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Plant Disease Detection Using CNN Algorithm With Streamlit

Sardarni Sarabjeeth Kaur[1], Dr.Ch.V.Phani Krishna[2]

[1]PG Scholar, Department of CSE, Teegala Krishna Reddy Engineering College (Autonomous Institution),Medbowli, Meerpet, Saroornagar,Hyderabad

[2]Professor, Department of CSE, Teegala Krishna Reddy Engineering College (Autonomous Institution), Medbowli, Meerpet, Saroornagar, Hyderabad

ABSTRACT

Pests and diseases that affect plants and crops significantly impact agricultural productivity within a nation. Typically, farmers or agricultural experts meticulously monitor plants to detect and diagnose diseases. However, this process is often labor-intensive, costly, and prone to inaccuracies. Plant disease detection can be achieved through the identification of lesions or other symptomatic markings on the leaves of affected plants. The primary objective of this research is to develop a Disease Recognition Model based on the classification of leaf images. This model employs image processing techniques, utilizing Convolutional Neural Networks (CNNs) to identify plant diseases. A CNN is a specialized form of artificial neural network designed to process pixel-based input, commonly applied in image recognition tasks.

Agriculture remains the cornerstone of the national economy, with approximately 70% of the population relying on agricultural activities. The productivity of the agricultural sector plays a pivotal role in sustaining the Indian economy. The advent of plant diseases poses a significant threat, often leading to substantial losses in crop yield, economic downturns, and diminished quality and quantity of agricultural outputs. Timely and accurate detection of plant diseases is critical to mitigate these losses and protect agricultural production. As numerous crops suffer damage from diseases and infections, leading to wasted resources, particularly in large-scale production areas, the application of deep learning techniques for plant disease prediction is a promising solution to prevent such detrimental impacts.

Keywords: Convolutional Neural Networks, F-RCNN, (VGG-19), DenseNet, MobileNet

I. INTRODUCTION

Agricultural production is one of the oldest and most essential means of food procurement, serving as a critical source of livelihood for individuals globally. Food is a fundamental necessity for all living beings, with plants playing an indispensable role not only for humans but also for animals,

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providing them with food, oxygen, and various other life-sustaining resources. Governments and experts worldwide are undertaking significant efforts to enhance food production, and these initiatives are yielding positive results in many regions.

However, when plants become infected with diseases, the entire ecosystem can be affected in various ways. Plant diseases can manifest in different parts of the plant, including the stem, leaves, and branches, and can be caused by diverse pathogens, such as bacteria and fungi. The specific nature of the diseases affecting crops is influenced by various factors, including climatic conditions. A growing concern is food insecurity, which is often a consequence of inadequate crop yields. In addition, adverse climatic changes can severely disrupt plant growth, with such natural disasters being largely inevitable.

Early detection of plant diseases is paramount in preventing widespread crop failure. Farmers must be vigilant in applying appropriate pest control measures. Excessive pesticide use can harm both the crops and the surrounding environment. Expert guidance is essential to ensure that chemicals are applied judiciously to avoid detrimental effects on the plants and the land.

Numerous research efforts have been dedicated to supporting farmers and other stakeholders in agriculture. Detecting diseases with the naked eye becomes relatively straightforward once symptoms become visible. However, this detection typically occurs only when the disease has progressed significantly, or when crop yields have already been compromised.

Recent advancements in technology have introduced automated systems for disease detection, which are beneficial to both small and large-scale farming operations. These systems provide accurate and rapid diagnoses of plant diseases. These innovations leverage deep learning algorithms, particularly Convolutional Neural Networks (CNNs), to identify and distinguish between healthy and diseased plant leaves. The CNN model is specifically designed to process images of both healthy and infected leaves, using these images to train the model, with the outcome determined by the input leaf image. This approach significantly enhances the precision and efficiency of plant disease detection, benefiting farmers and contributing to sustainable agricultural practices.

ii. RELATED WORK

Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition.

Author: Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala

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Summary: The Smart Farming System, leveraging essential infrastructure, represents an innovative technological advancement aimed at enhancing both the quality and quantity of agricultural output, including the cultivation of tomatoes. Tomato farming involves considering various factors such as environmental conditions, soil health, and sunlight exposure, all of which contribute to the inevitability of plant diseases. The rapid evolution of advanced computer systems, facilitated by deep learning technologies, has enabled the capture and analysis of tomato leaf diseases via camera systems.

This research presents a novel solution for efficient disease detection in tomato plants. A motorized image-capturing apparatus was developed to photograph all four sides of each tomato plant, enabling the detection and identification of leaf diseases. The experiment focused on the Diamante Max variety of tomato plants as the test subjects. The system was engineered to detect specific diseases, including Phoma Rot, Leaf Miner, and Target Spot. A dataset containing both healthy and diseased tomato leaves was compiled, and a deep convolutional neural network (CNN) was trained to classify the three identified diseases. The system utilized a Convolutional Neural Network to classify and identify the diseases affecting the monitored tomato plants. An anomaly detection model based on F-RCNN yielded a confidence score of 80%, while a Transfer Learning-based disease recognition model achieved a high accuracy of 95.75%. The automated image-capturing system was successfully implemented in real-world conditions, registering a recognition accuracy of 91.67% in identifying tomato leaf diseases.

CNN based Leaf Disease Identification and Remedy Recommendation System.

Author: Sunku Rohan , Triveni S Pujar ,Suma VR Amog Shetty, Rishabh F Tated .

Summary: Agriculture plays a crucial role in shaping our lives and is a cornerstone of the global economy. Farmers often face significant challenges in accurately identifying leaf diseases, which can lead to reduced crop yields. However, advancements in image and video analysis offer a more effective means for agricultural scientists to assess plant health, potentially providing better solutions for disease management. Early detection of diseases is vital, as crops with compromised health are less likely to offer high nutritional value.

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With the rapid progress of technology, devices are now sophisticated enough to recognize and diagnose plant diseases, enabling prompt intervention to mitigate the adverse effects on crop production. This paper focuses on the application of image processing techniques for the detection of plant diseases. Utilizing an open-access dataset consisting of 5,000 images of both healthy and diseased plant leaves, the study employs semi-supervised learning techniques to classify crop types and identify diseases across four distinct categories.

Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolution Neural Networks .

Author: Bin Liu , Peng Jiang, Yuehan Chen, Dongjian He, Chunquan Liang .

Summary: This paper addresses the identification of five distinct types of apple leaf diseases: Aria leaf spot, Brown spot, Mosaic, Grey spot, and Rust. The study employs advanced deep learning methodologies, specifically enhanced Convolutional Neural Networks (CNNs), to detect these diseases on apple leaves. The dataset utilized, referred to as the Apple Leaf Disease Dataset (ALDD), comprises both complex images and laboratory-generated images. Additionally, data augmentation and image annotation techniques were employed to generate an expanded dataset for the development of a novel apple leaf disease detection model, leveraging deep CNNs, Rainbow concatenation, and the GoogLeNet Inception architecture.

For testing purposes, a dataset of 26,377 apple leaf disease images was utilized to train the proposed INAR-SSD model, which is capable of detecting the five aforementioned apple leaf diseases. Experimental results indicate that the INAR-SSD model achieves a detection accuracy of 78.80%, with a high detection rate of 23.13 frames per second (FPS). These findings illustrate that the innovative INAR-SSD model offers a superior solution for the early detection of apple leaf diseases, outperforming previous models in both accuracy and detection speed, and enabling real-time monitoring capabilities.

Identification of plant leaf diseases using a nine-layer deep convolution neural network

Author: Geetharamani G. , Arun Pandian J.

Summary: This paper presents the identification of plant leaf diseases using a deep learning approach based on Convolutional Neural Networks (CNN). The CNN model was trained on an open dataset consisting of over 39 distinct classes of plant leaf diseases, supplemented with background images. The dataset incorporated six

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distinct data augmentation techniques, including gamma correction, image flipping, principal component analysis (PCA) for color augmentation, rotation, noise injection, and scaling. It was observed that the use of data augmentation significantly enhanced the model's performance.

The model was trained across various ranges of epochs, batch sizes, and dropout rates. When comparing the performance of the CNN model to transfer learning techniques, the proposed CNN model demonstrated superior results, particularly when evaluated using validation data. Through simulation, the proposed model achieved a classification accuracy of 96.46%. This performance outperforms that of the transfer learning models, illustrating the efficacy of the CNN approach in plant leaf disease classification.

A Segmentation Improved Robust PNN Model for Disease Identification in Different Leaf

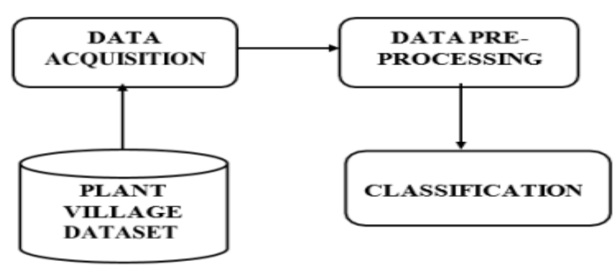
Author: Rekha Chahar, Priyanka Soni

Summary: This paper focuses on agricultural image analysis, encompassing images of vegetables, fruits, crops, and flowers, with a specific emphasis on leaf diseases. The identification of diseases is correlated with different components of the agricultural products, such as roots, seeds, and leaves. This research is particularly valuable for enabling disease identification remotely, akin to a virtual laboratory setup. The approach is divided into two main phases.

In the first phase, a ring-based segmentation model is developed to extract and analyze key features from leaf images. Once these features are successfully identified, the second phase applies a Probabilistic Neural Network (PNN) classifier to determine the presence of diseases. The primary objective of this work is to assess the health status of plants by detecting infected areas through feature-based region identification. The study utilizes a set of leaf images randomly collected from various online sources for
testing and analysis.

III. IMPLEMENTATION

The System comprises of data acquisition from a huge dataset, processing at different convolutional layers and then the classification of plant diseases which declares if the plant image is of a healthy class or diseased class.



System Architecture

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a) Data Acquisition:

The Dataset used in building this model is Tobacco Dataset which is gathered by C.T.R.I organization as a part of Research. The Dataset is a Collection of images, which are classified into their respective Diseases.

b) Data Pre-Processing:

In the data preprocessing phase, the dataset must be appropriately prepared before being fed into the chosen model. To achieve more accurate results, it is essential to partition the dataset into three distinct subsets: the Training Dataset, the Validation Dataset, and the Test Dataset. Each subset serves a unique and critical function in the overall process.

The Training Dataset typically holds the majority of the images and is utilized to train the model. This set is pivotal for allowing the model to learn and adjust its parameters. The Validation Dataset, on the other hand, is used during the training process to assess the model's performance at various stages, providing feedback on its accuracy after each epoch. The validation set plays a crucial role in determining how well the model is generalizing and whether further adjustments are necessary. The accuracy, often considered a measure of model efficiency, is expected to fall within the optimal range of 85-98%.

Lastly, the Test Dataset serves as a final evaluation tool. After the model has been trained and validated, the test set is used to assess the model's ability to make accurate predictions on unseen data. This final validation step ensures that the model is robust and performs effectively in real-world scenarios, such as in the context of Plant Disease Detection using CNNs. By passing the images from the test set through the model, we can confirm the model's reliability and determine its practical applicability.

c) Classification: This phase is regarded as the most critical component of the entire system. In this stage, we employ the concept of transfer learning, where we leverage pre-existing, pretrained models and adapt them to our specific task. The key modification involves replacing the topmost layer of the model with a new output layer that aligns with our required class outputs. Notably, the weights of the existing model—responsible for connecting nodes—remain unchanged; only the output layer is reconfigured to suit the target problem. The choice of the pretrained model is pivotal in determining the system's overall accuracy, as each model comes with its unique set of hyperparameters, image input size, and architectural characteristics.

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Some prominent examples of Keras Application models include ResNet, Inception series, MobileNet, VGG, and DenseNet. Each of these models varies in terms of build time, accuracy, and classification speed, all of which depend on the underlying weights. After carefully considering the trade-offs between accuracy and computational efficiency, I selected the Inception V3 model for constructing the system. This model supports an input image size of 224x224 with three color channels. The model was trained for 20 epochs, achieving an accuracy of approximately 96.1%.

IV. ARCHITECTURE

CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE (VGG-19):

A Convolutional Neural Network has three layers: a convolutional layer, a pooling layer, and a fully connected layer. Fig 4-a shows all layers together.

Convolution Layer Convolutional layer: produces an activated map by scanning the pictures several pixels at a time using a filter. Fig 3 shows the internal working of the convolution layer.

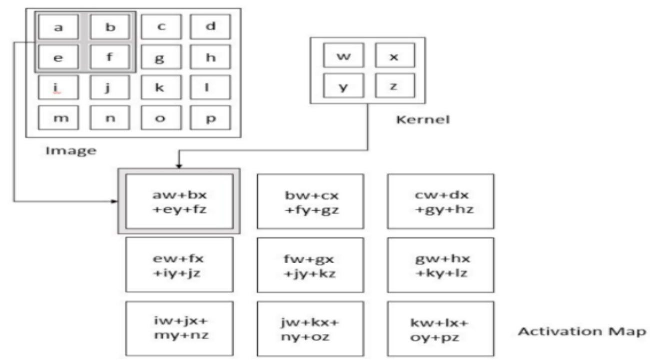

Fig. 4.2.a. Convolution Layer

- Pooling Layer Pooling layer: It reduces the data created by the convolutional layer so that it is stored more efficiently. Fig 4-b shows the internal working of the pooling layer

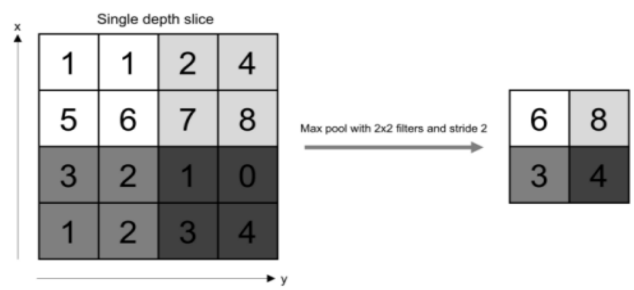

Fig. 4.2.b. Pooling Layer

- Fully Connected Layer: Fully Connected Input Layer - In this stage, the outputs from the preceding layers are "flattened" into a one-dimensional vector, which is subsequently used as input for the next layer in the network.
- First Fully Connected Layer - This layer assigns weights to the input features

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derived from the previous layers' analysis, and performs a weighted sum to predict the most probable label.

- Fully Connected Output Layer - The final layer outputs the probability distribution across all possible labels, providing the likelihood for each potential class in the classification task.

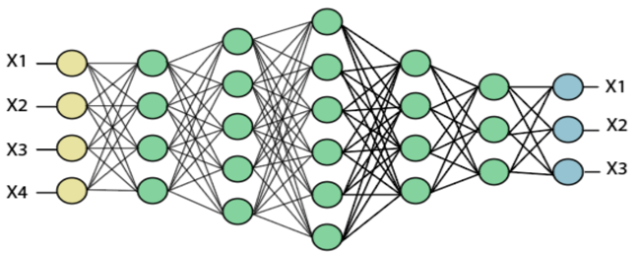

Fig. 4.2.c. Fully connected layer

- VGG19 is an advanced convolutional neural network (CNN) that incorporates pre-trained layers, offering an intricate understanding of an image's definition in terms of shape, color, and structure. This deep neural architecture has been extensively trained on millions of images, allowing it to effectively address complex classification challenges with remarkable accuracy.

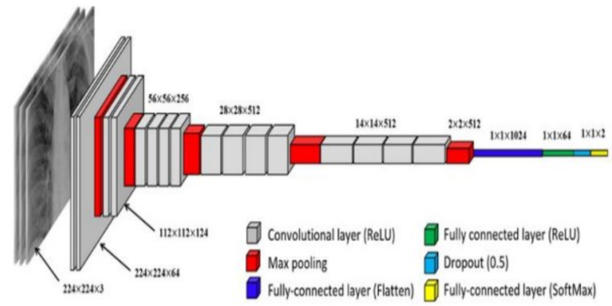

Fig. 4.2.d. vgg-19

V. Results

Run your file:

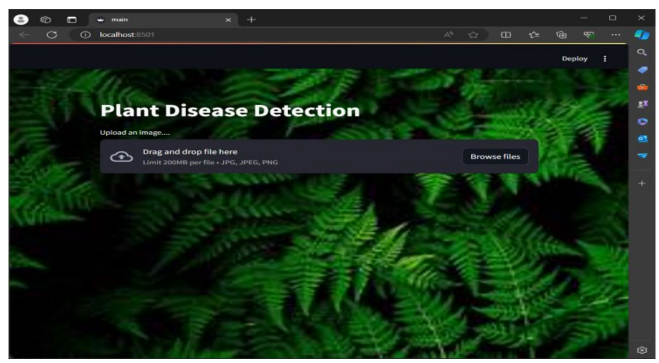

Fig:1 Run Streamlit App

Upload an image:

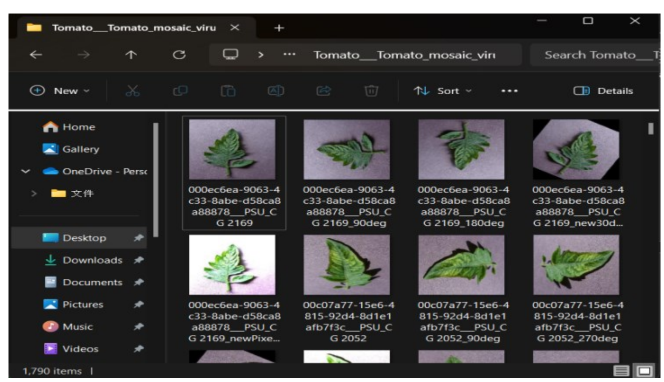

Fig:2, Select an Image

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Classify image:

Fig:3, Output

VI. CONCLUSION

This project introduces a deep convolutional neural network (CNN) model designed to accurately identify and classify leaf diseases. The proposed model is capable of autonomously extracting discriminative features of various leaf diseases and facilitates an end-to-end learning pipeline with high precision. The architecture builds on the ResNet model by modifying its structure—removing certain fully connected layers, incorporating additional pooling layers, and integrating components from the GoogLeNet Inception framework. These enhancements aim to improve the model's efficiency and adaptability.Future iterations could benefit from incorporating detailed information about the diseases and their treatments. Additionally, access to a larger and more diverse dataset with more class labels would enhance the model's performance and generalization capabilities. Exploring advanced pre-trained models could further improve accuracy while reducing the time required to train the system, thanks to pre-initialized weights and the application of transfer learning techniques.The model achieves competitive results when compared to current state-of-the-art systems in image classification. It leverages recent advancements in computer vision and neural networks to deliver accurate and efficient disease detection. This application is especially beneficial for farmers, enabling them to identify diseases promptly and take preventative measures, thereby reducing the risk of widespread crop damage.

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