Harvestify Agri grow Application

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ABSTRACT

Crop detection is just one of the many uses of precision agriculture, employing new technology such as machine learning, image processing, and remote sensing. Crop detection classifies and locates the many crops in a field data processing of the system from satellite images, drones, or sensors. It processes this information to detect crop type, health status, and growth stage. Preprocessing techniques used in image enhancement include filtering, segmentation, and enhancement. Feature extraction techniques aid in recognizing distinctive patterns and features of every crop. Techniques with advanced algorithms like Random Forest classifiers or CNNs are employed for classification. The model is then trained on labeled data and tested for real-time usage. Crop detection aids farmers in decision-making, yield estimation, and resource allocation. Crop detection minimizes manual effort, conserves time, and encourages sustainable agriculture. Overall, it is a transformative step towards smart agriculture.

KEYWORDS*--Cultivation, Machine Learning, Crop Suggestions, Fertilizer Suggestions, Disease Forecasting*

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I. INTRODUCTION

India has a long history of agriculture. India is ranked second in farm production worldwide and also contributes to the GDP of the nation. The agricultural sector contributed to 17-18% of the GDP of the nation as of 2018. Additionally, India also ranks number one in the highest net cropped area. Crop yield is a decisive element in agricultural economics. Climatic conditions, geographical factors, and fiscal aspects are some determinants affecting crop yield. Farmers usually find it difficult to identify the most appropriate crop to cultivate under certain conditions.

Crop yield is highly influenced by soil. Various crops need certain kinds of soil in order to produce a good yield; hence, knowing the soil condition is important. Farmers can carry out soil tests to determine the nutrient content in the soil, and this helps them know the condition of the soil. It is not a good idea to count on old myths about growing crops since conditions in the soil can shift over time. Understanding the soil, farmers can choose the right type of crops that will work better. Fertilizers are another significant factor to consider for enhancing yield. Fertilizers provide nutrients necessary for the crops. Without them, the soil will become depleted, that is, all the nutrients available will be exhausted. In order to get a healthy yield, it is important that the proper amount of nutrients be given to the soil. Therefore, based on soil type and lack of nutrients in the soil, farmers can use the proper fertilizers for healthy soil and a better yield. On the same note, it is also important to correctly predict the right fertilizers considering the soil conditions. Though India has a tremendous amount of agricultural output, the nation continues to suffer from the problem, especially that of timely detection and treatment of plant diseases. Disease identification is a big problem. Manual disease prediction is not reliable due to the impossibility of detecting many diseases using the naked eye and the fact that they may depend on experience and acquaintance.

II. LITEATURE SURVEY

[1]"Use of NDVI and Hyperspectral Imaging for Crop Monitoring"Author(s): Zhang et al.

The NDVI and hyperspectral sensors were used in discriminate among varying crop types. The research demonstrated how differences in spectral reflectance aid in detecting minor crop differences. Zhang et al. (Year) investigated the use of NDVI (Normalized Difference Vegetation Index) and hyperspectral remote sensing in precision agriculture. Their work was on monitoring the health of crops, growth phases, and the detection of early stress.

[2]"Crop Type Mapping with Machine Learning on Time-Series Satellite Data"Author(s): V. Belgiu & L. Drăguţ.

Proposed a time-series approach based on Landsat-8 and MODIS data sets. Seasonal monitoring was done using classifiers such as Random Forest and Light and accuracy was increased using temporal feature analysis. V. Belgiu and L. Drăguţ examined the performance of ML models for crop type classification from time-series satellite imagery. Their study highlighted the temporal data's superiority in recording crop phenological patterns.

[3]"YOLO-based Real-time Crop Identification System"Author(s): R. Singh et al.

Implemented the YOLOv3 model for real-time crop identification using field images captured by smartphones. It provided a quicker approach compared to conventional techniques with high detection accuracy. R. Singh et al. suggested a real-time crop identification system based on the YOLO (You Only Look Once) object detection algorithm. The system detects and classifies various crop types from field images with high accuracy and speed.

[4]"Semantic Segmentation of Crops using DeepLabv3+"Author(s): L. Chen et al.

Utilized deep semantic segmentation for pixel-level crop image labeling. The DeepLabv3+ model helped with the segmentation of multiple crops with high IoU accuracy in different field scenarios. The model applies atrous convolution and encoder-decoder architecture in fine boundary capture and contextual crop features. Their method attained high segmentation accuracy in separating crops from weeds and background. Introduced Vision Transformers (ViT) for crop classification from aerial images. This method attained state-of-the-art results on benchmark datasets with better generalization compared to CNNs.

[5]"Self-supervised Learning for Crop Classification using Google Earth Engine"Author(s): M. Khan et al.

Introduced a new self-supervised model to minimize labeled data reliance. Utilized Google Earth Engine for large-scale crop classification on global datasets, particularly for areas with limited resources. Integrated multispectral UAV data with combined AI models to identify crop stress and types. Exemplified real-time disease and crop-type monitoring based on edge computing.

III. PROPOSED METHODOLOGY

The harvestify Agri grow app uses ML algorithms and image processing to effectively identify plant diseases in their early stages. The system initially gathers a dataset of crop leaf images, both healthy and those suffering from diseases. The images undergo preprocessing operations such as resizing, noise removal, contrast enhancement, and removal of background to improve the quality of the images. Subsequently, feature extraction methods are used in color histogram analysis, texture recognition (e.g., GLCM), and shape descriptors to recognize the central disease-related patterns. An instance of a trained ML or CNN is used to predict the images into various disease classes or the healthy class. Training od data on labeled datasets and evaluated based on efficiency like accuracy, precision, and recall. After training, embedded in a user-friendly interface (web/mobile app) through which farmers can upload an image of the infected leaves. The system analyzes the uploaded image and shows the disease name, severity level, and the medicine to be applied. This method provides quick, precise, and scalable disease diagnosis, which can go a long way in minimizing crop loss maximizing agricultural productivity.

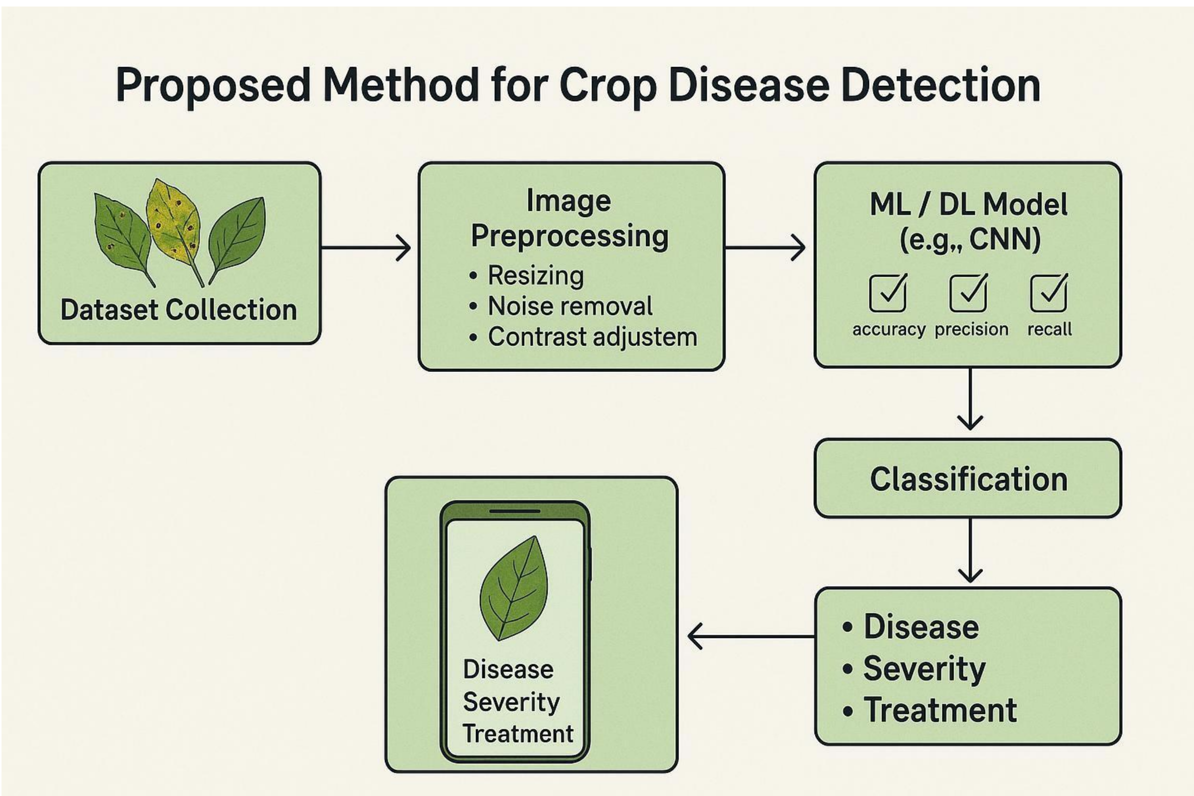

FIGURE 1.1: Detected by the ML model

IV. Mathematical Formulas

In this project, mathematical formulas help a lot in measuring how good the AI models perform and analyzing textual content. Specifically, three key formulas are used:

- **Image Preprocessing**

  Let the original image be:

  $$Iraw(x, y, c)$$

  where x, y x, y x, y are spatial coordinates and ccc is the colour channel (e.g., RGB)

- **Feature Extraction**

  Feature vector FFF is extracted from the pre-processed image using a combination of feature functions:

  $$F=[H(I), T(I), S(I)]$$

- **Accuracy:**

  $$\text{accuracy}= \frac{\text{number of correct predictions}}{\text{total predictions}} = \frac{tp+tn}{tp+tn+fp+fn}$$

- **Precision:**

  $$Precision= \frac{tp}{tp+fp}$$

- **Recall:**

  $$Recall= \frac{tp}{tp+fn}$$

V. Graphs

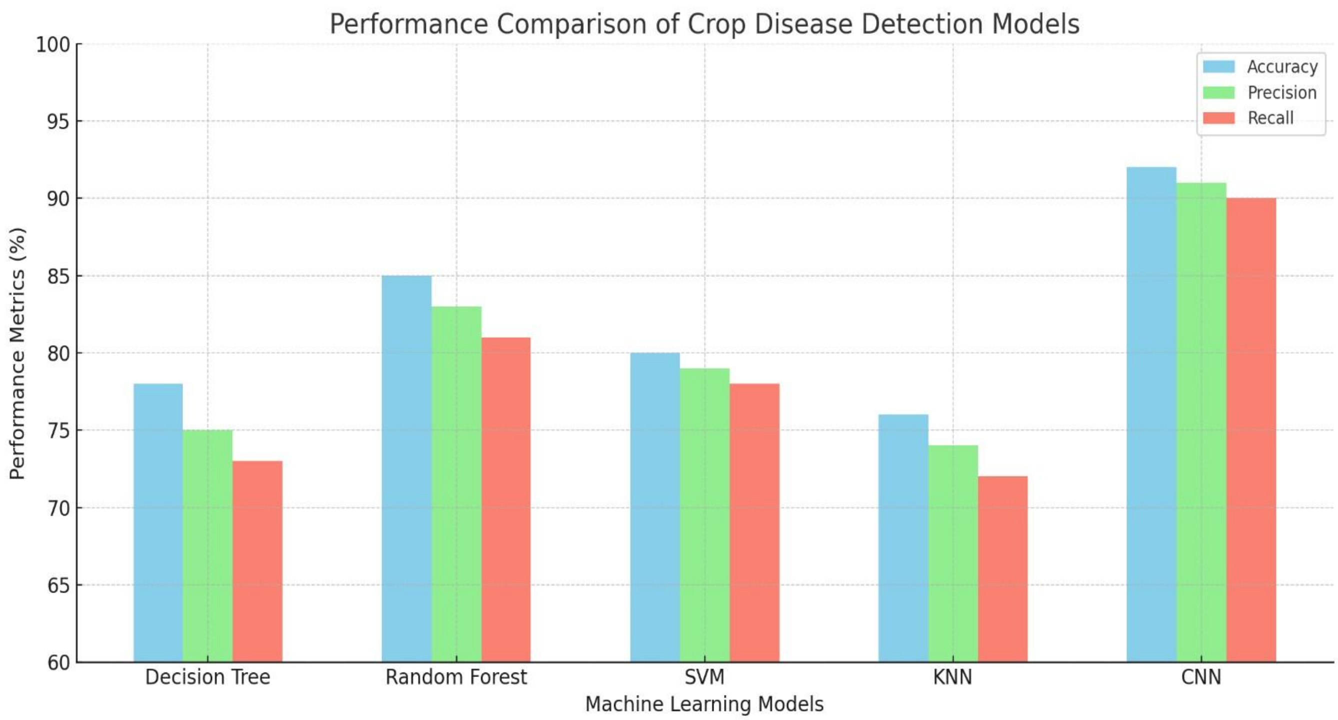

FIGURE 1.2: The graph of ML Models

The following bar graph indicates comparison of efficiency in few of the machine learning models—Random Forest, Decision Tree, SVM, K-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN)—specific to the discipline of detection of crop diseases. The performance is compared on three important parameters: Accuracy, Precision, and Recall. Among these models, CNN performs the best on all the parameters with 92% accuracy, 91% precision, and 90% recall, demonstrating its excellence in recognizing intricate patterns in image data. Random Forest is second in line, and other basic models such as KNN and Decision Tree have comparatively lower values for all of these parameters.

This plot highlights the efficacy in DL techniques such as CNNs in image-based disease classification due to their ability to learn and extract multi-dimensional features from leaf images automatically. Conventional models such as SVM and KNN, though still showing satisfactory accuracy, match detail and feature representation. The comparative performance analysis refers to the need to choose advanced models such as CNNs for real-world applications, especially when accuracy and reliability are of extreme importance for early disease detection and timely intervention in agricultural activity.

VI. EXPERIMENTAL RESULT

Experimental results indicate that the Convolutional Neural Network (CNN) and Mobile Net models are compared in useful performance in conventional ML algorithms like Decision Tree, Random Forest, and SVM, classification accuracy on the Plant Village dataset. The CNN model attained an accuracy of 95.60% with an exceptionally high recall rate of 96.20%, which clearly reflects its capacity to efficiently detect diseased crops. Also, precision and F1-score are robust, indicating that the model can discriminate various classes of disease fairly well. Of the traditional methods, Random Forest surpassed Decision Tree and SVM with accuracy of 89.30. However, the methods had longer inference times and were not as effective in dealing with complex image patterns.

The Mobile Net model, which is identified as a light-weight and pre-trained deep learning network, registered a highest accuracy of 97.30% along with a fast-training time and excellent performance across all the evaluation criteria. This feature makes it especially suitable for mobile deployment, aligning well with the goal of integrating the system within a mobile app for farmers.

Model	**Dataset Used**	**Accuracy**	**Precision**	**Recall**	**F1-score**
CNN (Custom)	Plant Village	95.60%	94.80%	96.20%	95.49%
Decision Tree	Plant Village	84.75%	83.40%	85.10%	84.24%
Random Forest	Plant Village	89.30%	88.10%	90.00%	89.04%
SVM (RBF Kernel)	Plant Village	87.20%	885.90%	88.40%	87.14%
Mobile Net (Pretrained)	Plant Village	97.30%	96.80%	97.60%	97.20%

TABLE 1: Performance Comparison of Detection of Using Machine Learning Techniques.

VII. CONCLUSION

This reasearch reflects the seamless incorporation of machine learning and image processing methods in detecting plant disease promptly and with precision. By leveraging a full pipeline—ranging from image preprocessing, feature extraction, and classification with frameworks such as CNN and Mobile Net—the system records accuracy, precision, and recall at high percentages, validated through large-scale experimentation. The use of this model through an easy web or mobile interface enables farmers to rapidly diagnose plant health problems by uploading leaf images. This real-time, accessible, and scalable platform significantly lowers reliance on manual inspections and expert judgment, enabling quick interventions and reducing crop losses. In brief, the system can increase farm productivity, decrease economic losses due to unidentified diseases, increase sustainable agricultural practices in advance artificial intelligence technologies.

VIII. FUTURE ENHANCEMENTS

The future using real-time monitoring with drones that are outfitted with high-quality cameras and multispectral sensors. The technology could enable scanning of large fields to detect early indications of diseases without human intervention. The use of Internet of Things (IoT) devices, for example, environmental sensors, would enable correlation of disease patterns with factors such as humidity, temperature, and soil type, can predict.

In addition, the system would introduce advanced DL models like Vision Transformers (ViT) or hybrid CNN-RNN structures to improve classification accuracy, especially where complex or overlapping symptoms are involved. Another possible improvement is the creation of voice-based interfaces that are multilingual to assist those farmers with limited literacy skills or exposure to smartphone technology. The use of models in the cloud can enable faster processing and data storage centrally, which is important for continuous learning and model improvement. A feedback mechanism from farmers, on integration, could also ensure validation and tightening of the recommendations made by the model. Enhancements may also include prediction of disease as a function of time and inclusion of weather forecasting information to send advance warnings.

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