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PLANT DISEASE DETECTION AND CLASSIFICATION USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

The economic growth of a nation cannot expand without agricultural output, yet plant diseases pose significant obstacles to both the quantity and quality of food. For the sake of everyone's health and well-being, it is crucial to identify plant illnesses as soon as possible. Typically, a pathologist would visit the site and physically inspect each plant to make a diagnosis. However, manual examination of different plant diseases is not always feasible due to lower precision and a lack of human resources. The development of automated technologies capable of rapidly identifying and classifying various plant diseases is crucial to address these challenges. Factors that complicate accurate identification include low-intensity background and foreground information in images, very similar colors in healthy and diseased plant areas, noise in the samples, and differences in the size, position, chrominance, and structure of plant leaves.Our reliable plant disease categorization system, built on the InceptionV3 architecture, addresses these challenges. Our study proposes an InceptionV3-based deep learning approach for detecting plant leaf diseases, achieving a 99% accuracy rate in disease prediction. Our objective is to identify and categorize plant diseases accurately. A total of 70,295 plant image sourced from the Kaggle website were used in the research. These images depicted various crops including apples, blueberries, cherries, corn (maize), grapes, oranges, peaches, bell peppers, potatoes, raspberries, soybeans, strawberries, and tomatoes. When applied to various plant regions, this approach can handle complex scenarios and accurately diagnose a variety of illnesses.

Index Terms: Plant Disease, Early Detection, Human Resources, Deep Learning, CNN, InceptionV3, Plant Images

I.INTRODUCTION

The capacity for plants to produce food is fundamental to human survival. The increasing production of grains, fruits, and vegetables is of utmost importance for developing countries with large populations, such as India. Increases in both output and quality are necessary to improve the public's health. On the other hand, problems like the spread of diseases that may have been prevented with early identification reduce the output and quality of food. The loss of agricultural output is a direct result of the infectious nature of many of these diseases. The dispersed nature of agricultural fields, low levels of knowledge and awareness among farmers, and the scarcity of plant pathologists all contribute to the ineffectiveness and failure of human-assisted disease detection to fulfill expectations.
It is critical to automate crop disease detection using technology and make machine-assisted diagnosis affordable for farmers in order to address the limitations of human-assisted disease diagnosis. In recent years, several agricultural issues have been significantly alleviated by the use of computer vision systems and robotics.

There has been some research into the potential benefits of image processing for precision agricultural methods, plant growth monitoring, weed and pesticide technology, and plant nutrition management [1][2]. There has been very little success in automating plant disease diagnosis, despite the fact that plant pathologists can often identify many plant diseases only by looking at the plants, soil, and environmental factors (such as noticeable color changes, wilting, spots, and lesions). Commercial investment in agriculture-technology links is still smaller than in more lucrative sectors, such as human health and education. Promising research programs have failed to produce results because of hurdles such as high implementation costs, solution scalability, and farmers' lack of access to plant pathologists. A scalable, cost-effective, and widely applicable solution to agricultural diseases is now within reach, thanks to recent developments in cloud computing, mobile technology, and artificial intelligence (AI). In emerging markets like India, internet-connected mobile phones are quickly becoming the norm. By using easily available cameras and affordable mobile phones with GPS capabilities, individuals have the ability to share geolocated images. Advanced cloud-based backend services can administer a centralized database, do data analytics via widely available mobile networks, and handle computation-intensive operations. They can communicate with these services. Accurate image identification and classification are now possible because to AI-based image analysis, which has recently progressed beyond the capabilities of human vision. In artificial intelligence (AI), the fundamental algorithms are NNs, or neural networks. These networks are made up of layers of neurons with a connection architecture that mimics the visual cortex. These networks are "trained" using a massive library of previously classified "labeled" photographs so they can achieve good classification accuracy on freshly unseen photos. As of 2012, when "AlexNet" took first place in the ImageNet competition, deep convolutional neural networks (CNNs) were the prevailing architecture for computer vision and image processing [3]. The incredible development in CNN capabilities is a result of many factors, including large image data sets, improved NN algorithms, and more computing power. Not only has AI become more accurate, but open-source frameworks like TensorFlow have also made it more accessible and affordable [4].

A number of picture classification tasks have shown excellent results for the InceptionV3 architecture, which is among the most advanced models in this area. The InceptionV3 model's capacity to predict plant diseases is a testament to its deep and effective design. Because of its exceptional skill in handling the intricacy and unpredictability of symptoms related to plant illnesses, this model is an ideal match for our proposed automated approach for diagnosing these diseases.

Relevant past work includes initiatives to gather healthy and ill crop photographs [5], spectral patterns [8], RGB images [7], image analysis utilizing feature extraction [6], and fluorescence imaging spectroscopy [9]. Although neural networks have been used to identify plant illnesses in the past, the focus was on textural qualities. Through the use of cutting-edge mobile, cloud, and artificial intelligence technologies, our proposal aims to construct a comprehensive crop diagnostic system that offers farmers access to the expertise (or "intelligence") of plant pathologists. Furthermore, it enables collaborative efforts to gradually increase the disease database and, when needed, seek advice from specialists to improve the precision of NN classification and track outbreaks.

II.LITERATURE SURVEY

- The researchers shruthi.U, V. Nagaveni, and B. K. Raghavendra, agriculture is crucial to India because of the country's growing population and increasing food need. This means that agricultural output must be increased. Infections caused by bacteria, viruses, and fungi are a major factor in lower agricultural yields. In order to prevent plant diseases, methods for identifying them may be used. Machine learning methods have the potential to be used in illness identification due to their ability to prioritize activities and assess data. Their study lays out the procedures for a general plant disease detection system and compares many machine learning classification algorithms utilized for this goal. Their evaluation indicates that convolutional neural networks perform well when it comes to detecting several crop diseases.

- Sehgal, Aman, and Sandeep Mathur describe how plants are vulnerable to diseases introduced by pathogens such as infections, microorganisms, and parasites. It is globally recognized that pathogens cause significant yield losses. Researchers have explored enhancing plant resistance to pathogens by studying resistance genes and developing monitoring and analysis systems to predict disease progression based on leaf symptoms. Their review aims to showcase the application of AI to plant resistance detection.
- Gahizi Emmanuel, and Andi WR Emanuel explain that agriculture is the mainstay of Tanzania's economy. Besides climate change, diseases significantly reduce the production of staple foods like maize and cassava, leading to economic losses and food

insecurity. Early disease detection is crucial. Image processing techniques for detecting diseases on plant leaves offer a promising solution, replacing the time-consuming and cumbersome visual inspection by experts. Their paper surveys current studies in image processing techniques and machine learning models used for disease classification, highlighting their strengths, weaknesses, and performance in real-world scenarios.

- Plant disease analysis, according to Aasia Khanum, Shoab A. Khan, and Arslan Shaukat, is essential for agriculture. Identifying and categorizing plant diseases automatically helps increase agricultural productivity. In their research, they evaluate how well different machine learning methods perform when it comes to recognizing and categorizing patterns of plant disease in leaf photos. They put into practice a three-phase framework that consists of feature extraction using conventional methods, illness type classification, and picture segmentation for detecting sick areas. The results of their experiments show how effective their suggested strategy is; Support Vector Machines outperform other approaches to illness categorization.
- Elangovan, K., and S. Nalini emphasize the importance of disease classification in preventing losses in agricultural yield and product quality. Manual monitoring and treatment of plant diseases is labor-intensive and time-consuming, prompting the use of image processing for detection. Their paper outlines the critical steps in plant disease classification: image loading, pre-processing, segmentation, feature extraction, and SVM classifier application.

III.PROBLEM STATEMENT

Crop disease poses a significant threat to food safety, yet rapid detection remains challenging globally due to inadequate infrastructure. Manual methods of disease detection rely heavily on visual inspection by trained experts, making it labor-intensive and potentially subjective due to variations in expertise. This approach is limited in scalability across large agricultural areas and often lacks real-time monitoring capabilities, which are crucial for timely intervention and effective disease management. In contrast, computer vision techniques leverage advancements in digital imaging and machine learning to automate the identification and classification of plant diseases. By analyzing digital images captured by increasingly prevalent digital cameras, computer vision systems can provide rapid and objective disease diagnosis. This automation not only enhances detection accuracy but also enables real-time monitoring on a large scale, thereby supporting precision agriculture practices, optimizing yield estimation, and facilitating early disease intervention in smart greenhouse environments. As digital technologies continue to evolve, the integration of computer vision promises to revolutionize agricultural practices, ensuring food security and sustainable crop production worldwide.

In a recent study, researchers worked with an open dataset containing 54,306 images of cropped leaves. They trained a residual network to classify these images. The study found that the proposed Inception-v3 model achieved the highest accuracy on the test set,

demonstrating the effectiveness and practicality of their approach.
This research underscores the potential of advanced machine learning models for revolutionizing agricultural practices by enabling timely and accurate detection of crop diseases, thereby mitigating risks to agricultural productivity and food security.

IV.PROPOSED MODEL

Developing a model that will recognize certain agricultural diseases and distinguish healthy from sick crop leaves is the primary objective of this research.The study utilized a dataset comprising 70,295 images encompassing both healthy and unhealthy plant leaves. A CNN, specifically employing the InceptionV3 Architecture model, was trained on this dataset to recognize different crop species, distinguish between healthy and diseased leaves, and classify various disease classes.
The trained model demonstrated high accuracy when evaluated on a separate test set, indicating its effectiveness in identifying and diagnosing crop diseases. The Inception V3 Architecture facilitated the recognition of leaf types through its initial layers, while subsequent layers were instrumental in identifying potential diseases affecting plants. This methodology leverages deep learning techniques, which excel in achieving superior accuracy by analyzing image data down to individual pixels.

Overall, the research underscores the utility of deep learning in agricultural applications, particularly in disease diagnosis and management. By accurately identifying and categorizing crop diseases from digital images, this approach holds promise for enhancing agricultural productivity and ensuring food security.

V.SYSTEM ARCHITECTURE DIAGRAM

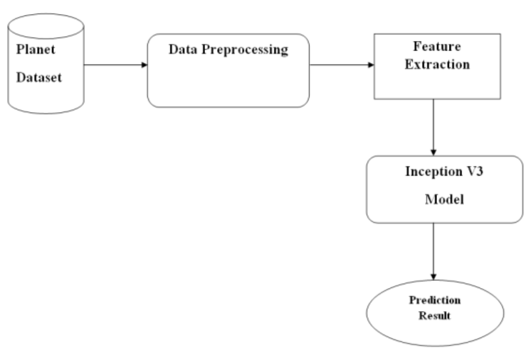

Figure1.System Architecture Diagram

The diagram illustrates a machine learning workflow for predicting outcomes using the Inception V3 model. The Planet Dataset, a collection of data used for training and testing models.The first step is Data Preprocessing, where raw data is cleaned and prepared for analysis by normalizing values, handling missing data, and transforming it into a suitable format.

Subsequently, relevant properties are retrieved from the preprocessed data using a process called feature extraction. These attributes are crucial for making predictions. Subsequently, these features are inputted into the Inception V3 Model, a pre-trained convolutional neural network widely recognized for its effectiveness in image recognition tasks. The model processes these features to identify patterns and relationships within the data.

Finally, the model generates Prediction Results, which provide anticipated outcomes based on the input features. This workflow outlines the essential steps from obtaining the dataset to generating predictions using a sophisticated machine learning model like Inception V3.

VI.ALGORITHMS

Inceptionv3 Architecture:

Inception-v3 is a powerful convolutional neural network architecture renowned for its depth, consisting of 48 layers. A pretrained version, trained with a massive dataset consisting of over a million photos sourced from the ImageNet database, is accessible; it was first developed by Google. This pretrained model performs well when it comes to classifying images into more than a thousand unique item types.

The Inception-v3 model utilizes a combination of symmetric and asymmetric building blocks and incorporates features like as dropouts, convolution, average pooling, max pooling, concatenations, and fully connected layers. One thing that sets it apart is how often it uses batch normalization. Training is more consistent and takes less time when inputs to each layer are normalized. Loss computation in Inception-v3 utilizes Softmax, a popular choice for multiclass classification tasks. This activation function transforms the output into probabilities corresponding to each class, enabling the model to make accurate predictions.

In summary, Inception-v3 stands out not only for its architectural complexity and depth but also for its demonstrated accuracy in image recognition tasks. Its versatility and efficiency make it a valuable tool in various domains, including computer vision, where precise classification of objects from images is crucial.

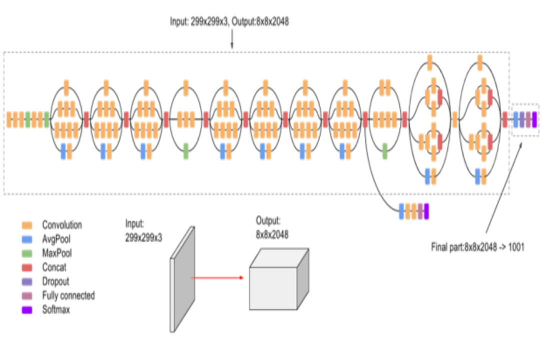

Figure.2. Inceptionv3 Architecture

VII.MODULES DESCRIPTION

- **Dataset Acquisition:** Initially, the system was developed to compile a comprehensive dataset for training and testing purposes. The 70,295 plant photos included in this dataset can be found in the model folder. The species represented include apple, blueberry, bell pepper ,cherry, corn (maize), potato, grape, orange, peach,strawberry ,raspberry, soybean, and tomato.
- **Library Imports:** Following dataset acquisition, the necessary libraries were imported to construct the plant disease detection system using Python. Key libraries include Keras for model building, scikit-learn (sklearn) for dataset splitting, PIL for image conversion to numerical arrays, alongside essential libraries such as pandas, numpy, matplotlib, and tensorflow.
- **Image Retrieval and Preprocessing:** The next step involved retrieving images along with their corresponding labels. Each image was resized to (224,224) pixels to ensure uniformity for recognition purposes. Subsequently, all images were converted into numpy arrays, compatible with machine learning algorithms.

- **Dataset Splitting:** A training set comprising 80% of the data and a testing set comprising 20% of the data were created from the dataset in order to ascertain the model's performance.

- **Model Development:** The focus then shifted to constructing an InceptionV3 CNN model. InceptionV3, known for its efficiency in computational power utilization compared to previous architectures like VGGNet, was chosen for its ability to optimize network parameters and resource costs effectively.
- **Model Training and Evaluation:** The model was compiled and trained using the fit function with a batch size of 10. Post-training, graphs depicting accuracy and loss were plotted, showcasing an average validation accuracy of 99%. With a 99% accuracy rate on the test set, the model showed strong performance in classifying diseases.

- **Model Serialization:** To transition the trained model into a production-ready environment, it was serialized and saved as a .h5 file using the pickle library. This step ensured that the model could be easily deployed and utilized for real-world applications.
- **Prediction in Real-Time:** Upon deployment, a web application was designed to facilitate user interaction. Users could upload plant images for disease prediction. Each uploaded image underwent preprocessing, including resizing to (224,224) pixels and conversion into a numpy array. The trained InceptionV3|CNN model was then applied to classify the plant disease, providing prompt feedback on the detected disease type or confirming the plant's health status based on the model's evaluation. This real-time prediction capability significantly enhances agricultural decision-making, enabling proactive disease management and fostering improved crop health and productivity.

VIII.RESULTS

Figure .4 Home Page

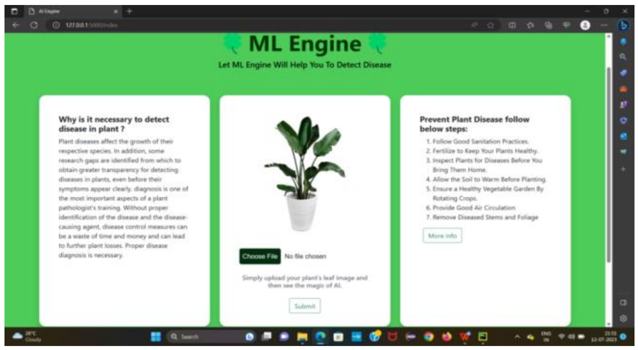

Figure .4 ML

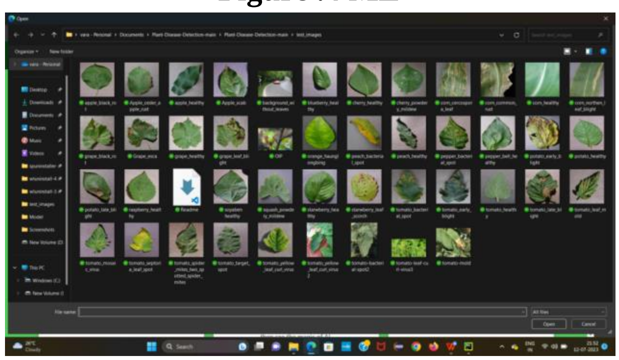

Figure .5 Plant Leaf

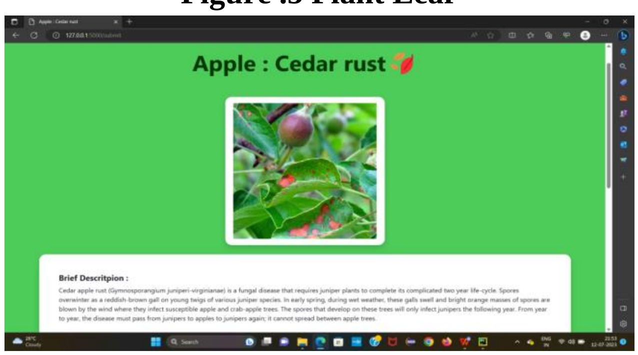

Figure .6 Disease Detection

Figure .7 Healthy

Figure .8 Corn Leaf

IX.CONCLUSION

Plants are essential to human diets, constituting more than 80 percent of our food intake. Ensuring access to abundant, affordable, and nutritious food is crucial for promoting healthy lifestyles. One major threat to food security, however, is plant diseases, which affect both the quantity and quality of crops.Addressing these challenges is particularly critical in organic agriculture, where conventional chemical treatments are not utilized. Instead, effective plant protection relies on a deep understanding of crop varieties and their vulnerabilities to pests, pathogens, and weeds.In our research, we employed the InceptionV3 architecture to detect plant diseases using images of leaves from both healthy and diseased plants. Our experimental findings successfully distinguished between various disease categories affecting different plants, with the InceptionV3 model achieving a remarkable accuracy of 99% in plant disease identification. The incredible potential of innovative deep learning techniques to revolutionize agricultural disease diagnostics is borne out by this astounding accuracy. In organic systems, maintaining plant health through balanced nutrition and optimal soil conditions plays a pivotal role in disease prevention. Healthy plants grown under such conditions exhibit greater resilience to pest and disease pressures.

By leveraging advanced deep learning techniques like InceptionV3, our study contributes to enhancing disease detection capabilities in agriculture. This approach helps with early disease detection and also encourages sustainable agriculture practices by reducing reliance on chemical treatments. Ultimately, our research aims to bolster food security by safeguarding crop health and productivity in organic farming environments.

X.FUTURE ENHANCEMENTS:

Enhanced plant disease identification and classification using multiclass subcategories that can adapt to changing disease severity across plant development cycles is one goal of future deep learning advancements.Integrating these models into real-time applications will empower farmers with instant disease assessments via mobile or web platforms, facilitating timely interventions and optimizing resource management. The focus is on scalable, user-friendly solutions that provide actionable insights, revolutionizing agricultural practices for improved crop health and global food security.

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