RESEARCH ON THE RECOGNITION MODEL OF CROP DISEASES BASED ON DEEP LEARNING

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Abstract— Rapid mortal population growth requires a corresponding increase in food products. easily spreadable conditions can have a strong negative impact on plant yields and indeed destroy whole crops. That is why early complaint opinion and prevention are of truly high significance.[1]Traditional styles calculate on lab analysis and mortal moxie which are generally precious and unobtainable in a large part of the uninhabited world. Since smartphones are becoming increasingly present indeed in the most pastoral areas, in recent times scientists have turned to automated image analysis as a way of relating crop conditions. This paper presents the most recent results in this field and a comparison of the deep knowledge approach with the classical machine learning algorithms.[1]For the problem that the network predicated on natural image type is not suitable for crop pest and complaint identification tasks, this paper has bettered the network structure that can take care of both recognition speed and recognition delicacy.

Keywords—Deep learning, Convolutional Neural Network, Data, Augmentation, Multi-model fusion, Scalability, Feature extraction, Transfer learning, Performance evaluation, Deep learning.

I. INTRODUCTION

Ensuring the health of crops is paramount for economic stability and food safety. As you mentioned, the growth and condition of leaves are vital indicators of a crop's health. Diseases affecting crops can result in decreased yields, lower quality produce, and in severe cases, complete crop loss.[1] This not only impacts the livelihoods of farmers but also disrupts food supply chains, leading to potential food shortages and economic instability.[1]Addressing crop diseases requires a multifaceted approach that includes research into disease-resistant crop varieties, innovative farming techniques, effective pest and disease management strategies, and international cooperation to monitor and control the spread of plant pathogens.

II. RELATED WORK

In this article, the literature on detecting leaf diseases using deep learning is looked at in detail, alongside other important research.[2] The use of AI in healthcare and the agriculture sector has greatly increased recently. Artificial intelligence has found its way into imaging, particularly in the medical and agricultural realms.Sanjiv Sannakki and others utilized artificial intelligence and image processing in an attempt to come up with a diagnosis for various diseases. Monika Jhuria and her team employed an image processing method to assess fruit quality and spot illnesses. An artificial neural network was used to classify diseases[2]. Kaiyi Wang and colleagues came up with a unique strategy of identifying insect pests and plant diseases by utilizing image processing and computer vision techniques.While examining images of insect pests and plant diseases taken by smartphones, automatic assessments were carried out on various NLP datasets. Models of varying sizes all based on GPT-3 were trained for this purpose.[2]

Several diseases can result in the loss of chlorophyll in leaves, causing dark or black patches to develop on the surface. The use of machine learning techniques for classification, feature extraction, image preprocessing, and image segmentation has been key in identifying these issues. Features are extracted via the Grey Level Cooccurrence Matrix (GLCM).The Support Vector Machine has proven to be effective in categorizing diseases.[3]The Convolutional Neural Network (CNN) technique showed improved recognition accuracy when compared to SVM. For instance, apple leaves were identified with a 99% accuracy overall, while the classification of plants achieved a 97.71% accuracy rate.[3]In addition, a method for detecting rice leaf diseases was developed using machine learning techniques. Three common diseases that affect rice plants were detected: leaf table, bacterial leaf blight, and brown spot diseases.[2]Clear images of damaged rice leaves set against a white background were used as the input. After preprocessing, the dataset underwent training using machine learning techniques such as KNN (K-Nearest Neighbor), J48 (Decision Tree), Bayesian Network, and Logistic Regression. After 10-fold cross-validation, the decision tree method attained an accuracy exceeding 97% when applied to the test dataset.[2]Crop diseases and insect pests are numerous. Various external factors such as plant attributes, weather conditions, and the presence of weeds and pests in the environment influence crop health. To prevent the spread of new diseases, farmers will utilize the trained models for timely identification and classification. This project aims to implement image analysis classification algorithms for detecting and categorizing leaf diseases.[4]

III.METHODS AND EXPERIMENTAL DETAILS

CNN models excel in object recognition and classification tasks using image databases.[3]However, they still face challenges such as prolonged training durations and the need for extensive datasets. Deep CNN models are essential for extracting intricate features from images, intensifying the training complexity.[4]To mitigate these issues, transfer learning approaches are employed. Transfer learning utilizes pre-trained networks, allowing learned model parameters from one dataset to be applied to other tasks. In this section, we explore the methodologies utilized in this study, emphasizing transfer learning and its role in overcoming the aforementioned challenges.

A) Multi-Class Classification

Plant disease datasets contain multiple images of both infected and healthy plant samples, each categorized into specific classes.[2]For example, all images depicting healthy and infected banana plants are categorized under the banana class.

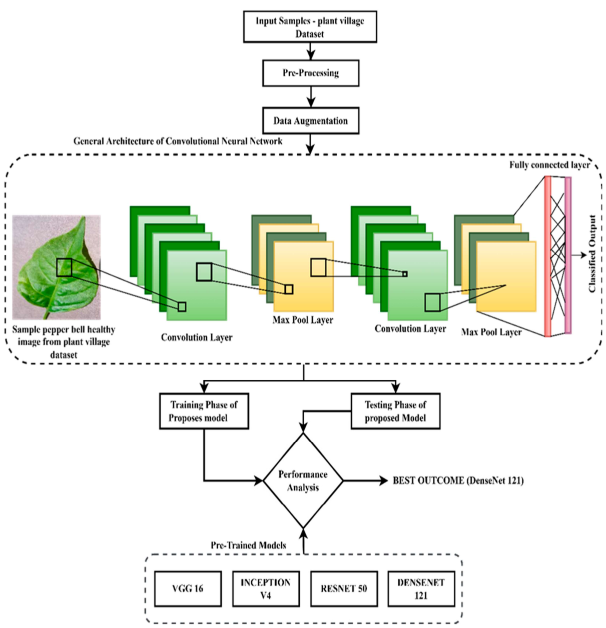

Fig.Architecture of the process

During classification, the features extracted from the source image determine the class of the target image.[5]Using the example of banana plants, the banana class comprises four sets of diseases: xanthomonas wilt, fusarium wilt, bunchy top virus, and black sigatoka. When a sample of a particular disease is inputted after being trained with all four disease sets under the banana class, the testing phase accurately identifies the disease from the mapped categories.[2]Thus, multi-class classification is mutually exclusive, in contrast to multi-label classification where each category within a class is considered a separate class. If there are N classes, then there are N multi-classes. Moreover, if each of the N classes has M categories, then each category within each of the N classes is itself considered a class.

C) Transfer Learning Approach

Training most state-of-the-art models from scratch typically requires days or weeks, even with high-end GPU machines. Building a CNN model from scratch using a publicly available plant disease dataset achieved only 25% accuracy after 200 epochs.[5]Conversely, employing a pre-trained CNN model through transfer learning achieved a significantly higher accuracy of 63% in nearly half the number of iterations (over 100 epochs). Transfer learning encompasses various approaches, and the choice depends on the pre-trained network model for classification and the specific characteristics of the dataset[6].

D) ResNet-50

ResNet-50 is a convolutional neural network consisting of 50 deep layers, organized into five stages with convolution and identity blocks. These networks serve as a backbone for computer vision tasks and introduce the concept of stacking convolution layers.[7]Additionally, they implement skip connections to mitigate the vanishing gradient issue. The skip connections bypass the original input to reach the output of the neural network, and they can be placed before the activation function.[4]This design resolves issues associated with deeper models, as deeper layers tend to accumulate more errors. The shortcut connections in the residual neural network are based on identity mapping, contributing to improved model performance.It is a CNN model to give input and trained with datasets.It compares the datasets between trained and original datasets.

B) VGG-16

The VGG-16 network model, also referred to as the Very Deep Convolutional Network for Large-Scale Image Recognition, was created by the Visual Geometry Group at Oxford University. It features a depth expanded to 16–19 weight layers and contains 138 million trainable parameters.[2]The model's depth is further accentuated by reducing the size of the convolution filters to 3 × 3. However, this improvement necessitates longer training times and occupies more disk space.[7].VGG is a very deep convolutional neural network which is a visual geometry group.It can experiments with various crops

IV. RESULTS AND DISCUSSIONS

Training a model for leaf disease classification requires a dataset containing examples of both healthy and diseased leaves.[9]We sourced image data from Kaggle.com, a prominent platform for data science courses and content

Dataset:
The dataset was divided into training, test, and validation samples. We utilized 80% of the PlantVillage samples for training pre-trained models such as Inception V4, VGG-16, ResNet, and DenseNet-121.[9]Each model underwent 30 epochs, with convergence typically observed after 10 epochs, achieving high accuracy levels. Particularly noteworthy was the recognition accuracy of the Inception V4 model[9].

Preprocessing and Data Augmentation:
The dataset consisted of 38 classes, including 26 diseases and 14 crop species. For experimentation, we utilized color images from the PlantVillage dataset, as they align well with transfer learning models[8]. Images were standardized by resizing them to 256 × 256 pixels to accommodate the varying input sizes required by the chosen pre-trained network models. VGG-16, DenseNet-121, and ResNet-50 required input sizes of 224 × 224 × 3 (height, width, and channel width), while Inception V4 required 299 × 299 × 3. Despite the dataset's substantial size of around 54,000 images depicting various crop diseases, they closely resemble real-life images captured by farmers using diverse image acquisition techniques such as Kinect sensors, high-definition cameras, and smartphones. Given the dataset's size, measures were implemented to mitigate overfitting, including data augmentation post preprocessing.[8]

Network Architecture Model:
Pre-trained network models were chosen based on their suitability for the plant disease classification task. Each network employs varying filter sizes to extract specific features from feature maps, with filters playing a pivotal role in feature extraction.Further, each filter, when convolved with the input, will extract different features from it, and the specific feature In our experimentation, the extraction of features from the maps relied on the specific filter values within the actual pre-trained network models, maintaining their respective convolution layer combinations and filter sizes.[8]

Tuning Details for VGG-16:
The VGG-16 network was configured with input image dimensions of 224 × 224 × 3. Its initial two layers comprised 64 channels each, utilizing 3 × 3 filters with a stride of 2. Following this, two subsequent layers featured 256 channels with 3 × 3 filters, succeeded by a max-pooling layer employing a stride of 2.[2]Additionally, two convolution layers with 256 channels and 3 × 3 filters were included, alongside two sets of three convolution layers each, coupled with pooling layers utilizing 3 × 3 filters. The network architecture also included a flattened layer, five max-pooling layers, and two dense layers.[2]

Tuning Details for Inception V4:
The Inception V4 block encompassed two phases: feature extraction and fully connected layers. It consisted of a stem block, Inception A, B, and C blocks, followed by reduction blocks A and B, and an auxiliary classifier block.[7]We utilized state-of-the-art deep learning models with a transfer learning approach for diagnosing plant diseases. Leveraging the PlantVillage dataset, previously trained with the ImageNet dataset, further training of the pre-trained deep CNN networks was conducted. Each model was standardized with a learning rate of 0.01, a dropout rate of 0.5, and 38 output classes. Dataset partitioning into training, test, and validation samples allocated 80% of PlantVillage samples for training the pre-trained Inception V4, VGG-16, ResNet, and DenseNet-121 models.[7] Convergence, typically observed after 10 epochs out of the total 30, yielded high accuracy levels. To mitigate vanishing gradient issues stemming from skip connections, regularization techniques like batch normalization were implemented. [5]Despite challenges such as overfitting, covariate shifts, and increased training time complexity with deeper models, hyperparameter fine-tuning was applied to address these issues. Evaluation metrics included sensitivity analysis to predict the proportion of truly healthy plants classified as healthy (true positive), and healthy plants misclassified as unhealthy (false negative). Results indicated that ResNet-50 and DenseNet-121 outperformed the VGG-16 and Inception V4 models.[6]

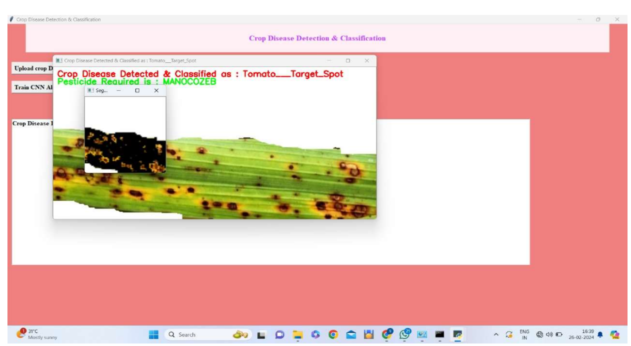

Fig:Output screen

It predicts the diseases for crops and suggests pesticides.

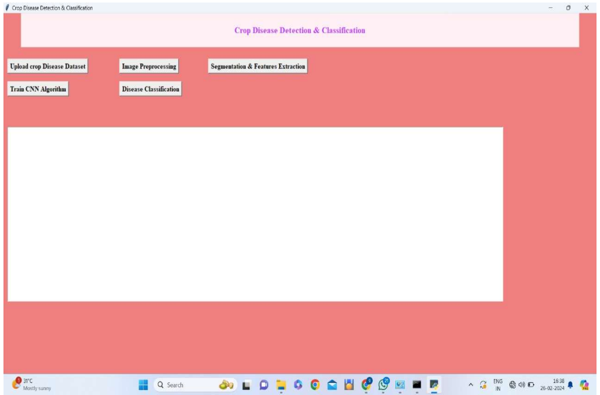

Fig. Input screen 1

This screen is the first page of our project.It contains upload an image,image preprocessing, Disease classification icons.

Fig:Confusion matrix

It is a table that is used in classification problems to assess Errors in model were made.Using the table it is easy to see which predictions are wrong.

V.CONCLUSION

In this study, we conducted a successful analysis of various transfer learning models suitable for accurately classifying 38 different classes of plant diseases.[9]Our approach involved standardizing and evaluating state-of-the-art convolutional neural networks (CNNs) using transfer learning techniques, focusing on classification accuracy, sensitivity, specificity, and F1 score.[9]Through performance analysis of different pre-trained architectures, we observed that DenseNet-121 surpassed ResNet-50, VGG-16, and Inception V4 in terms of effectiveness. Training the DenseNet-121 model proved to be straightforward due to its fewer trainable parameters and reduced computational complexity.Consequently, DenseNet-121 emerges as the preferred choice for plant disease identification, especially when incorporating new diseases into the model, as it exhibits reduced training complexity. A holistic approach involves seamlessly integrating these methodologies to develop a robust language model. By prioritizing precision in model training, enhancing conversational capabilities, and ensuring responsible and safe interactions, we can fully leverage the potential of our project in engineering applications.[9]

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