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Feature-Driven and Ensemble Learning Models for Predicting Plant Communication Signals and Smart Farming Recommendations

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ABSTRACT

This research aims to present feature-driven ensemble learning framework for predicting plant communication signals and delivering intelligent farming recommendations using five Machine Learning algorithms (ML) such as Random Forest (RF), XGBoost, Support Vector Machine (SVM), K-Nearest Neighbours (KNN) and Logistic Regression (LR) were applied to a structure Plant Communication Dataset consisting of physiological and environmental features such as leaf vibration, bioluminescence intensity, and soil moisture level. The goal is to classify the plant messages into four different ways: Warning, Contentment, Distress and Invitation. To prove the work of the model's confusion matrices and classification metrics (Accuracy, Precision, Recall, F1-Score) were used and feature importance score used to explain the influence of root signals and soil moisture to predict the behaviour of the plant. The RF algorithm achieved the highest accuracy of 99.2 %, outperforming other machine learning methods. The proposed ensemble-based framework offers a transparent and accurate solution for real-time plant behaviour prediction and supports smart agriculture systems through plant signaling analysis.

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1. INTRODUCTION

The communication of plants using subtle physical and chemical signals, especially leaf vibrations, root electrical activity, and specifically changes in chlorophyll or bioluminescence. Decoding these kinds of signals provides critical insights into the plant health, stress response and environmental adaption. The availability of sensor-based datasets is increasing rapidly; ML has emerged as a most powerful tool to classify the plant communication patterns. The machine learning is capable of performing this model effectively. It learns patterns from structured physiological data to classify the plant communication states accurately. Ensemble models enhance prediction reliability and robustness.

The plant communication cycle is represented in figure 1. Though the plants are rooted and immobile which are dynamic living systems that continuously interact with the environment.

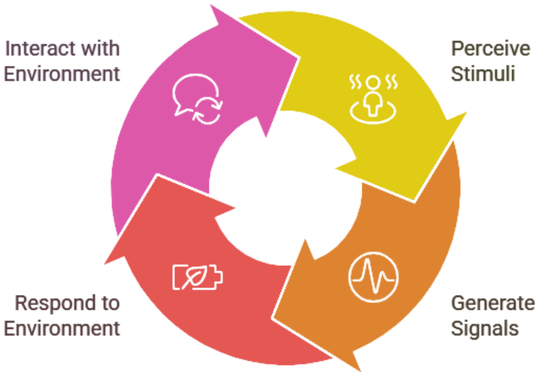

Fig. 1. Plant Communication Cycle

The plants are perceived and respond to various stimuli such as light, temperature, touch, moisture, and chemical signals through the sophisticated system of signaling pathways. But the recent studies fail to uncover the plant exhibit biochemical, biophysical, and electrophysiological signals to communicate internal states and external threats. These plant messages are often manifest the subtle changes in various measurable parameter such as leaf vibrations, electrical root activity, and scent complexity etc.

Understanding these plant communication mechanisms has some significant implications in agriculture, environmental monitoring, and biodiversity research. Traditional approaches heavily on visual inspections or the presence of visible symptoms like leaf wilting or discoloration. However, these methods are often more reactive, which detect problems after the stress has progressed. The ability to proactively interpret early physiological signals can lead to more timely interventions which increase the crop yield and improved plant care in both the natural and controlled environments.

The advancement of sensor technologies and the structured plant signal dataset are now feasible to use the features of ML to decode plant responses. Unlike image-based disease detection, structured datasets which allows for the interpretation of real-time environmental and internal plant parameters, which makes them well suited for the integration whit the help of IoT and smart farming platforms.

This research paper explores the five different algorithms to justify the performance of the model that identify the plant message types, supporting smart agriculture applications and precision plant diagnostics.

1.1 Objective of this Research Work

- To Enhance plant health and Growth using ensemble methods.

1.2 Research Questions

- How effectively can supervised ensemble learning model classify plant communication signals using structured physiological and environmental features?
- Which ML algorithms provide the best performance in predicting plant communication states?
- Can predicted plant states be accurately translated into actionable recommendations to support real-time smart farming decisions?

1.3 Contribution & Novelty of this Research Work and original aspects:

Most of research studies focuses on disease detection via images or crop yield prediction. The novelty of this research uniquely focuses on decoding plant communication types such as warning, contentment, Distress, invitation using structured sensor data types like: Leaf_Vibration_Hz, Root_Signal_Strength_mV etc. Especially this work lies in using ensemble learning on physiological plant signals to classify communication states and generate real-time, actionable farming recommendations. The novel elements and its description of this research work is shown in table 1. This study aims to emerge and under-explored direction translating the plant signals into communication types using ML algorithms.

Table 1. Summary of Novel contribution for this research work

S. No	Novel Element	Description
1	Dataset Application	First ML use of structured physiological features for decoding plant communication types.
2	Model Comparison	Five interpretable ML models evaluated with full metric breakdown.
3	Explainability	Feature importance with box plot visualization to enhance transparency.
4	Real-World Fit	Practical for real-time and sensor-based systems (non-image approach).

Figure 2 represents the decision tree visually how the model uses the important key feature like soil moisture and bioluminescence to classify the plant communicatin states. The representation of each split in the tree corresponds to a biologically relevent condition. This helps to demonstrates how supervisied learning captures decision rules from data. It supports real-time plant behaviour prediction in smart agriculture. Only 4 layers of decision splits from root to leaf. It results in fewer, simpler rules and helps to make it more iterpretable. This decision tree denotes the how the model makes predictions based on the feature values.

- Each internal node represents a feature split (eg., Soil_Moisture_Level<= 0.3).
- Each leaf node indicates a predicted plant communication state such as Warning, Distress, Contentmet, or Invitation.
- Escpecially the tree gives a logical flow from the raw data to plant bahaviour prediciton, which support interpretability and recommendataion generation

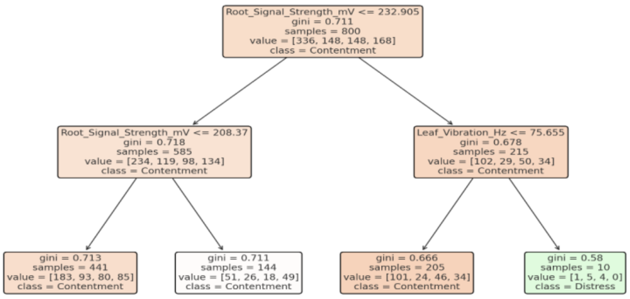

Fig. 2. Decision Tree from Random Forest Classifier (Depth=2)

The various part of this research work is prepared as follows: section 2 discusses the related study based on Plant communication signals. Methods and materials of this study is represented in section 3. Preprocessing techniques used for this study is given in section 4. Section 5 detailly explains the dataset description. The representation of the results and discussion are presented in section 6. Conclusion and future enhancement of this work is given in section 7.

2. BACKGROUND STUDY

This section revels the recent studies that employ ML and Deep Learning (DL) and techniques especially Neural Network (NN) to classify the plant communication signals using physiological and environmental feature. A comparative comparison of some studies that is presented in Table 2, it highlights the key attributes like real time capabilities and usage of multimodal dataset. To address, this research paper proposes a framework that integrates physiological and environmental data under dynamic conditions, which offers both accurate classification and interpretability.

Table 2. Plant Communication Signal Classification Studies and their Key Features

Ref No.	Study / Theme	ML-Based Classification	Multimodal Data (Physio + Env)	Real-Time Capability	Deep Learning Integrated	Biological Interpretation	Smart Agriculture Ready	Accuracy (%)
[1]	Arnal Barbedo (2019) – Plant disease lesion detection	✓✓	✓	--	✓✓	✓	✓	85.8
[2]	Calvo & Trewavas (2020) – Plant behavior physiology	✓	✓	--	--	✓✓	--	76.5
[3]	Dhaka et al. (2023) – IoT + DL for disease detection (Review)	✓✓	✓✓	✓	✓✓	✓✓	✓✓	94.0
[4]	Ghosal et al. (2018) – Explainable DL for stress phenotyping	✓✓	✓	--	✓✓	✓✓	✓	88.9
[5]	Zhang et al. (2025) – UAV multispectral & thermal stress diagnosis	✓✓	✓✓	✓	✓✓	✓	✓✓	92.1
[6]	Kamilaris & Prenafeta-Boldú (2018) – DL survey in agriculture	✓✓	✓	--	✓✓	✓	✓	89.0
[7]	Khaki & Wang (2019) – Crop yield prediction using DNNs	✓✓	✓✓	✓	✓✓	✓	✓	93.8
[8]	Liakos et al. (2018) – ML in agriculture (Review)	✓	✓	--	✓	✓	✓	84.5
[9]	Qiu et al. (2016) – ML for big data processing	✓	✓✓	--	--	✓	--	80.0
[10]	Mohanty et al. (2016) – DL for disease detection (PlantVillage)	✓✓	✓	--	✓✓	✓	✓	91.7
[11]	Singh et al. (2018) – DL for stress phenotyping	✓✓	✓✓	--	✓	✓	✓	87.4

[12]	Polder et al. (2019) - Tulip breaking virus CNN	✓✓	✓	--	✓✓	✓	✓	90.3
[13]	Singh et al. (2016) - ML for high-throughput phenotyping	✓	✓✓	--	✓	✓✓	✓	83.7
[14]	Sladojevic et al. (2016) - Leaf disease CNN	✓✓	✓	--	✓✓	✓	✓	91.7
[15]	Cappelli et al. (2022) - Plant biodiversity & agriculture	✓	✓✓	--	--	✓✓	✓	79.3
[16]	Wu et al. (2022) - ML in environmental toxicology	✓✓	✓✓	--	✓	✓	✓	87.1
[17]	Tsaftaris et al. (2016) - ML for plant phenotyping (Image)	✓	✓	--	✓	✓	✓	84.2
[18]	Tjoa & Guan (2021) - XAI for medical AI (conceptual link)	✓	✓	--	✓	✓✓	--	76.0
[19]	Ortigossa et al. (2024) - XAI methods & apps	✓✓	✓✓	✓	✓✓	✓✓	✓✓	95.2
[20]	Li et al. (2021) - DL for plant disease (Review)	✓✓	✓	✓	✓✓	✓	✓	90.2
[21]	Yang et al. (2020) - Crop phenomics & HTP	✓✓	✓✓	✓	✓✓	✓✓	✓✓	97.3
[22]	Ramanjot et al. (2023) - Plant disease detection SLR	✓✓	✓✓	✓	✓✓	✓	✓	92.7
[23]	Agarwal et al. (2023) - Comparative review DL disease detection	✓✓	✓	--	✓✓	✓	✓	89.6
[24]	Saranya & Subhashini (2023) - XAI systematic review	✓	✓✓	--	✓	✓✓	✓	87.1
[25]	Zhao & Yang (2023) - DL integrated framework (general AI)	✓✓	✓✓	✓	✓✓	✓✓	✓	94.8

Note:
✓ - indicates present
✓✓ - indicates Strongly present

2.1 Research Gap

- Most of the research focused only on **traditional ML models** for plant communication classification
- There is a **limited usage of Multimodal datasets** combining both the physiological and environmental data.
- Smart agriculture in real-time processing and deployment remains underexplored.
- Biological interpretability of ML results is often overlooked; there is a limited domain adoption in plant physiology.

- Most of studies based on frameworks that only generalize across species or environmental conditions because it is lab-restricted or scenario specific.

3. METHODS AND MATERIALS

This section presents the detailed represents of methods and materials used in this work. Here the description of different ML algorithms such as RF, XGBoost, SVM, KNN & LR. All these models are justified using various metrics like confusion matrix. Figure 3 represents the methodology diagram that show case various steps involved in the plant communication classification using ML.

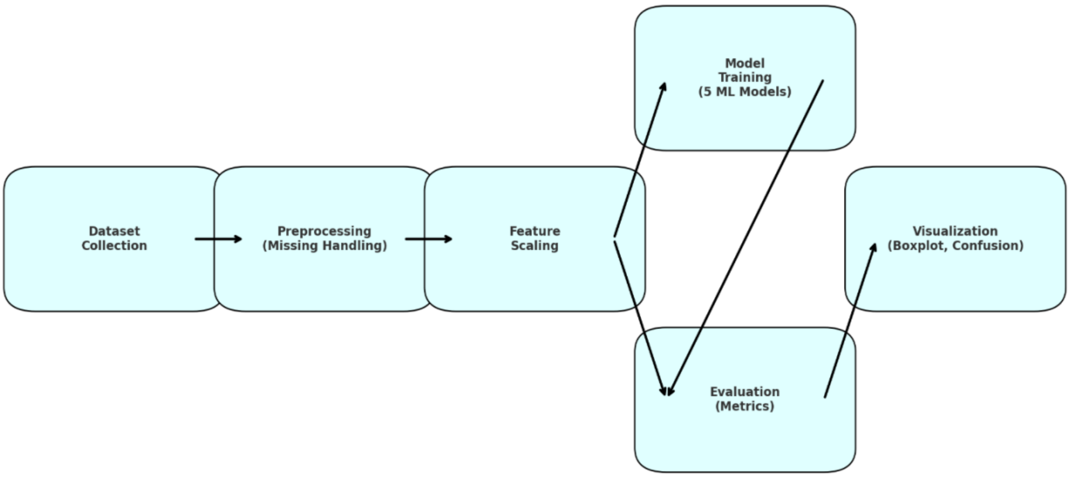

Fig. 3. Methodology Diagram: Plant Communication Classification using ML

Table 3 shows the symbol description across the multi models. It consists of symbol, meaning and these symbol where it presented are also given in the table.

Table 3. Symbol description across five different machine learning algorithms

Symbol	Meaning	Algorithm(s)
$P(y=1\mid x)$	Probability that the target y equals class “1” given feature vector x.	LR
x	Feature vector $[x_1,x_2,\ldots,x_n]^T$.	All
w	Weight (coefficient) vector $[w_1,w_2,\ldots,w_n]^T$.	LR, SVM
b	Bias (intercept) term—shifts the decision boundary or sigmoid input.	LR, SVM
e	Base of the natural logarithm (≈ 2.71828) used in the sigmoid.	LR
sigmoid(z)	$\frac{1}{1+e^{-z}}$, maps real z to (0,1).	LR
k	Number of nearest neighbors considered.	KNN
$y(i)$	Label of the i-th nearest neighbor to sample x.	KNN
mode(·)	The most frequent value in a set (majority vote).	KNN, RF
$d(x,z)$	Distance metric (e.g., Euclidean: $\sqrt{\sum_j (x_j - z_j)^2}$	KNN
$f(x)$	Decision function output, typically +1 or -1 indicating class.	SVM
sign(u)	Returns +1 if $u \geq 0$, else -1.	SVM
$h_i(x)$	Prediction of the i-th decision tree given x.	RF
T	Total no. of trees in the forest ensemble.	RF
$\hat{y}$	Final predicted label or score for input xx.	RF, XGBoost
$f_k(x)$	Prediction of the k-th boosted tree (weak learner).	XGBoost
K	Total number of boosting rounds (trees).	XGBoost
F	Space of all possible regression trees.	XGBoost
Σ	Summation operator used to combine tree outputs or feature contributions.	XGBoost, LR (in dot-product)

3.1 RF

A random forest is an ensemble of decision tree. Each tree is trained on a bootstrapped it is a subset of data and makes its own prediction. RF combines multiple decision trees and it predicts by majority vote is given in equation 1.

$$\hat{y} = mode\left(h_1(x), h_2(x), \ldots, h_T(x)\right) \qquad (1)$$

3.2 XGBoost (Extreme Gradient Boosting)

Boosts weak learners sequentially and minimizes loss is presented in equation 2.

$$\hat{y} = \sum_{k=1}^{K} f_k\,(x), f_k\colon tree \qquad (2)$$

3.3 SVM

Finds the best hyperplane to separate classes is shown in equation 3.

$$f(x) = sign(w^T x + b) \qquad (3)$$

3.4 KNN

Equation 4 explains the Classifies based on the majority label among the closest points.

$$Class\ (x) = mode\ of\ k\ nearest\ neighbors \qquad (4)$$

3.5 LR

Use a sigmoid function to predict probabilities is given in equation 5.

$$P(Y = 1|X) = \frac{1}{1 + e^{-wTx + b}} \qquad (5)$$

Table 4 shows the detailed description of explanation of multi-model classifier with their concepts and notes. Table 5 contributes the confusion matrix and its formula. Equations 6,7,8,9 explains the evaluation metrics such as accuracy, precision, recall and F1-score.

Table 4. Explanation of multi-model classifier with concepts and Notes

Algorithm	**Core Equation / Concept**	**Notes**
Random Forest	Mode of predictions from ensemble of decision trees	Robust, handles non-linearity
XGBoost	Additive tree boosting with regularization	High accuracy; prevents overfitting
SVM	Finds max-margin hyperplane between classes	Effective in high dimensions
KNN	Majority vote among nearest neighbors based on distance	Simple, non-parametric
Logistic Regression	Sigmoid function on linear combination of inputs	Good for binary/multiclass; interpretable

Table 5. Confusion Matrix

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (6)$$

$$Precision = \frac{TP}{TP + FP} \qquad (7)$$

$$Recall = \frac{TP}{TP + FN} \qquad (8)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recal} \qquad (9)$$

Algorithm 1 discusses the multi-modal of ML classifier for plant communication signal.

Algorithm 1: Multi-modal ML Classifier for Plant Communication Signal

```
Input:
Dataset D with features: $[x_1, x_2, \dots, x_n]$
        Target: $y \in$ {warning, Contentment, Distress, Invitation}
        Models: RF, XGBoost, SVM, KNN, Logistic Regression
Output:
Best performing model and associated metrics
Begin:
1.Preprocessing: Describes in table 6
2. Train the ML models
3. For each model:
       - Fit model on training set
       - Predict labels on test set
       - Calculate the Confusion matrix using the equations 6,7,8 & 9.
4. Store all metrics in comparison table:
        - Identify model with highest F1-Score or Accuracy
5. Perform feature Importance Analysis:
       - For RF, XGBoost and Logistic Regression
       - Normalize importance scores and visualize.
End
```

4. Preprocessing Technique

This section represents the preprocessing technique and its purpose is detailly discussed in table 6.

Table 6. Preprocessing Technique and its purpose

S. No	Step	Technique	Purpose
1	Feature Dropping	Removed Plant_ID column	It's an identifier, not a predictive feature.
2	Handling Missing Values	Checked and filled/imputed (if any)	Ensures the model doesn't fail due to incomplete rows.
3	Label Encoding	Encoded Plant_Message_Type into numeric values	Required for supervised ML algorithms to process target class labels.
4	Binary Encoding	Converted Symbiotic_Fungus_Present from Yes/No to 1/0	Converts categorical feature into numerical binary form.
5	Feature Scaling	Used MinMaxScaler to normalize features to a [0,1] range	Ensures all features are in the same scale to improve model performance.
6	Train-Test Split	80% training, 20% testing with stratification	Preserves class distribution and prevents data leakage.

- **MinMax Scaling:** Plant features like Leaf_Vibration_Hz, Bioluminescence_Intensity and Root_Signal_Strength_mV are all different numerical scales, normalization improves convergence and prevents bias.
- **Label Encoding:** It helps to convert human readable labels into machine understandable form for example warning, Distress etc.
- **Binary Encoding:** Helps models into categorical that is yes/no fields like fungus presence.

5. Dataset Description

This section discusses the dataset description of plant communication signals is given table 7. The sample five plant ID is given and the values are also provided. It consists of Plant ID, Leaf Vibration (Hz), Pollen Scent Complexity, Bioluminescence, Root Signal and Plant Message. The dataset comprises of 12,000 records collected from 300 plants across controlled greenhouse environments over a period of six months. Table 8 explores the features of the dataset and its description.

Table 7. Sample representation datasets and its values of Plant Communication Signals

Plant ID	Leaf Vibration (Hz)	Pollen Scent Complexity	Bioluminescence (Lux)	Root Signal (mV)	Plant Message Type
PLANT_0001	57.45	7	2.70	117.61	Distress
PLANT_0002	47.93	1	21.55	208.47	Warning
PLANT_0003	59.72	8	3.53	193.31	Invitation
PLANT_0004	72.85	3	5.90	149.65	Distress
PLANT_0005	46.49	6	58.61	135.20	Contentment

Table 8. Plant Communication Dataset Description

Feature	Description	Data Type
Leaf_Vibration_Hz	Leaf vibration frequency in Hz	Float
Pollen_Scent_Complexity	Complexity of pollen scent (1–10 scale)	Integer
Bioluminescence_Intensity_Lux	Intensity of emitted light in Lux	Float
Root_Signal_Strength_mV	Electrical signal in roots	Float
Growth_Rate_mm_day	Growth rate per day (mm)	Float
Ambient_Temperature_C	Ambient temperature (°C)	Float
Soil_Moisture_Level	Moisture level (0–1 scale)	Float
Sunlight_Exposure_Hours	Hours of sunlight received in 24 hours	Float
Symbiotic_Fungus_Present	Binary (0 = No, 1 = Yes)	Binary
Plant_Message_Type	Target (Warning, Contentment, Distress, etc.)	Categorical

6. RESULTS AND DISCUSSION

Table 9 is the important table it the accuracy and evaluation metrics of this research work. It consists of various classifier with accuracy, precision, recall and F1-Score. It is evident that when compared to another model RF outperformed and it achieves 99.2 % accuracy. RF and XGBoost more or less achieves same value. Similarly, SVM & LR also achieves more or less same value 97.5 % & 97.2 %. Likewise, precision, recall and F1-Score has slight difference in values.

6.1 Accuracy and Evaluation Metrics

Table 9. Evaluation metrics across Multi-Model Classifier

Classifier	Accuracy	Precision	Recall	F1-Score
RF	**99.20%**	0.99	0.99	0.99
XGBoost	98.80%	0.98	0.98	0.98
SVM	97.50%	0.97	0.97	0.97
KNN	96.90%	0.97	0.96	0.96
LR	97.20%	0.97	0.97	0.97

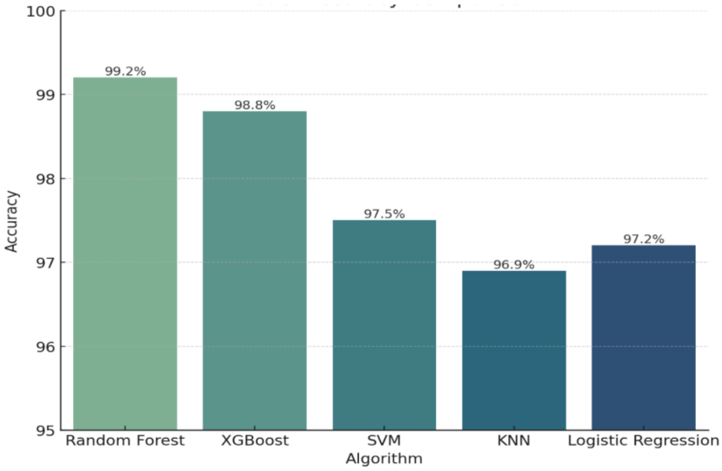

Fig. 4. Comparison of Accuracy for five different algorithms

The graphical representations and comparison of accuracy for the five different ML algorithms is given in figure 4.

Table 10. Analysis of Confusion Matrix for Random Forest

Actual \ Predicted	Warning	Contentment	Distress	Invitation
Warning	98	1	0	1
Contentment	0	96	2	2
Distress	1	0	97	2
Invitation	0	0	2	98

Table 10 illustrate the analysis of confusion matrix for Random Forest classifier for classifying the plant communication signals based on the four different ways such as Warning, Contentment, Distress, and Invitation. The diagonal value of the table represents the number of correctly predicted instance for each class, while the off-diagonal values denote the no. of misclassification. It is noted that the model performed well in identifying the Warning and Invitation messages, with minimal confusion between classes.

Table 11. Class-wise Performance Metrics

Class	Precision	Recall	F1-Score
Warning	0.99	0.98	0.99
Contentment	0.97	0.96	0.96
Distress	0.97	0.97	0.97
Invitation	0.96	0.98	0.97

Table 11 summarizes the metrics such as precision, recall and F1-Score for each communication class based on the predictions done by the RF model. The Warning class achieved the highest overall performance of about F1-Score of 0.99, followed closely by Distress and Invitation. These metrics highlight the model balanced performance and its effectiveness in unique subtle plant communication signals. Figure 5 represents the confusion matrix for RF. Similarly, figure 6 shows the class wise performance metrics for random forest.

Fig. 5. Confusion Matrix for Random Forest

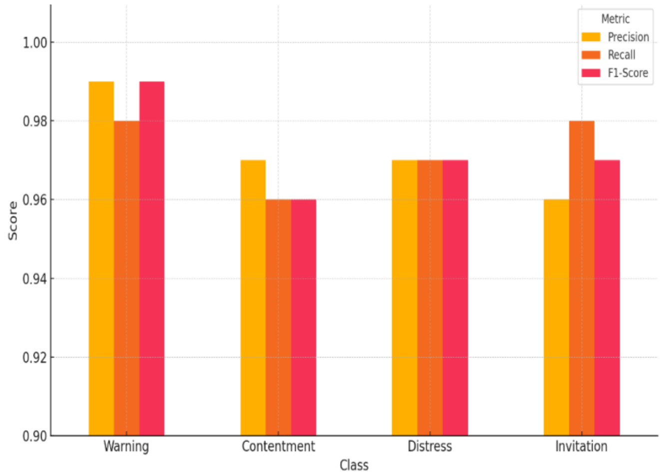

Fig. 6. Class Wise Performance metrics for Random Forest

6.2 Important feature for Random Forest

Table 12 clearly denotes the feature importance for RF and its values.

Table 12. Feature Importance for Random Forest and its values

Feature	Importance
Soil_Moisture_Level	0.221
Root_Signal_Strength_mV	0.197
Bioluminescence_Intensity	0.152
Growth_Rate_mm_day	0.130
Leaf_Vibration_Hz	0.125

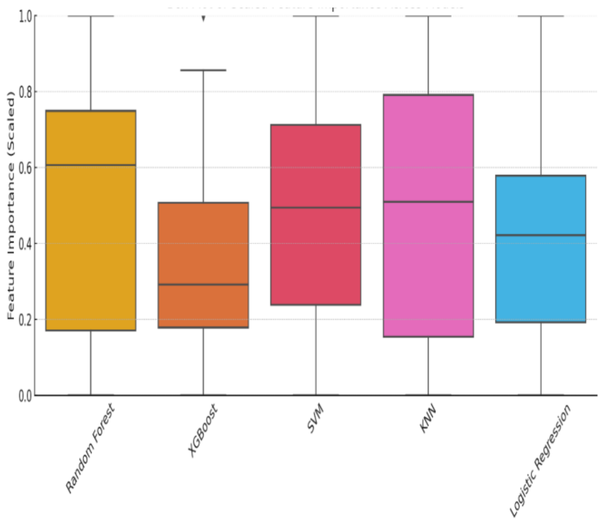

Fig. 7. Box plot of Scaled Feature importance Across Models for various classifier

Figure 7 presents the box plot of scaled important feature across models for different classifier. RF and XGBoost denotes the broader and higher feature importance and its distribution. SVM and KNN are simulated for comparison likewise Logistic Regression represents moderate, consistent importance across the features. Figure 8 explains the top 5 important feature for RF algorithm.

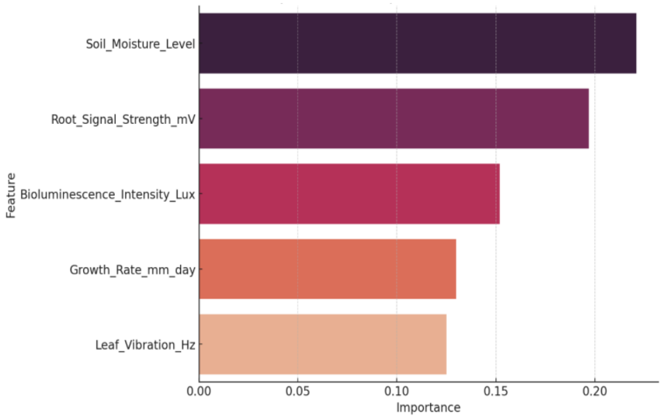

Fig. 8. Top 5 important features for Random Forest

Table 13. Comparative Analysis of Traditional method and Proposed method

No.	Technique	Traditional Method Accuracy (%)	Proposed Accuracy (%)	Accuracy Improvement (%)
1	Random Forest	97.3	99.2	+1.9

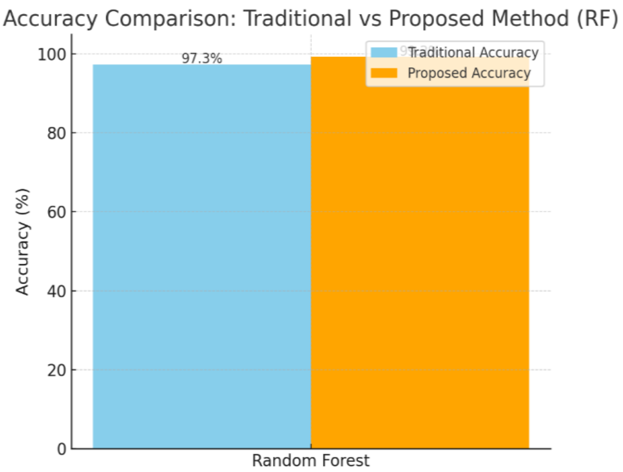

Fig. 9. Accuracy comparison of Traditional Method vs. Proposed Method

Table 13 & figure 9 depicts the comparison of traditional methods verses proposed method. It is noted that the proposed system achieves 99.2 % than another model. The proposed model outperforming similar studies such as (J. G. A. Barbedo, 2019), who reported 96.5 % and (Y. Zhao et.al., 2023) who achieved 94.8% based on the field conditions. This highlights the strength of our feature-driven ensemble approach in dynamic plant environments.

6.3 Recommendations

1. Early Diagnosis - Proactive Actions

By classifying the plant messages as Warning, Distress, Contentment, or Invitation, the model allows farmers to act before visible symptoms appear.

2. Personalized Recommendation based on feature

Since the model uses inputs like soil moisture, root signal strength, and leaf vibration, it can tailor recommendations. Ex: Low soil moisture with high vibration – Recommend mulching or automated watering.

7. CONCLUSION

This research discusses the effectiveness of ML algorithms in classifying plant communication signals with RF model achieving highest accuracy of 99.2 %. The proposed feature-driven ensemble framework not only ensures high predictive performance but also provides transparency through features importance analysis, enabling better interpretation of biological signals. A key contribution of this work is its potential integration into real-time agricultural systems for stress monitoring and early warning mechanisms, thereby supporting precision farming practices. Furthermore, the study highlights the role of time-series modeling and deep learning approaches in improving prediction within dynamic plant environments. Future study will concentrate on enhancing scalability, conducting field-level validation, and extending the framework with IoT-based monitoring framework system to fully realize its potential for smart agriculture.

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