SMART PLANT DISEASE DETECTION USING ENSEMBLE MACHINE LEARNING AND EXPLAINABLE AI

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ABSTRACT

With the Plant diseases pose a significant threat to global agriculture, leading to reduced crop yield and economic losses. Traditional disease detection methods, such as manual inspection and chemical analysis, are time-consuming, labor-intensive, and require expert knowledge. To address these limitations, this research presents a plant leaf disease detection system using ensemble learning and Explainable AI (XAI). The proposed model combines multiple machine learning classifiers, such as Convolutional Neural Networks (CNNs), Random Forest, and Support Vector Machines (SVMs), to enhance classification accuracy and robustness. By leveraging ensemble learning, the system ensures improved generalization and adaptability across different plant species and disease types. Additionally, XAI techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM) and SHapley Additive exPlanations (SHAP),** are integrated to provide interpretability, allowing users to understand the decision-making process of the model. The dataset used includes images of diseased and healthy leaves, and performance evaluation is conducted using accuracy, precision, recall, and F1-score. Experimental results demonstrate that the ensemble learning approach outperforms single models, achieving high classification accuracy while maintaining explainability. The proposed system has applications in precision agriculture, automated disease monitoring, and decision support for farmers. Future enhancements include real-time deployment on mobile applications and integration with IoT-based smart farming solutions.

INTRODUCTION

Accurate calorie estimation is Agriculture plays a crucial role in global food security, but plant diseases remain a major challenge, leading to significant crop losses and economic damage. Traditional methods of disease detection, such as visual inspection by experts or laboratory testing, are often impractical for large-scale farming due to their time-consuming and expensive nature. Early and accurate identification of plant leaf diseases is essential for effective disease management and prevention of outbreaks.With the rise of artificial intelligence (AI) and machine learning (ML), automated plant disease detection has gained attention as a cost-effective and scalable solution. While deep learning models such as CNNs have demonstrated promising results in disease classification, they often suffer from overfitting, lack of interpretability, and poor generalization to new datasets. To overcome these challenges, this study introduces an ensemble learning approach, which combines multiple ML models to improve classification accuracy and reliability. By leveraging diverse algorithms such as CNNs, Decision Trees, and SVMs, the system enhances robustness against variations in lighting, background noise, and disease symptoms.Additionally, a critical challenge in AI-based plant disease detection is the lack of interpretability, which limits trust and adoption by farmers and agricultural experts. This research integrates Explainable AI (XAI) techniques such as Grad-CAM and SHAP to visualize the key features influencing predictions, allowing users to understand why a model classifies a leaf as diseased. The performance of the proposed system is evaluated on a publicly available dataset of diseased and healthy plant leaves, using metrics like accuracy, precision, recall, and F1-score. The objective is to develop an accurate, transparent, and scalable solution for automated plant disease detection that can be implemented in precision agriculture and smart farming systems.

LITERATURE REVIEW

1. Ensemble Learning for Robust Plant Leaf Disease Detection

Author(s): Sharma, R., & Patel, V.

Plant diseases significantly impact agricultural productivity, necessitating robust detection techniques. Sharma and Patel (2021) proposed an ensemble learning approach combining Random Forest, Gradient Boosting, and Convolutional Neural Networks (CNNs) for plant disease classification. Their hybrid model, trained on PlantVillage dataset, achieved 95.6% accuracy, outperforming individual classifiers. The study highlights the advantage of ensemble methods in handling diverse leaf textures, lighting variations, and noise. However, the model struggles with rare diseases due to dataset limitations. Future enhancements could include self-supervised learning techniques to improve disease detection in underrepresented plant species.

2. Explainable AI in Plant Disease Detection: A SHAP and LIME Approach

Author(s): Nair, S., & Mehta, K.

Explainability in AI is crucial for trustworthy agricultural decision-making. Nair and Mehta (2022) integrated SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) with an XGBoost-based ensemble classifier for plant disease detection. Their study provided visual interpretability of model predictions, helping farmers understand which leaf regions contribute to disease classification. The model achieved 92.4% accuracy but showed limitations in handling multi-class disease identification. Future research should explore attention mechanisms and saliency maps for better transparency in AI-driven agricultural applications.

3. Hybrid CNN-RF Model for Disease Classification in Crops

Author(s): Banerjee, A., & Iyer, R.

Deep learning models excel at feature extraction, but traditional classifiers provide better decision boundaries. Banerjee and Iyer (2020) introduced a hybrid CNN-Random Forest (CNN-RF) ensemble model, which extracts deep features via ResNet-50 and classifies them using Random Forest. This method achieved a 96% accuracy in distinguishing diseases like powdery mildew and leaf blight. The study emphasizes how ensemble strategies enhance generalization but notes that computational overhead can limit real-time deployment. Future improvements could focus on edge AI optimization for lightweight, mobile-friendly disease detection models.

4. Multi-Modal Disease Diagnosis Using Fusion-Based Ensemble Learning

Author(s): Singh, V., & Rao, P.

Leveraging multiple data sources improves plant disease classification. Singh and Rao (2021) developed a multi-modal deep learning framework that integrates RGB leaf images and hyperspectral data using a fusion-based ensemble model. Their approach utilized ResNet, EfficientNet, and LightGBM to extract hierarchical features, achieving a 97.2% classification accuracy. The fusion model enhanced the identification of early-stage diseases, but its reliance on hyperspectral imaging makes it expensive for small-scale farmers. Future studies should explore cheaper alternatives like smartphone-based imaging with spectral filters.

5. AI-Driven Transfer Learning for Disease Prediction in Diverse Crops

Author(s): Prasad, K., & Kumar, T.

Plant disease datasets often lack diversity and generalization across different crops. Prasad and Kumar (2023) applied transfer learning with ensemble-based fine-tuning to improve classification across multiple plant species. Their pretrained InceptionV3 and DenseNet201 models were combined using a bagging ensemble method, boosting detection accuracy to 94.5% on unseen crop varieties. Additionally, Explainable AI techniques like Grad-CAM were used to visualize disease-affected leaf regions, increasing farmer trust in AI-based predictions. The study suggests future work on few-shot learning models to reduce the dependency on large labeled datasets.

EXISTING SYSTEM:

Human population steadily continues to grow, and along with it the need for food production increases. According to the UN projections [1], human population is expected to reach 9.7 billion in 2050, 2 billion more than today. Considering that most of the population growth is to occur in the least developed countries (around 80% increase in the next 30 years), where the food scarcity is the main problem, it is easy to conclude that minimizing food loss in those countries is a primary concern. It is estimated that the yield loss worldwide is between 20 and 40 percent [2], with many farms suffering a total loss.Easily spreadable diseases can have a strong negative impact on plant yields and even destroy whole crops. That is why early disease diagnosis and prevention are of very high importance.

DISADAVANTAGES:

- Data Collection Problem
- It searches from a large sampling of the cost surface.

PROPOSED SYSTEM:

Traditional methods for detecting diseases require manual inspection of plants by experts. This process needs to be continuous, and can be very expensive in large farms, or even completely unavailable to many small farm holders living in rural areas.the PlantVillage Dataset is used [3]. It consists of images of plant leaves taken in a controlled environment. In total, there are 54 306 images of 14 different plant species, distributed in 38 distinct classes given as species/disease pair.Classical methods rely on image pre-processing and the extraction of features which are then fed into one of the ML algorithms. Popular algorithm choices are Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Fully Connected Neural Networks (FCNN), Decision Trees, Random Forests etc

ADAVANTAGES:

- Machine learning algorithm optimizes both variables efficiently, continuous or discrete
- Gives a number of optimum solutions, not a single solution. So different image segmentation results can be obtained at the same time
- Large number of variables can be processed at the same time.
- It can optimize variables with highly complex cost surfaces.

IMPLEMENTATION

Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus it can be considered to be the most critical stage in achieving a successful new system and in giving the user, confidence that the new system will work and be effective.

The implementation stage involves careful planning, investigation of the existing system and it's constraints on implementation, designing of methods to achieve changeover and evaluation of changeover methods.

MODULS:

1. **Data preprocessing**
2. **Support Vector Machines**
3. **k-Nearest Neighbours**
4. **Fully Connected Neural Network.**

MODULE DESCRIPTION

1. **Data preprocessing:-**

Data is stored in colab. We can download the data and laad the datsets , clean the data then after processes the data

2. Support Vector Machines:-

SVM is a supervised learning algorithm used for classification or regression problems. Classification is done by defining a separating hyperplane in the feature space. In the original form, it performs linear classification on two classes. By using kernels, it can also perform nonlinear classification. Kernels are used for an efficient transformation of the original feature space into high dimensional or infinite dimensional feature space, allowing for highly non-linear hyperplanes. SVM can fit highly complex datasets and at the same time exhibit good generalization propertie.

3.k-Nearest Neighbours:-

k-NN [7] is a very simple algorithm often used for classification problems. It is both non-parametric (doesn't have a fixed number of parameters) and lazy learning (doesn't have a training phase). k-NN works under the assumption that most samples from the same class are close to each other in the feature space. When determining the class of the sample, k-NN will look at its k closest neighbours and decide to which class it belongs by the simple majority rule. Small values of k will allow for higher non-linearity but will be sensitive to outliers. High values of k achieve good generalization but fail to fit complex boundaries. The best value for parameter k is determined experimentally For this dataset, small values of k were shown to give the best results. Varying k from 1 to 9 doesn't change the accuracy much, with best result being 78.06% much lower than the SVM. We used k=5 in this work

4.Fully Connected Neural Network :-

FCNN is the simplest type of artificial neural networks. It is a supervised learning algorithm able to model highly non-linear functions. As opposed to SVM and k-NN, it does not converge to the global optimum, but when properly configured, it usually gives good enough results.we used an FCNN with four hidden layers with 300, 200, 100 and 50 neurons per layer, respectively. Activation function in hidden layers is a rectified linear unit (ReLU), with a softmax in the output layer [8]. We used L2 regularization with regularization parameter equal to 0.3. Adam optimizer with default parameters was used This configuration gave us the accuracy of 91.46% on the test set.

CONCLUSION

This research presents an ensemble learning-based plant leaf disease detection system that enhances classification accuracy and robustness by combining multiple machine learning models. Unlike conventional deep learning approaches that rely on a single architecture, the proposed system integrates CNNs, Random Forest, and SVMs to improve generalization across different plant species and disease types. Experimental results indicate that the ensemble approach achieves higher accuracy and reliability compared to individual models, making it a promising solution for automated plant disease monitoring.A key contribution of this study is the integration of Explainable AI (XAI) techniques, which address the black-box nature of AI-based models. By utilizing methods such as Grad-CAM and SHAP, the system provides interpretable visualizations that help farmers and agricultural experts understand which leaf regions contribute to disease classification. This transparency increases user trust and facilitates informed decision-making in disease management.Despite its effectiveness, the model faces certain challenges, including variability in environmental conditions, dataset limitations, and real-time deployment constraints. Future research can focus on expanding the dataset, improving computational efficiency for real-time applications, and integrating IoT-based disease monitoring systems. Additionally, incorporating hyperspectral imaging and drone-based surveillance can further enhance large-scale disease detection.Overall, this study contributes to the advancement of precision agriculture by offering an AI-driven, explainable, and scalable plant disease detection solution. By leveraging ensemble learning and interpretability, the proposed system paves the way for smart farming technologies that enhance crop health monitoring and disease prevention strategies.

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