Plant Disease Detection Project

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Abstract- *The identification and detection of diseases of plants is one of the main points which determine the loss of the yield of crop production and agriculture. The studies of plant disease are the study of any visible points in any part of the plant which helps us differentiate between two plants, technically any spots or colour shades. Plant diseases affect the growth of their respective species, therefore their early identification is very important. Many Machine Learning (ML) models have been employed for the detection and classification of plant diseases but, after the advancements in a subset of ML, that is, Deep Learning (DL), this area of research appears to have great potential in terms of increased accuracy. Many developed/modified DL architectures are implemented along with several visualization techniques to detect and classify the symptoms of plant diseases. Moreover, several performance metrics are used for the evaluation of these architectures/techniques. This review provides a comprehensive explanation of DL models used to visualize various plant diseases. In addition, some research gaps are identified from which to obtain greater transparency for detecting diseases in plants, even before their symptoms appear clearly.The sustainability of the plant is one of the key points that is for agricultural development. The identification of plant diseases is very difficult to get right. The identification of the disease requires lots of work and expertise, lots of knowledge in the field of plants and the studies of the detection of those diseases. Hence, image processing is used for the detection of plant diseases. The Detection of diseases follows the methods of image acquisition, image extraction, image segmentation, and image pre-processing.*

In this paper we will show the detection of diseases of plants by getting their images of leaves, stems and fruits. We will also discuss the use of image extraction, and image pre-processing which will be used for making this project.

Keywords- plant disease, deep learning, convolutional neural networks (CNN), segmentation, pre-processing, extraction, identification, plants

I. INTRODUCTION

The problem of efficient plant disease protection is closely related to the problems of sustainable agriculture and climate change In India, Farmers have a great diversity of crops. Various pathogens are present in the environment which severely affects the crops and the soil in which the plant is planted, thereby affecting the production of crops .Various disease are observed on the plants and crops .The main identification of the affected plant or crop are its leaves. The various coloured spots and patterns on the leaf are very useful in detecting the disease.

The Deep Learning (DL) approach is a subcategory of Machine Learning (ML), introduced in 1943 when threshold logic was introduced to build a computer model closely resembling the biological pathways of humans. This field of research is still evolving; its evolution can be divided into two time periods-from 1943–2006 and from 2012–until now. During the first phase, several developments like back propagation, chain rule, Neocognitron, hand written text recognition (LeNET architecture), and resolving the training problem were observed. However, in the second phase, state-of-the-art algorithms/architectures were developed for many applications including self-driving cars, healthcare sector, text recognition, earthquake predictions, marketing, finance, and image recognition. Among those architectures, AlexNet is considered to be a breakthrough in the field of DL as it won the ImageNet challenge for object recognition known as ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in the year 2012. Soon after, several architectures were introduced to overcome the loopholes observed previously. For the evaluation of these algorithms/architectures, various performance metrics were used. Among these metrics, top-1%/top-5% error, precision and recall, F1 score, training/validation accuracy and loss, classification accuracy (CA) are the most popular.

The past scenario for plant disease detection involved direct eye observation, remembering the particular set of disease as per the climate, season etc. These methods were indeed inaccurate and very time consuming. The current methods of plant disease detection involved various laboratory tests, skilled people, well equipped laboratories etc.

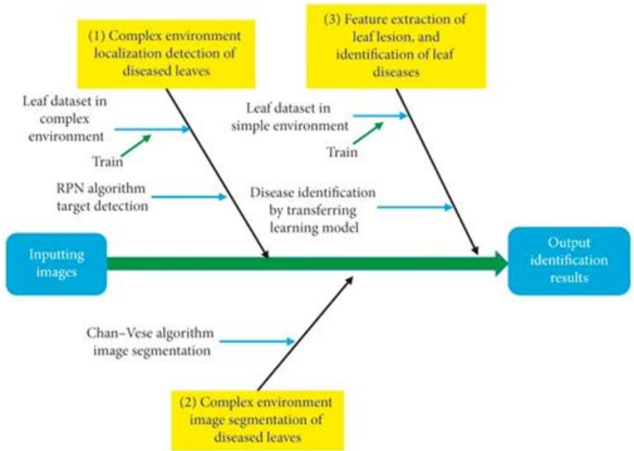

Fig -1: Process

II. REQUIREMENTS

2.1 Hardware Components

2.1.1 Smart Phone

Smartphones are portable and can be easily carried to different locations in the field, allowing for on-the-spot disease detection without the need to transport samples back to a lab. Smartphones provide a familiar and user-friendly interface for interacting with the detection system. Developers can create intuitive mobile applications that enable users to capture images, input data, view results, and receive recommendations or alerts related to plant diseases.

Fig -2: Smartphone

2.1.2 Graphics Processing Unit

GPUs are optimized for parallel processing, allowing them to perform multiple computations simultaneously. This is particularly beneficial for tasks like image processing and feature extraction, which are fundamental to plant disease detection algorithms. With a GPU, it's feasible to perform real-time analysis of plant images captured in the field. This capability is crucial for providing timely feedback to farmers and researchers, allowing for immediate action to be taken to manage and mitigate the spread of diseases.

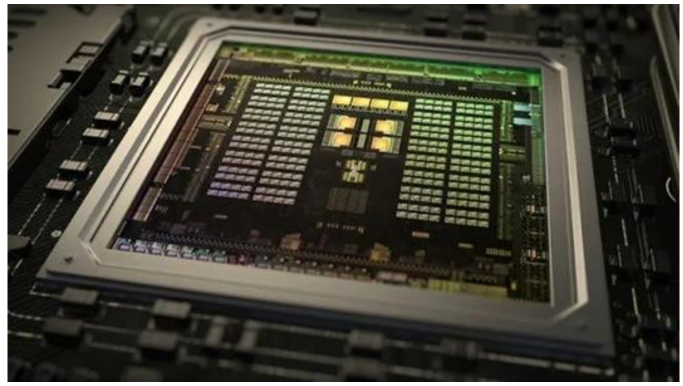

Fig -3: GPU

2.2 Software component

2.2.1 Android application

The mobile application can perform initial image processing and analysis directly on the device, leveraging the smartphone's processing power. This allows for immediate feedback to users, indicating the likelihood of disease presence and suggesting potential actions. Users can input additional data such as plant species, location, environmental conditions, and observed symptoms through the mobile application. This contextual information helps improve the accuracy of disease detection algorithms and enables researchers to gather valuable insights. The mobile application can serve as a platform for engaging with users, providing educational resources about plant diseases, prevention measures, and sustainable farming practices. Interactive features such as quizzes, tutorials, and forums can enhance user engagement and knowledge sharing.

Fig -4: Android app

2.2.2 Tensor flow

TensorFlow provides a comprehensive set of tools and APIs for building and training deep learning models, including convolutional neural networks (CNNs), which are highly effective for image recognition tasks. Researchers and developers can leverage TensorFlow's flexibility to design custom architectures tailored to the specific requirements of plant disease detection. Transfer learning, a technique supported by TensorFlow, enables developers to transfer knowledge from pre-trained models to new tasks with limited data. In the context of plant disease detection, developers can use transfer learning to retrain pre-trained CNNs on a dataset of plant images, thereby leveraging the feature representations learned from general image recognition tasks.

2.2.6 CNN

CNNs are adept at automatically learning relevant features from raw input data, making them well-suited for image analysis tasks. In the context of plant disease detection, CNNs can extract discriminative features from images of plant leaves, capturing patterns indicative of various diseases or abnormalities. CNNs can be trained to classify plant images into different categories corresponding to healthy plants or specific disease types. By learning from annotated datasets containing labelled images, CNNs can generalize patterns and make accurate predictions about the presence or absence of diseases in unseen images.CNN models optimized for efficiency, such as lightweight architectures or model quantization techniques, can enable real-time inference on resource-constrained devices like smartphones or embedded systems. This capability allows for on-device disease detection in the field without relying on cloud-based processing.

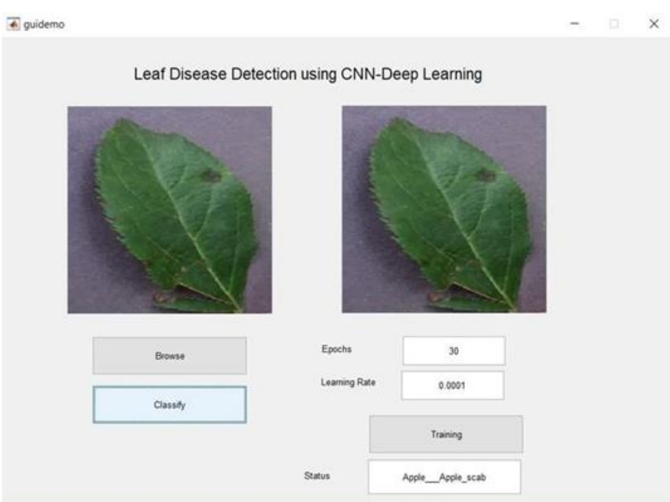

Fig -5: CNN

3. Flow of system

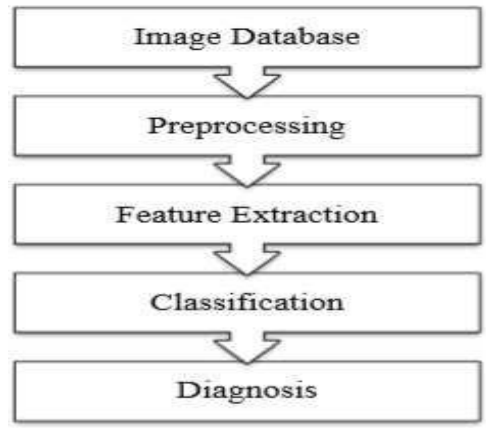

Fig -4: Flow of system

Fig -5: Android app

III. CLASS DIAGRAM

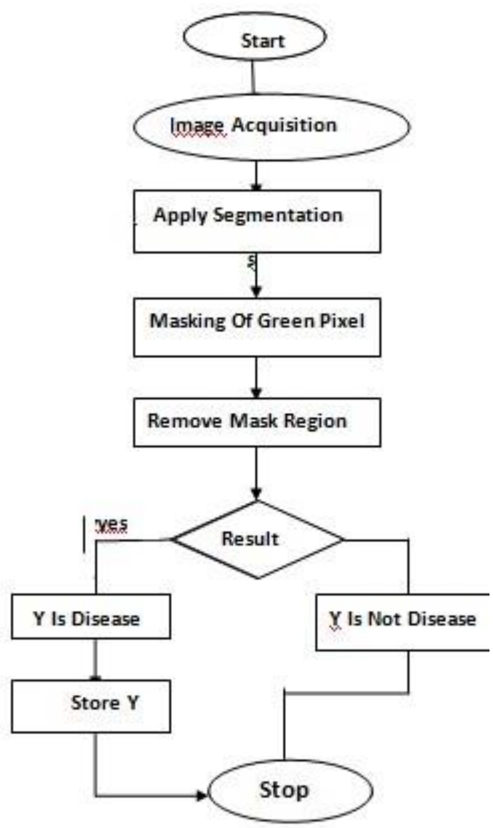

Fig -6: Class Diagram

IV. IMPLEMENTATION METHODOLOGY

Gather a diverse dataset of plant images, including both healthy plants and plants affected by various diseases.

Ensure the dataset covers different plant species, growth stages, and environmental conditions relevant to the target application. Clean and standardize the collected images by resizing them to a uniform resolution and normalizing pixel values. Augment the dataset by applying transformations such as rotation, flipping, and cropping to increase its diversity and robustness. Evaluate the trained model on the test set to assess its performance metrics such as accuracy, precision, recall, and F1 score. Analyse the model's confusion matrix to identify common misclassifications and areas for improvement. Validate the deployed system in real-world scenarios to ensure its effectiveness and usability. Collect feedback from users and stakeholders to identify areas for improvement and potential enhancements. Iterate on the implementation based on feedback, incorporating new features, optimizing performance, and addressing any issues or limitations.

Image Acquisition:

Basically this step consists of taking in the leaf image from the mobile device. The application uses a camera module which enables the user to take images. Since the images are taken from different mobile devices hence, the images obtained may be of different qualities. This may affect the accuracy of the system. Hence, to avoid this we send the image for pre-processing where the image quality is improved for further process.

Fig 9. App screenshot

Pre-processing of the Images:

Resize images to a consistent resolution to ensure uniformity across the dataset. This step helps reduce computational complexity and standardizes the input size for the model. Normalize pixel values to a common scale, typically between 0 and 1 or -1 and 1. Normalization helps stabilize training by preventing gradient explosion or vanishing during optimization. Crop images to focus on the region of interest (e.g., plant leaves) and remove irrelevant background noise. Centring the cropped region within the image helps improve the model's ability to detect and classify diseases.

Extraction of features:

Texture features capture the spatial arrangement of pixel intensities in an image, which can be indicative of disease symptoms. Techniques such as Grey-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor filters can be used to extract texture features from plant images. Colour histograms represent the distribution of pixel intensities across different colour channels (e.g., red, green, blue). By quantifying colour information, colour histograms can capture variations in leaf coloration caused by diseases and serve as discriminative features for classification. LBP is a texture descriptor that characterizes local patterns and textures in an image by comparing the intensity of each pixel with its neighbouring pixels. LBP features are robust to variations in illumination and can effectively capture texture information relevant to disease detection.

Disease detection and classification:

Images of plant leaves or affected areas are acquired using cameras or mobile devices. It's essential to capture high-quality images under consistent lighting conditions to ensure accurate analysis. Pre-processing techniques, such as resizing, normalization, and noise reduction, are applied to the acquired images to enhance their quality and prepare them for analysis. Relevant features are extracted from the pre-processed images using techniques like texture analysis, colour histograms, convolutional neural networks (CNNs), or other feature extraction methods mentioned earlier. These features capture important characteristics of the images that are indicative of disease symptoms. The extracted features are combined with labels indicating the presence or absence of diseases to form a labelled dataset. The dataset is split into training, validation, and test sets for model training and evaluation.Machine learning models, such as support vector machines (SVMs), decision trees, random forests, or deep learning models like CNNs, are trained using the labelled dataset. The models learn to classify images into different disease classes based on the extracted features.

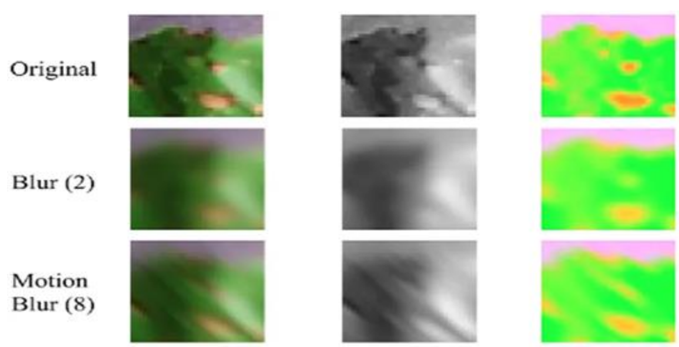

Fig -10: Detection of disease

V. RESULTS

For binary classification tasks (e.g., healthy vs. diseased), the acquired result indicates whether the input image depicts a healthy plant or a plant affected by a disease. This binary outcome helps farmers and agricultural experts quickly identify plants that require further attention or treatment. In multi-class classification tasks (e.g., classification of multiple disease types), the acquired result specifies the detected disease class or category along with the associated confidence score. This information allows stakeholders to prioritize interventions based on the severity and type of disease present. Alongside the acquired result, the system may provide recommendations or actionable insights based on the detected diseases. These recommendations could include suggested treatments, preventative measures, or further diagnostic steps to mitigate the impact of diseases on crop health and yield.

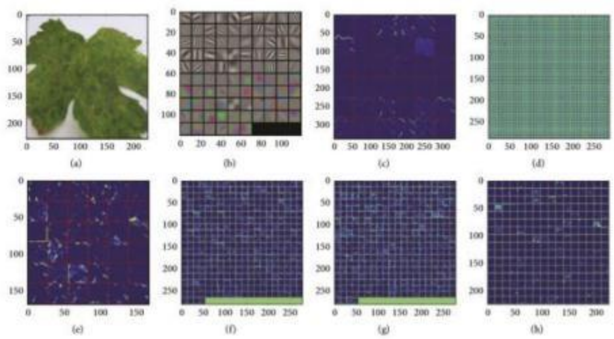

Fig -12: Convolution and Pooling

VI. FUTURE SCOPE

The development of advanced sensing technologies, such as hyperspectral imaging, drone-mounted sensors, and Internet of Things (IoT) devices, offers new opportunities for remote and real-time monitoring of plant health. These technologies enable more comprehensive and timely detection of diseases across large agricultural landscapes. Integrating data from multiple sources, including images, weather data, soil information, and genetic data, can provide a more holistic understanding of plant health and disease dynamics. Machine learning algorithms can be leveraged to analyse and interpret these multi-modal datasets, leading to more accurate and robust disease detection models. Integration of plant disease detection technologies with precision agriculture practices and decision support systems can optimize resource allocation, crop management strategies, and treatment protocols. Real-time data analytics and predictive modelling can inform farmers and agronomists about optimal timing for disease control measures and crop protection interventions.

VII. CONCLUSION

In this paper, in conclusion, plant disease detection projects represent a critical intersection of agriculture, technology, and data science with the potential to revolutionize crop management practices and enhance food security worldwide. Through the implementation of advanced sensing technologies, machine learning algorithms, and data analytics techniques, these projects aim to address the challenges posed by plant diseases and optimize agricultural productivity in a sustainable manner.Plant disease detection projects play a vital role in safeguarding crop health, promoting agricultural sustainability, and ensuring food security for present and future generations. By harnessing the power of technology, data, and collaboration, these projects contribute to a resilient and thriving agricultural ecosystem that meets the challenges of a rapidly changing world.

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