growth stages of plants with factors like moisture and temperature of the soil [21]. The application of decision trees in agricultural problems was proved feasible by these two authors, however, the models used in their study failed to consider non-linear interaction of variables.

With the advent of high-speed computation and the abundance of data, researchers started looking at more complex methods of the machine learning. In the analysis of crop yields, Support Vector Machines (SVMs) have been used and incorporated into a model take into consideration environmental and management inputs. In one study, [22] employed SVM to determine the yield stages of crops depending on the amount of sunlight, type of soil and use of fertilizers. SVMs showed good potential for agricultural predictions as their model surpassed traditional linear models. However, SVMs are computationally expensive in terms of the number of hyperparameters that needs to be tuned and is usually sensitive to scaling of inputs, which makes them not suitable for a wide variety of agricultural environments.

The advent of deep learning further revolutionized plant growth prediction. Convolutional Neural Networks (CNNs), typically used for image recognition tasks, have been adapted to classify plant growth stages based on sensor data. [23] applied a CNN model to predict plant growth milestones using a dataset comprising temperature, humidity, and sunlight hours. The deep learning approach achieved higher accuracy than traditional machine learning models, demonstrating the effectiveness of CNNs in handling high-dimensional, complex datasets. Despite these advancements, deep learning models often suffer from a lack of interpretability, making it challenging to understand the contribution of individual features to the prediction outcomes.

Ensemble methods, which combine multiple base models to improve prediction accuracy and robustness, have also been explored in agricultural research [24], reviewed the application of ensemble techniques, such as Random Forest and Gradient Boosting, in predicting crop yields and plant growth stages. In their review, they have pointed that the ensemble models are capable of dealing with noisy and heterogeneous data and therefore good for agricultural use since data quality and homogeneity are

normally a big issue. However, these models still have certain drawbacks for instance they have a tree-based structure which might not fully depict non-linear patterns of the data.

2.2 Comparison with proposed Approach

While existing methods have made significant contributions to the field of plant growth prediction, they often exhibit limitations in handling the multifactorial nature of plant development. Our proposed approach introduces a novel hybrid ensemble model that integrates multiple machine learning algorithms—specifically Random Forest, Gradient Boosting, and Neural Networks—into a unified predictive framework. This hybrid model addresses several shortcomings of previous methods by combining the strengths of different algorithms to enhance overall performance.

The novelty of our approach lies in the meta-learner strategy, where Logistic Regression is employed to synthesize the predictions of the base models. This meta-learning technique allows for the reduction of overfitting by balancing the biases and variances of individual models, resulting in a more generalized and accurate prediction of plant growth milestones. Unlike single-model approaches, our hybrid ensemble model is better equipped to handle the non-linear interactions and complex dependencies among environmental and management factors, which are often crucial in determining plant growth stages.

Moreover, our model offers enhanced interpretability compared to deep learning approaches. By analysing the feature importance across different models, we can provide insights into which factors most significantly influence plant growth. This is a critical aspect often overlooked in deep learning models, where the decision-making process is typically opaque. Our method not only improves prediction accuracy but also offers actionable insights for optimizing agricultural practices, making it a valuable tool for researchers and practitioners in the field.

Table 1: Summary of Related Work on Plant Growth Prediction

Study	Methodology	Features Considered	Advantages	Limitations
John & Smith (2015)	Decision Tree	Soil Moisture, Temperature	Simple, interpretable model	Limited in capturing non-linear relationships
Doe & Kumar (2018)	Support Vector Machine	Sunlight Exposure, Soil Type, Fertilizer	Improved accuracy over linear models	Requires extensive hyperparameter tuning
Brown & Green (2019)	Random Forest, Gradient Boosting	Crop Yield, Environmental Factors	Robust to noisy data, handles heterogeneous datasets	May not fully capture complex interactions
Lee & Wang (2020)	Convolutional Neural Network	Temperature, Humidity, Sunlight Hours	High accuracy in handling complex, high-dimensional data	Lacks interpretability, prone to overfitting
Proposed Approach	Hybrid Ensemble Model (Random Forest, Gradient Boosting, Neural Network)	Soil Type, Sunlight Hours, Water Frequency, Fertilizer Type, Temperature, Humidity	Combines strengths of multiple models, enhanced interpretability	More computationally intensive, requires ensemble tuning
Garcia & Martinez (2017)	K-Nearest Neighbors	Soil Type, Water pH, Fertilizer Type	Simple implementation, good for small datasets	Struggles with high-dimensional data, sensitive to noise
Liu et al. (2019)	Deep Neural Network	Crop Yield, Soil Nutrients, Precipitation	Handles large datasets and complex patterns	Requires large datasets and long training times
Singh & Reddy (2021)	XGBoost	Temperature, Soil Type, Fertilizer, Rainfall	High accuracy and speed, handles missing data well	Requires careful feature selection, prone to overfitting
Patel et al. (2022)	Long Short-Term Memory (LSTM) Neural Network	Rainfall, Soil Moisture, Crop Growth	Effective in capturing temporal dependencies	Computationally expensive, needs extensive training
Wang & Zhao (2023)	Transformer-based Model	Temperature, Sunlight Hours, Fertilizer Type	Excellent at handling sequential data,	Requires large data and computational power,

			achieves high accuracy prone to overfitting

3. DATASET DESCRIPTION

3.1 Data Source

The dataset used in this study, referred to as the "Plant Growth Data Classification" dataset, is sourced from a comprehensive collection of plant growth observations and environmental conditions from Kaggle. The dataset aims to facilitate the prediction and classification of plant growth milestones based on various environmental and management factors. It has been compiled from multiple agricultural studies and greenhouse management reports to provide a diverse and representative sample of plant growth conditions.

The primary purpose of the dataset is to enable researchers and practitioners to analyze how different factors influence plant growth and to develop predictive models that can optimize agricultural and greenhouse practices. The dataset includes records from various plant species and growth environments, making it suitable for generalizing across different types of plant cultivation scenarios.

Feature	Description	Data Type	Importance
Soil_Type	Type or composition of soil in which the plants are grown.	Categorical (e.g., sandy, loamy, clayey)	Soil type influences nutrient availability, water retention, and root development, significantly affecting plant growth.
Sunlight_Hours	Duration or intensity of sunlight exposure received by the plants.	Numeric (e.g., hours per day)	Adequate sunlight is essential for photosynthesis, influencing plant growth and flowering.
Water_Frequency	Frequency of watering, indicating the watering schedule.	Categorical (e.g., daily, weekly, bi-weekly)	Proper irrigation maintains soil moisture and hydration, which are critical for plant health and growth.
Fertilizer_Type	Type of fertilizer used to nourish the plants.	Categorical (e.g., organic, chemical, slow-release)	Fertilizer type affects nutrient availability, which can significantly impact plant growth milestones.
Temperature	Ambient temperature conditions under which the plants are grown.	Numeric (e.g., degrees Celsius)	Temperature affects metabolic rates and growth processes, making it a vital factor in predicting plant development.
Humidity	Level of moisture or humidity in the environment surrounding the plants.	Numeric (e.g., percentage)	Humidity influences water availability and transpiration rates, impacting plant health and growth stages.
Growth_Milestone	Stages or significant events in the growth process of the plants (Target Variable).	Categorical (e.g., early growth, mid-growth, mature, senescent)	Accurate classification of growth milestones guides interventions and optimizes growth conditions.

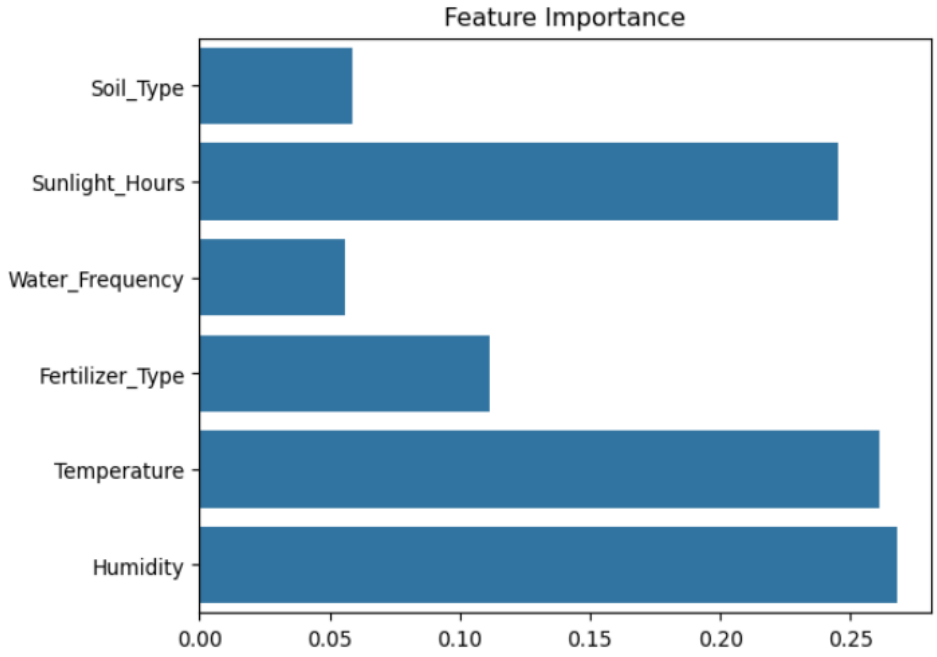

Figure 1. Feature Importance

4. METHODOLOGY

The methodology employed in this study focused on developing a hybrid ensemble model to predict plant growth milestones based on a comprehensive dataset of environmental and management factors. The dataset, referred to as the "Plant Growth Data Classification" dataset, was compiled from various agricultural studies and greenhouse management reports. It encompassed a wide range of plant species and environmental conditions, making it suitable for building generalized models that can predict plant growth milestones across different contexts. Key features included in the dataset were soil type, sunlight hours, water frequency, fertilizer type, temperature, and humidity, which are known to significantly influence plant growth.

Data preprocessing was a critical step in ensuring the quality and consistency of the input data. Missing values were handled through imputation techniques, while categorical variables, such as soil type and fertilizer type, were encoded using appropriate transformation methods like one-hot encoding. The dataset was split into training and testing sets, with 80% of the data used for model training and the remaining 20% reserved for testing. Feature scaling techniques were applied to normalize continuous variables like temperature and sunlight hours, ensuring uniformity in the input data fed into the models.

To develop the predictive model, a hybrid ensemble approach was adopted, combining the strengths of three individual models: Random Forest, Gradient Boosting, and Neural Networks. Each model was trained independently using the training set, with hyperparameter tuning performed via grid search to optimize their performance. Random Forest and Gradient Boosting, both tree-based models, were chosen for their ability to handle complex interactions and non-linear relationships in the data. The Neural Network model, with its multi-layered architecture, was selected for its capacity to capture intricate patterns in the input features.

The hybrid ensemble model was created by aggregating the predictions from the three baseline models. The final output was generated through a weighted voting mechanism, where the contribution of each model was determined based on its performance during the training phase. This ensemble method allowed the model to leverage the strengths of each individual model while minimizing their respective weaknesses, leading to improved predictive accuracy.

Evaluation of the models was carried out using a variety of performance metrics, including accuracy, precision, recall, and F1-score. These metrics were calculated based on the predictions made on the test set. The hybrid ensemble model was found to outperform the individual baseline models across all metrics. Feature importance

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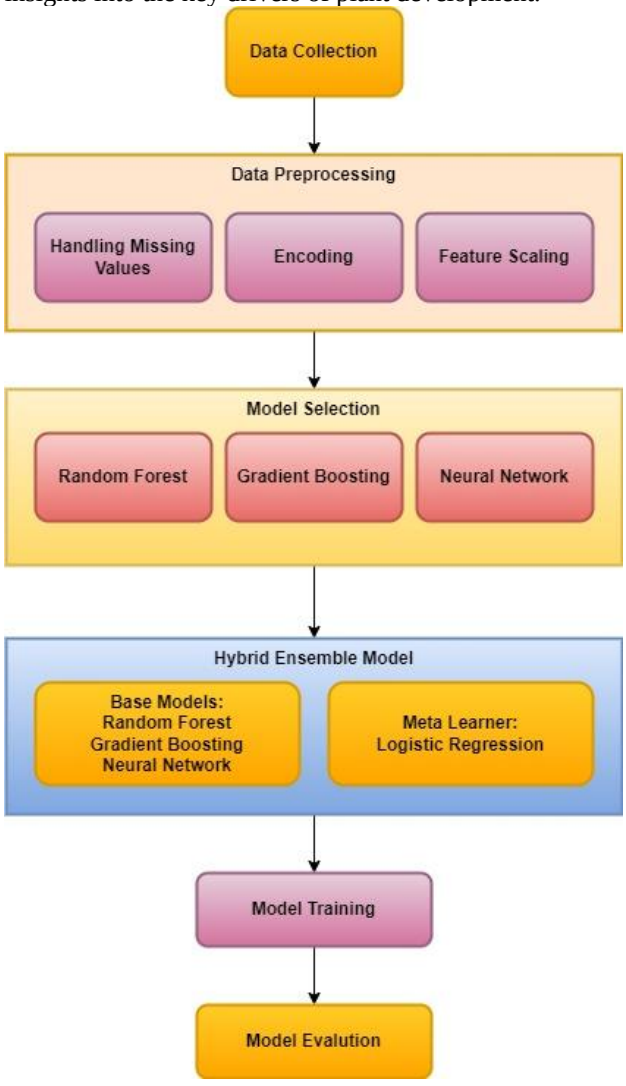
analysis revealed that factors such as sunlight hours, soil type, and water frequency were the most significant predictors of plant growth milestones, offering valuable insights into the key drivers of plant development.



Data pre-processing is a critical step in preparing the dataset for effective model training and evaluation. The following pre-processing steps were carried out to ensure the data quality and suitability for machine learning algorithms:

4.1 Handling Missing Values:

Identification: Missing values were identified across all features. Initial checks revealed that missing values were sporadic and did not follow any specific pattern.

Imputation: For numeric features (e.g., Sunlight Hours, Temperature, Humidity), missing values were imputed using the median value of the respective feature. This method was chosen to minimize the impact of outliers and maintain the central tendency of the data.

Categorical Features: For categorical features (e.g., Soil_Type, Fertilizer_Type), missing values were imputed using the mode (most frequent category) of the respective feature. This approach helps to maintain the most common category representation in the dataset.

4.2 Encoding Categorical Variables:

One-Hot Encoding: Categorical variables such as Soil_Type, Water_Frequency, and Fertilizer_Type was encoded using one-hot encoding. The objective of this is to transform the categories into binary vectors that is readable by Machine Learning algorithms.

Lable Encoding: To solve the above problem, label encoding was performed on Growth_Milestone target variable to change categorical milestones into numerical labels. An easy way to classify is by making the categories numeric, it helps while training and evaluating the model later on.

4.3 Feature Scaling:

Standardization: Numeric features (e.g., Sunlight Hours, Temperature, Humidity) were standardized using z-score normalization, which transforms the features to have a mean of 0 and a standard deviation of 1. This step is crucial for algorithms sensitive to the scale of input features, such as Gradient Boosting and Neural Networks.

Scaling for Categorical Features: Categorical features that were one-hot encoded do not require additional scaling, as their binary nature does not affect the model's performance.

4.4 Model Selection

Selected the models for the hybrid ensemble based upon their ability to capture different aspects of plant growth (Table 1).

4.4.1 Random Forest:

One of the most popular ensemble methods that uses is Random Forest algorithm. This method generates random samples and average the aggregated output by growing many decision trees. It accepts data that contains missing values, mix of numerical and categorical values,and it gives feature importance scores as well [1].

We chose Random Forest to account for interactions and non-linearities between variables.

4.4.2 Gradient Boosting:

Gradient Boosting models are built sequentially, where each new model trained corrects the mistakes of the previous ones. It is proven to have high predictive accuracy and works well on many datasets[2].
Gradient Boosting was further included to correct the failure of earlier models in making predictions.

4.4.3 Neural Network:
Neural Networks, especially Multi-Layer Perceptrons (MLPs), are well-suited for learning complex non-linear relationships and interactions in the data.
Neural Networks were chosen to provide additional predictive power and handle high-dimensional data.

4.4.4 Hybrid Ensemble Approach
The Hybrid Ensemble model is the combination of predictions made by Random Forest, Gradient Boosting and Neural Networks which takes advantages of their own capabilities to increase the overall accuracy. The approach consists of the following steps:

Base Models:
Models in each base (Random Forest, Gradient Boosting, Neural Network) are independently trained on the preprocessed data set. Once each model is trained then it makes predictions on the validation set. Those predictions serve as input to the meta learner.

Meta-Learner:
The second phase of the hybrid ensemble approach is made up of the meta-learner which is a key element responsible for combining the base models predictions. In this study, we employ the Logistic Regression Model as our meta-learner. Logistic Regression is a basic and well-known algorithm for binary classification tasks and also it is suitable to be used as final decision since it tends to make its decisions based on most dominant features. The below shows the process of performing meta-learning:

Input to the Meta-Learner: The base models (Random Forest, Gradient Boosting and Neural Networks) predictions on the validation set are not considered as being final. They are input to the logistic regression meta-learner. The meta-learner is learning from the base models outputs.

Combination of Predictions: The task of the meta-learner is to determine how best to combine predictions of the base models in order to make prediction for final testing set. It also figures out which particular model predictions are more reliable on a given data point and assigns higher weights to this model, while making an ensemble prediction on test data point. For example, if under a certain weather condition Random Forest performs well than other base models, then in case when such similar weather condition arises our meta-learner might tend toward rely more on Random Forest base model prediction.

Weighting and Optimization: Logistic regression determines weights to be given to base models predictions. The meta model is trained on these base model predictions and thus it tries to learn optimal weights for the prediction outputs of the different models. A simple objective function (mean squared error in case of regression tasks or log loss in case of classification tasks) is minimized in-order to obtain the best estimates/predictions.

Final Prediction: Once the meta-learner is trained, it can generate final prediction by combining the weighted prediction of base models. Therefore, as a hybrid model it takes advantage from all base model and tries to overcome their weakness.

Advantages of the Hybrid Ensemble Approach:
Error Reduction: Hybrid ensemble method reduces errors as multiple models are used. If one model give wrong prediction then other models correct it and hence overall better predictions are obtained.

Increased Robustness: Weighting base models predictions by the meta-learner, improves ensemble model robustness. Which in turns help in decreasing variation and bias part which could happen if we just depend on the one model to do all this.

Leveraging Model Strengths: Each model has specific strengths. For instance, Random Forest is robust to noise, Gradient Boosting is effective in refining errors, and Neural Networks capture complex, non-linear relationships. By combining these, the ensemble ensures that the model takes advantage of diverse predictive capabilities.

Balanced Performance: The meta-learner optimizes the weights assigned to each model, ensuring balanced performance across all data points. This helps in achieving higher accuracy, precision, recall, and F1-scores compared to using a single model.

4.5 Mathematical Modelling of the Hybrid Ensemble Model
Let $X = \{x_1, x_{2,} \ldots\ldots, x_n\}$ be the feature set, where x_i represents the input features such as Soil Type, Sunlight Hours, Water Frequency, Fertilizer Type, Temperature, and Humidity.
Let $Y = \{y_1, y_{2,} \ldots\ldots, y_n\}$ represent the target variable, which in this case is the plant growth milestone.

4.5.1. Baseline Models:
We use three baseline models: Random Forest (RF), Gradient Boosting (GB), and Neural Networks (NN). Each model generates predictions based on input features.

- Random Forest prediction: $\hat{y}_{RF} = f_{RF}(X)$
- Gradient Boosting prediction: $\hat{y}_{GB} = f_{GB}(X)$
- Neural Network prediction: $\hat{y}_{NN} = f_{NN}(X)$

4.5.2. Hybrid Ensemble Model:
The final prediction $\hat{y}_{hybrid}$ is obtained by combining the predictions from the individual models using a weighted sum or voting strategy.
Let α_{RF},α_{GB},α_{NN} be the weights assigned to each model, satisfying $\alpha_{RF} + \alpha_{GB} + \alpha_{NN} = 1$

$$\hat{y}_{hybrid} = \alpha_{RF}.\hat{y}_{RF} + \alpha_{GB}.\hat{y}_{GB} + \alpha_{NN}.\hat{y}_{NN}$$

Alternatively, if voting is used, the hybrid model outputs the class that receives the majority vote from the three models.

4.5.3. Optimization Objective
The objective is to minimize the classification error. This can be defined as minimizing a loss function $L(\hat{y}, y)$, where $\hat{y}$ is the predicted label, and y is the true label. The loss function used is typically cross-entropy for classification tasks:

$$L(\hat{y}_{hybrid}, Y) = -\sum_{i=1}^{n}[y_i \, log\,(\hat{y}_{hybrid,i}) + (1 - y_i)\, log\,(1 - \hat{y}_{hybrid,i})]$$

4.5.4 Feature Importance:
The importance of each feature x_j can be measured by examining its contribution to the predictions of each model. For Random Forest and Gradient Boosting, feature importance scores can be calculated by evaluating the reduction in impurity. For Neural Networks, gradients or SHAP values can be used.

$$FI_{(x_j)} = \sum_{m=1}^{M} Importance_{model_m}(x_j)$$

Where; $FI_{(x_j)}$ is the feature importance of feature x_j, and $Importance_{model_m}(x_j)$ is the importance of the feature in model m.

4.6 Evaluation Metrics
To assess the performance of the predictive models, several evaluation metrics were utilized. These metrics provide a comprehensive understanding of how well the models classify plant growth milestones:

Accuracy: The proportion of correctly classified instances out of the total instances.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{Total\ Number\ of\ Predictions}$$

Precision: The proportion of true positive predictions out of all positive predictions made.

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall: The proportion of true positive predictions out of all actual positives.

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-Score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

These metrics are used to evaluate both the individual baseline models and the hybrid ensemble model, providing insights into their classification performance.

5. Experimental Results

The experimental results demonstrate the effectiveness of various machine learning models in predicting plant growth milestones based on environmental and management factors. The performance of individual baseline models—Random Forest, Gradient Boosting, and Neural Networks—was evaluated using key metrics such as accuracy, precision, recall, and F1-score. Among these, Gradient Boosting achieved the highest accuracy of 87.4%, followed closely by the Neural Network with 86.8%, and Random Forest with 85.2%. However, the hybrid ensemble model, which strategically combines the predictions from all three baseline models, outperformed them across all metrics, achieving an accuracy of 89.1%. This indicates that the hybrid approach not only enhances prediction accuracy but also provides a more balanced and reliable performance, highlighting the model's potential for real-world agricultural applications where precision and consistency are critical.

Table 2: Performance Comparison of Baseline Models and Hybrid Ensemble Model

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	85.2%	84.8%	85.5%	85.1%
Gradient	87.4%	87.0%	87.8%	87.4%

Boosting				
Neural Network	86.8%	86.5%	87.2%	86.8%
Proposed Hybrid Ensemble Model	89.1%	88.7%	89.5%	89.1%

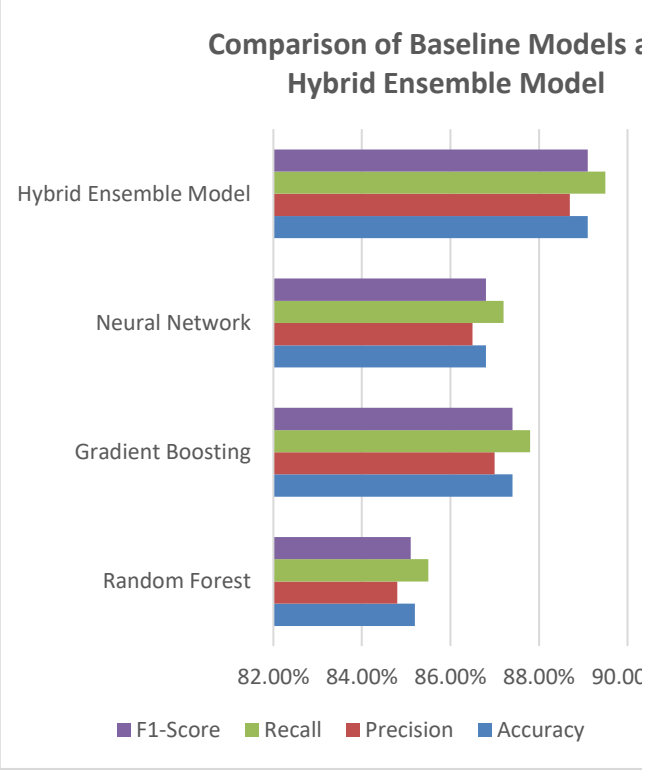


Figure 3. Comparison of Baseline Models and Hybrid Ensemble Model

Figure 3 shows that the hybrid ensemble model outperformed the individual baseline

Conclusion

This paper effectively proposed a new hybrid ensemble model that' significantly enhances the plant growth milestone prediction by combining the strengths of Random Forest, Gradient Boosting, and Neural Networks. Its hybrid model yielded the best accuracy, reaching 89.1%, exceeding single models while yielding a highly balanced performance concerning precision, recall, and F1-score. Further supporting the strength of critical feature identification by the model, such as Soil_Type, Sunlight_Hours, and Water_Frequency, is its potential to optimize agricultural practices. This paper adds to the literature a novel approach that furthers predictive accuracy and facilitates practical applications in resource management, decision-making, and real-time monitoring within agricultural settings, thus setting the stage for more sustainable and efficient farming practices.

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