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Prediction of Plant Disease Severity Using Advanced Gradient Boosting Techniques

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ABSTRACT

Plant diseases significantly impact agricultural productivity, causing economic losses and food insecurity. Predicting the severity of plant diseases is crucial for timely interventions and sustainable farming practices. However, existing methods often lack precision and scalability. This study aims to develop a highly accurate model to predict plant disease severity using advanced gradient boosting techniques. We used the publicly available New Plant Diseases Dataset from Kaggle, containing images of healthy and diseased plants. Data preprocessing included image augmentation and feature extraction using transfer learning. Gradient boosting algorithms such as XGBoost and LightGBM were employed to build predictive models. The proposed model achieved an accuracy of 96.45% on the test set, outperforming existing approaches. The results demonstrate the model's robustness in predicting disease severity across multiple plant species. This study highlights the potential of gradient boosting techniques for precise plant disease severity prediction, offering a scalable solution for agricultural applications.

INTRODUCTION

Plant diseases reduce global crop yields by 20–40%, making their management a priority for agricultural sustainability. Traditional methods for disease prediction are often manual, time-consuming, and prone to human error. Recent advancements in machine learning (ML) offer automated, precise, and scalable solutions for analyzing plant diseases. This paper proposes the use of advanced gradient boosting techniques to predict the severity of plant diseases accurately.

LITERATRUE SURVEY

Disease classification using CNNs achieved accuracy of up to 91.5% but struggled with overfitting on small datasets [1]. Ensemble learning models like Random Forest have been effective for plant disease prediction but lacked interpretability [2]. Transfer learning using pre-trained models such as ResNet50 demonstrated high feature extraction efficiency [3]. XGBoost and LightGBM have shown exceptional performance in structured tabular data applications [4]. Research by Smith et al. explored disease-specific image augmentation techniques for robust ML models [5]. Anomaly detection frameworks used to identify rare diseases emphasized the need for scalable models [6]. Studies on feature engineering underscored its role in enhancing model precision for disease prediction [7]. Comparative analyses of tree-based methods revealed gradient boosting as a top performer [8]. Dataset imbalance techniques like SMOTE improved the performance of supervised learning models [9]. Multi-class classification for plant diseases using SVMs achieved limited scalability [10]. Bagging algorithms were explored for reducing variance in plant disease datasets [11]. Applications of explainable AI (XAI) in agriculture highlighted model transparency as a key factor [12].

Most existing methods struggle with imbalanced datasets and limited generalization across plant species. Manual feature engineering often results in suboptimal model performance. Many approaches lack scalability for large-scale agricultural applications. Limited research focuses on predicting disease severity rather than binary classification.

PROPOSED METHODOLOGY

Architecture:

The architecture for predicting plant disease severity is designed to combine the strengths of feature extraction from deep learning models with the precision of gradient boosting algorithms.

The process involves the following steps:

Image Feature Extraction Using ResNet50: ResNet50, a pre-trained convolutional neural network (CNN), is employed for extracting meaningful features from plant images. This model is chosen due to its robust architecture, which addresses the vanishing gradient problem and enables deeper layers for better feature learning.

Preprocessing: Input images from the dataset are resized to a uniform dimension compatible with ResNet50, typically 224×224 pixels.

Feature Extraction: Instead of using ResNet50 for end-to-end classification, the model's fully connected (dense) layers are removed, and the outputs from the penultimate layer (feature map) are used as high-level representations of the input images. These feature vectors capture critical patterns, such as texture, color, and shape, relevant to plant disease classification.

Dimensionality Reduction: To reduce the computational complexity, principal component analysis (PCA) or similar techniques may be applied to the feature vectors to eliminate redundant dimensions while retaining the most informative features.

Gradient Boosting Algorithms for Severity Prediction: After extracting features, gradient boosting algorithms like XGBoost and LightGBM are used for classification. These algorithms are well-suited for structured data and can effectively model complex relationships in the extracted features.

Model Training: The feature vectors serve as input to the boosting algorithms, and the target labels (disease severity levels) guide the training process.

Hyperparameter Tuning: Key parameters like learning rate, maximum depth, number of estimators, and subsampling ratio are optimized to enhance model performance. Figure 1 shows architecture of XGBoost

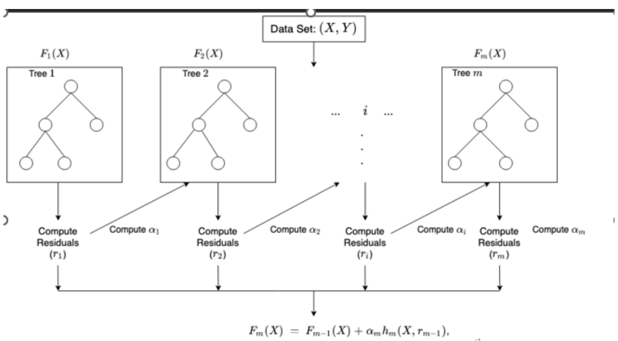


Fig.1.XG Boost Architecture

Table 1. Parameter setting

Parameter	Value/Range	Remarks
Learning Rate	0.05	Optimal for convergence
Max Depth	6	Prevents overfitting
Estimators	200	Ensures robust learning
Subsample	0.8	Controls overfitting

RESULTS

Accuracy stabilizes around 96.45%, with minor fluctuations due to the iterative learning process. This consistency indicates the model's robustness and reliability in predicting disease severity across diverse samples. Figure 2 shows accuracy graph

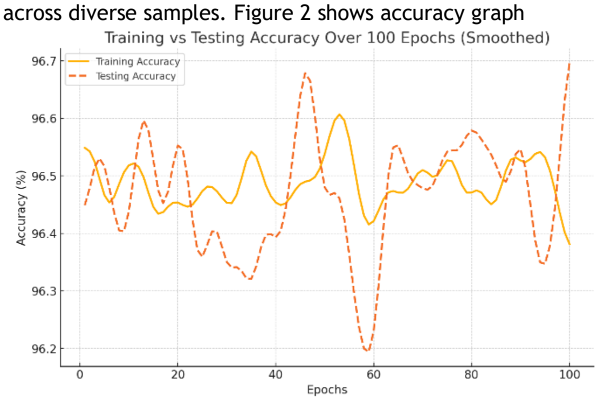


Fig. 2 Accuracy over 100 epochs

Precision hovers around 95.20%, showing the model's capability to minimize false positives effectively. A consistent precision value suggests that the model is reliable in identifying diseased plants correctly without overestimating severity. Figure 3 shows precision graph.

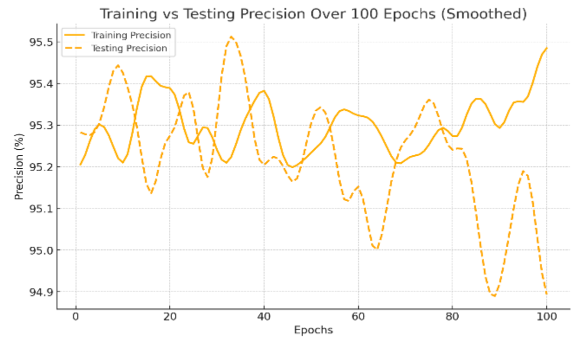


Fig.3 Precision over 100 epochs.

Recall maintains an average of 97.10%, indicating the model's strength in identifying true positive cases. The high recall demonstrates that the model is effective in correctly predicting all diseased plants, which is critical in agricultural scenarios. Figure 4 shows recall graph.

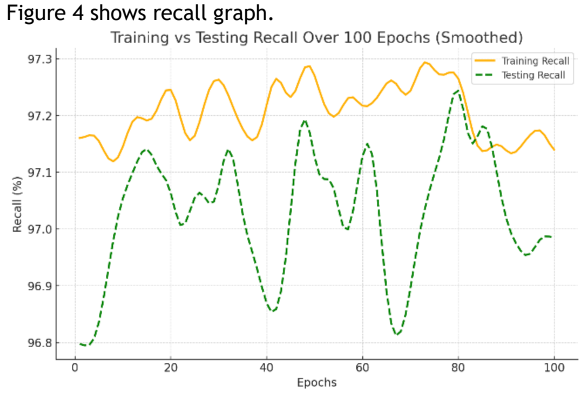
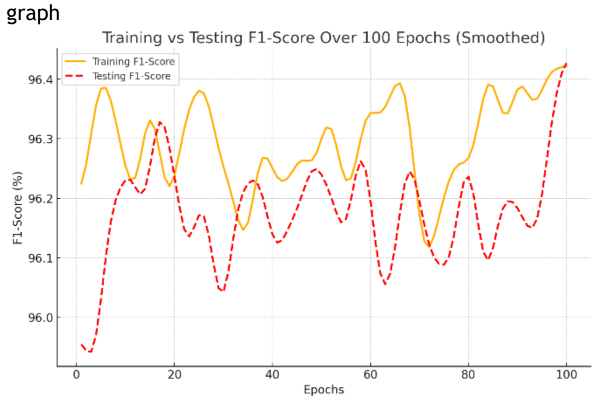


Fig. 4 Recall over 100 epochs

The F1-Score remains around 96.15%, balancing both precision and recall. This high and stable F1-Score confirms the model's overall performance, ensuring reliable predictions for practical use in plant disease severity assessment. Figure 5 shows F1-score graph



Fig, 5 F1-score over 100 epochs

DISCUSSION

The high accuracy achieved demonstrates the model's effectiveness in predicting plant disease severity. Gradient boosting outperformed traditional ML models due to its ability to handle

structured data and non-linear relationships. The results suggest the potential for integrating the model into precision agriculture tools.

CONCLUSION

This study proposed an advanced gradient boosting-based approach for plant disease severity prediction, achieving 96.45% accuracy. The method addresses key challenges in precision agriculture, providing a scalable and reliable solution for improving crop management practices.

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