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A Comparative Study on Deep Learning Models for Plant Disease Detection and Organic Solutions

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Abstract: Farming is essential to the economy of each and every country. Consistently, ranchers grow many harvests. Crop and forest products for both food and non-food products are included in agriculture. [First, agriculture was an important part of the development of sedentary human civilization.

One of the primary causes of crop devastation and inappropriate crop development is infection and disease. Several factors associated with plant disease diagnosis using deep learning techniques must be taken into consideration when developing a robust system for accurate disease management. This model utilizes profound learning and picture handling to distinguish plant sicknesses and prescribe natural answers for treating the plants. This model makes use of convolutional neural networks, which are crucial for visual imagery.

Images are processed and libraries are extracted with Tensorflow. Keras is likewise utilized for highlighting extraction expectations and adjusting hyperparameters. In light of the kind of plant and sickness, this model additionally suggests natural arrangements like fertilizer, vermicompost, bonemeal, etc. Moreover, the model distinguishes bothers and proposes natural cures, for example, rejuvenating balms, cow manure, and neem glue to safeguard the harvest from harm.

The project's objective is to reduce the economic and aesthetic damage caused by plant diseases and to provide farmers with an intuitive interface for organic plant cultivation. In order to provide the most precise Deep Learning results, this model looks for the ideal approach. Organic Solutions and a Model for Predicting Plant Diseases

Keywords: CNN, NLP, Data Pre-processing, MySQL

I. INTRODUCTION

The protection of plant health is essential in every industry. Plants not only provide non-food crops for energy, fiber, feed, and horticulture, but they also contribute to the world's food supply. The physiological functions of plants that are disrupted by persistent phytopathogenic organisms (biotic or infectious disease agents) are referred to as plant diseases. At various cultivation stages, it suffers from a variety of diseases. Because of the vast amount of land under individual farmers' control, the variety of diseases, and the occurrence of multiple diseases in the same plant, early detection and treatment of such illnesses is beneficial for ensuring high quantities and quality. In remote areas, expert knowledge in agriculture is unavailable, and the process takes time.

Fig 1: Plant Disease

It developed an automated method for farmers to send images of diseased leaves to our server, where a neural network will identify the disease and provide the farmer with the disease classification as well as the organic solution that corresponds to it because everyone nowadays has a cell phone. Using our plant disease dataset, which was gathered over several months, the proposed architecture developed a deep learning strategy inspired by work on convolution neural networks. Sequential pre-trained VGG-19 models that have been trained on a lot of ImageNet data are used to identify plant diseases.

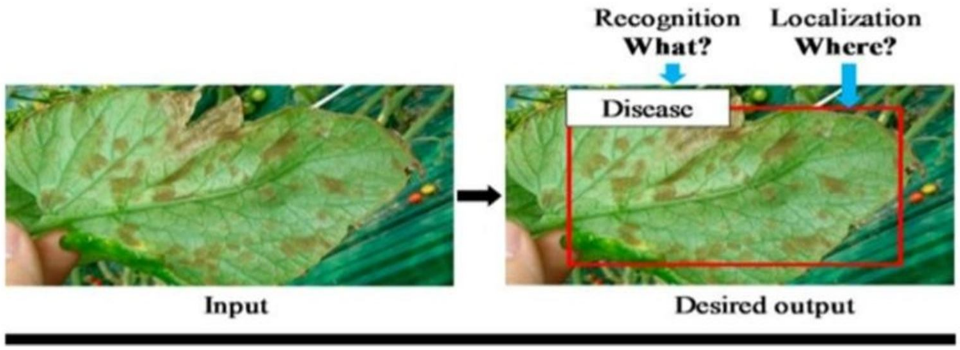

Fig: Recognizing the type of disease on the image

We must choose the most effective management strategies whenever we need to take control measures. Plant selection and cultural practices are the first lines of defence. As an essential component of agricultural sustainability, organic farming significantly enhances soil fertility.

Organic methods are cost-effective, improve the structure, texture, and aeration of the soil, increase its capacity to retain water, and encourage the development of healthy roots. Minerals, animal waste, sewage sludge, and even plants are all sources of organic fertilizer. Soil organic matter content increased as a result of vegetables, animals, and residue materials. As a result, it is recommended that you use integrated nutrient management, which involves the scientific management of animal manure, plant residue, and sewage sludge in order to improve soil productivity over time and maximize crop growth, yield, and quality.

The second section explains about the survey done to know about the plant disease detection using image processing and deep learning models,third section ensure to know about the various models used,its advantages,its architecture,the fourth section gives the description of datset and preprocessing the data,fifth section gives the details of results.

II. LITERATURE REVIEW

Preventing yield and quantity losses in agricultural products necessitates the detection of plant diseases. The study of patterns in plants that can be seen is an important part of research into plant diseases. For sustainable agriculture, disease detection and monitoring of plant health are essential. Plant diseases are extremely difficult to manually monitor. It requires extensive work, knowledge of plant diseases, and a prolonged processing time. Consequently, plant diseasesare detected through image processing. Disease detection involves several steps, including image pre-processing, image acquisition, feature extraction, image segmentation, and classification. Images of plant leaves can be used to identify diseases, as discussed in this paper [1]. The introduced technique exhibits a mechanized strategy for crop infection ID utilizing Nearby Twofold Examples (LBPs) for highlight extraction and One Class Order for arrangement on different leaf test pictures relating to various yield species. The proposed method makes use of a separate Class Classifier for each plant health condition, such as healthy, powdery mildew, downy mildew, and black rot. When tested in other crops, the vine leaf-trained algorithms displayed exceptionally high generalization behaviour. A unique algorithm that proposes conflict resolution between one-class classifiers provides correct identification when ambiguous data instances may belong to more than one condition. A total success rate of 95 percent was achieved for the 46 plant-condition combinations tested[2].

Agricultural productivity is an essential component of the Indian economy. Consequently, the contribution of food and cash crops is essential to humans and the environment. Consistently, crops are obliterated by various illnesses. Inadequate disease diagnosis and ignorance of disease symptoms and treatments result in the death of numerous plants. This study gives an outline of plant illness location utilizing different calculations. This paper proposes a CNN-based approach for identifying plant diseases. Simulation studies and analysesof time complexity and infected region area are carried out on sample images. It is achieved using a picture-handling strategy. The model wasfed 15 cases, 12 of which were successful [3].

It is difficult to localize and classify various insect species due to their high degree of similarity in features, making it even more challenging when dealing with those that have already been caught in traps. Inspired by the Deep Convolutional Neural Network (CNN) achievement, this paper proposes a method for identifying various species of trapped insects based on available images. This study developed a novel method for detecting plant diseases by combining four CNN models with a database of 200 images [4].

In this experiment, we used an open-source database of 36,258 images classified into 10 plant species and 61 classes of healthy and diseased plant leaves.

Two datasets were created from 36258 images. 4540 for the validation set and 31718 for the training set. Four CNN models, Commencement, Resnet, Origin Resnet, and Dense Net, were broadcastand the sequences of CNN models were processed using a stacking technique. Compared to the results obtained using a single CNN model,the accuracy rate obtained by the stacking method is 87%, a significant improvement. A relatively high accuracy rate suggests that a combination of CNN models was used [5].

Identifying plant diseases is essential to prevent loss of crop yield and quantity. It requires considerable labour, knowledge of plant diseases, and longer processing times. This makes it possible to detect plant diseases through image processing. Image acquisition, image pre- processing, image segmentation, feature extraction, and classification are all components of disease detection. This article described a strategy used to detect plant diseases using leaf images. In this article, we have discussed various methods of segmenting diseased parts of plants. In addition, this article described trait extraction and classification methods used to extract traits from infected leaves and classify plant diseases. Image processing can be used to accurately identify and classify plant diseases that are critical to successful crop cultivation. In this article, we have discussed various methods of segmenting diseased parts of plants. In addition, this article described trait extraction and classification methods used to extract traits from infected leaves and classify plant diseases. Classifying plant diseases using ANN methods such as self-organizing feature maps, backpropagation algorithms, and SVM. can be used effectively [6].

The color transform structure RGB is converted to HSV space since HSV is a good color descriptor. The application of biostatistics to detect plant leaf diseases is described. Cover and remove green pixels with a pre-processed cut-off level. The 32x32 patch size is used for segmentation in subsequent steps, thus yielding useful segments. These segments are used in texture analysis of the color co-occurrence matrix.Especially when you compare texture parameters to regular leaf parameters. [7]. Getting a high-quality image with as much color detail as possible was the hardest part of the job. Getting an image with all thedetails stored in a memory that can be processed is a common task. Such images are composed with a lofty goal and thus can be 6-10 MB in size. The Nikon D5200 camera used for this was very effective. The second hurdle was to eliminate the lighting conditions, as the lighting conditions are very different from the beginning to the end of the paddyseason, even though the shooting time is fixed. However, the answer to this is variable client-defined threshold management and a significant adjustment to LCC tint.

When plants get sick, the quantity and quality of produce is greatly reduced. Identifying disease side effects with the naked eye is difficult for ranchers. Computer-aided image processing is used to protect crops,especially on large farms, and diseased leaves can be identified by color. Depending on the application, many image processing methods have been learned and solved through design validation and several programmed applicators. This white paper provides useful overviews of these proposed systems in the following sections. Although there are many automated or computer vision methods for disease detection and classification, research on this topic is still lacking. No single method can identify all diseases [8]. This study used image processing and machine learning techniques to identify and classify cotton leaf diseases. Investigations into background subtraction and segmentation methods were also discussed. According to the results of this research, color space conversion from RGB to HSV is useful for background removal. Moreover, thresholding was found to outperform other background subtraction methods in terms of results. To perform color segmentation, we first removed the background from the image by erasing the green pixels and then thresholded the resulting binary image. This helps in pinpointing disease features. We found that SVM yields excellent results in terms of infection ordering accuracy. The proposed work consisted of five main steps, of which he carried out three. Image segmentation [9].

Target regions (prevalence patches) are then identified by R, G, and B color feature image segmentation. Image features such as borders, shapes, colors, and textures are later extracted for disease patches to identify the disease. Cotton leaf spots, cotton leaf color segmentation, edge detection-based image segmentation, and disease analysis andclassification are the three components of this work [10]. In this section, we propose and experimentally test a software solution for the automatic detection and classification of plant diseases by image processing. In rural India, farmers have limited access to agricultural experts who can examine images of their crops and offer advice. Farmers often get the right answers to their questions too late. This paper develops an image processing algorithm that can automatically identify crop problems based on image color, texture, and shape, and automatically detect diseases and other conditions that can affect crops. to address this issue and provide farmers with fast and accurate solutions. SMS [11].

III. MATERIALS AND METHODS

We used photos of potato leaf diseases from the public Plant dataset to train, validate, and evaluate the proposed model. The photographs in the collection showed two distinct conditions for potato leaves: typical

i.e sound and an unhealthy one. Right now, the dataset is being loaded: The plant leaves dataset is utilized without augmentation. It contains 56,725 images representing 39 plant species, of which 42,312 have been trained and 14,413 have been tested. For both the training and testing datasets, the class model is categorical, and the image and batch sizes are set to 48 and 64, respectively.

Manipulation of images: This produces groups of picture information as tensors from continuous datasets. In this step, the batch processing model is defined. When the input exceeds a certain threshold, the transform function activates a node; The output is zero when the input is less than or equal to zero.

The proposed system's detection of these diseases assists in selecting the appropriate treatment to prevent plant infection. A specialist in the field who is able to treat these diseases with the naked eye is required for detection; however, this is a prohibitively expensive procedure;consequently, there is a demand for detection systems for crop diseases.

1) The candid and computationally resourceful method for identifying leaf disease and recommending organic solutions is provided by the proposed system.
2) Concepts of Convolutional Neural Networks like VGG-19, Sequential, and Mobile-net are included.
3) This system enables the identification and recommendation of the name of the disease and the organic remedy that is specific to that disease.

Advantages of the Proposed System

a) To identify key elements without the need for human intervention; to detect leaf diseases using CNN algorithms in less time.
b) Following proper identification, organic solutions are recommended.

A. Methodology

1) Dataset

New Plant Disease Dataset: This dataset was reconstructed using an offline supplement from the original dataset. You can find the original data set in the GitHub repository. This dataset contains approximately 87,000 RGB photos of both healthy and diseased plant leaves and is divided into 38 classes. The directory structure is preserved as the full dataset is split into a specific ratio of training and validation sets. Later, 33 test photos are taken in a new directory for prediction purposes.

2) CNN Model

The architecture of Convolution Neural Networks (CNNs) determines how well the network performs. It consists of the fully linked layer, the pooling layer, and the convolution layer. A deep CNN called VGG is used to categorize photos.

3) Layers Flow

The input to this network was a fixed-size RGB image (256*256), sothe matrix was in the shape of a square (256,256,3).

The only pre-processing performed was to calculate the mean RGB value for each pixel in the entire training set, which was then subtractedfrom each pixel.

They covered the entire image using kernels with a size of (3 * 3) and a step size of 1 pixel. Spatial padding was used to preserve the spatial resolution of the images.

Max pooling was performed with side 2 across a 2 by the 2-pixel window. A rectified linear unit (ReLu) was then used to add non-linearity to the model to improve classification accuracy and computation time.

Unlike previous models that used tanh or sigmoid functions, this one performed much better.

B. Architecture of Plant Disease Detection

Therefore, due to the enormous amount of land under the control of individual farmers, the wide variety of diseases and the prevalence of many diseases in the same crop, early detection and treatment of such diseases is useful to ensure high quantity and quality. However, it is really difficult to do this.

Acquiring agricultural expertise is time-consuming and not possible in rural areas. Eliminating the need for image pre-processing and opening up built-in feature selection, convolutional neural networks have recently made great strides in image-based detection. Another problem that is quite difficult is finding huge datasets for such challenges. If the dataset is fairly small, it is preferable to use a model that has been previously pre-trained on a large dataset.

A neural network type called a Convolutional Neural Network or CNN or ConvNet is particularly good at processing inputs with a grid-like architecture like an image. A binary representation of visual data is a digital image. The brightness and color of each pixel is specified by its pixel value and they are arranged in a grid-like pattern. The human brain analyzes a vast amount of data and concepts while looking at an image. The entire visual field is covered by the connections between each neuron, each of which works in its own receptive field and has its own network of connections in the receptive field.

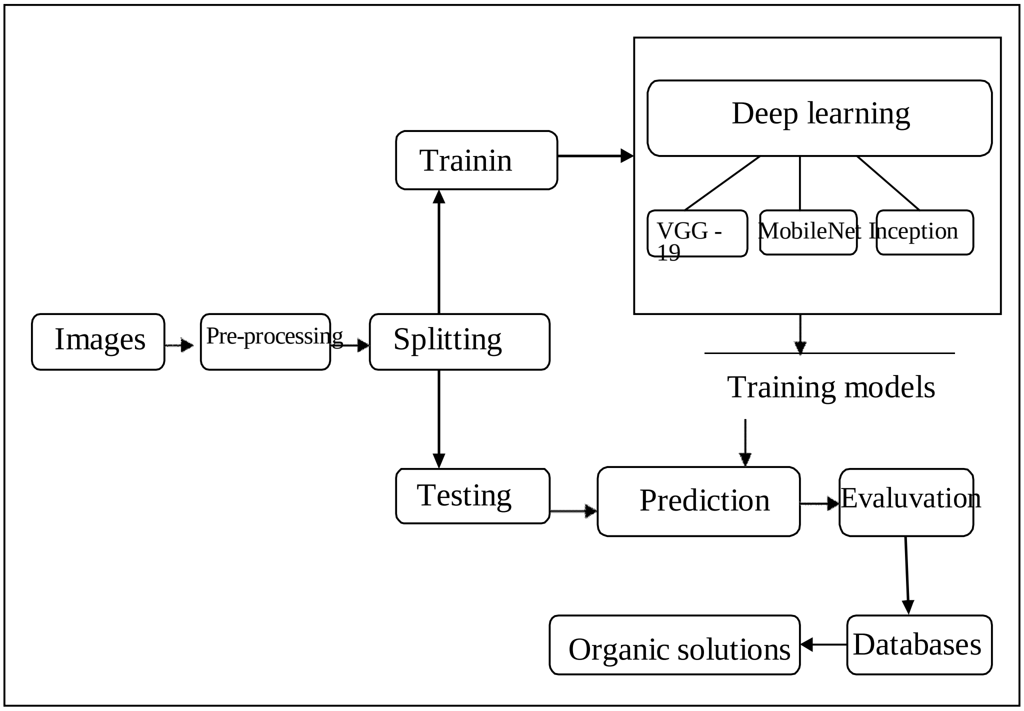

Fig 3.2.1. The architecture of plant disease prediction

CNN has Layers and Types of layers. They are Input Layer, Activation Function Layer, Pool Layer, Full-Connected Layer, and Convolution Layer

1) Input Later: The raw input images are 32 pixels wide, 32 pixels high, and three pixels deep, and are contained in the input layer.
2) Convolution Layer: In the convolution layer, the output quantity is calculated by using taking the dot product of every clear-out and the photograph patch. The output quantity is 32 32 x 12 if this accretion uses a total of 12 filters.
3) The output of the convolution layer is subjected to an element-smart activation function on this layer. commonplace activation functions include Tanh, Leaky RELU, RELU: max(0,x), Sigmoid: 1/(1+e-x), and others.
4) Pool Layer: this sediment is periodically injected into the covets, and its foremost characteristic is to reduce the quantity size, which hastens computation, saves reminiscence, and avoids overfitting. two not unusual kinds of pooling layers are most pooling and common pooling.

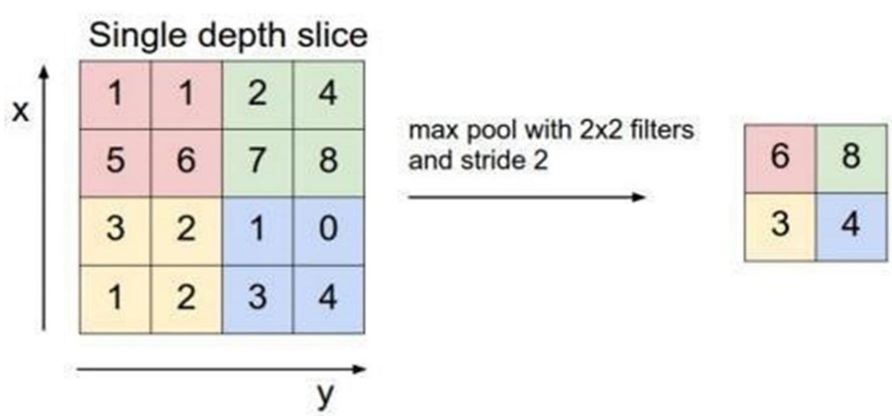

Fig 3.2.2: Max PoolingFully-Connected Layer:

This layer acts as a preferred neural network layer, taking input fromthe preceding layer, calculating class values, and developing a 1-D array with the same range of instructions as the previous layer.

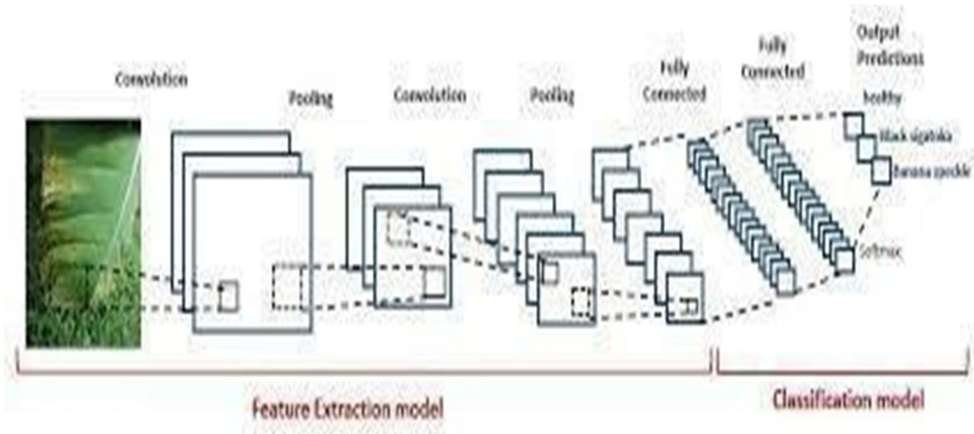

Fig 3.2.3. The architecture of convolutional neural networks

C. Algorithms

1) VGG-19

VGG-19 is a convolutional neural network with 19 layers. The ImageNet database has a pre-trained version of the network that has been trained on over a million photos. VGG19 is a variation of the VGG model that has 19 layers, including 16 convolutional layers, 3 fully connected layers, 5 MaxPool layers, and 1 SoftMax layer. OtherVGG variants include VGG11, VGG16, and others.

AlexNet, released in 2012, improved traditional convolutional neural networks and can be seen as the successor to AlexNet. VGG was developed by another team at Oxford University, hence the name Visual Geometry Group. The VGG network uses deep convolutional neural layers to increase accuracy and builds on concepts from its predecessors. It was created primarily to win the ILSVRC but has beenused for many other purposes.

The authors have made the models available to the public, and they canbe used either as is or with minor modifications for other similar tasks. Transfer learning can benefit from it, and weights are easily accessible and can be customized and used at the user's discretion on other frameworks like Keras.

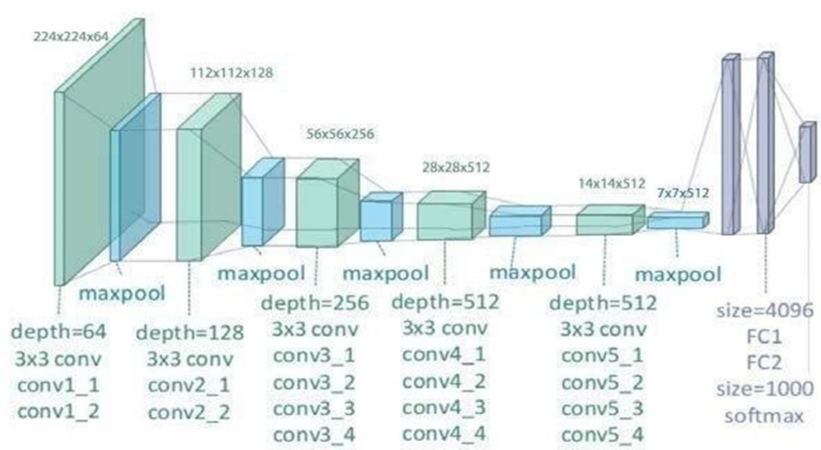

Fig 3.3.2: Network Architecture of VGG-19

2) Mobile Net

A novel type of convolutional layer known as Depth wise Separable convolution is used in the considerably quicker and smaller CNN architecture known as MobileNet. These models are thought to be highly useful for implementation on mobile and embedded devices due to their small size of the model.

The depth-wise and point-wise convolutions are the two layers that make up the depth-wise separable convolution. In essence, the input channels are filtered in the first layer, and they are combined in the second layer to produce a new feature.

It is a straightforward but effective convolutional neural network that requires little computational power for use in mobile vision applications. Several practical applications, such as object detection, fine-grained classifications, face traits, and localization, make extensiveuse of MobileNet.

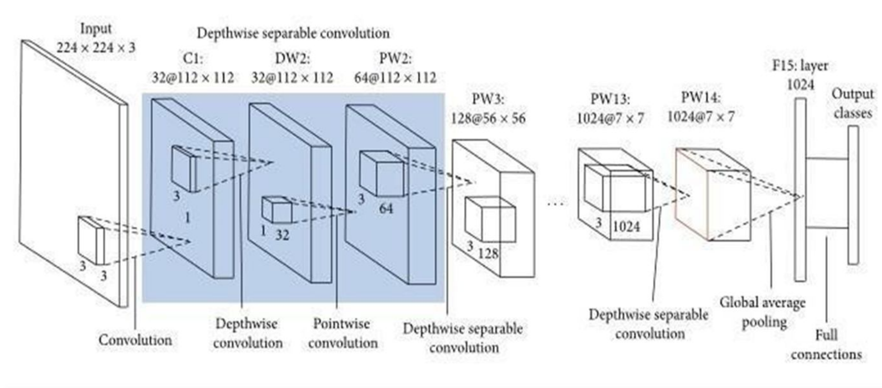

Fig 3.3.4. Mobile Net Architecture

3) Inception V3

The ImageNet dataset shows that the Inception v3 image recognition model can achieve 78.1% higher accuracy. This model is the result of many concepts developed by different researchers over the years. Convolutions, average sums, maximal sums, joins, dropouts, and fully joined layers are some of the symmetric and asymmetrical components that make up the model itself.

The model widely uses batch normalization, which is also applied to trigger inputs. Softmax is used to calculate the loss. The ImageNet dataset shows that the Inception v3 image recognition model can achieve 78.1% higher accuracy. This model is the result of many concepts developed by different researchers over the years.

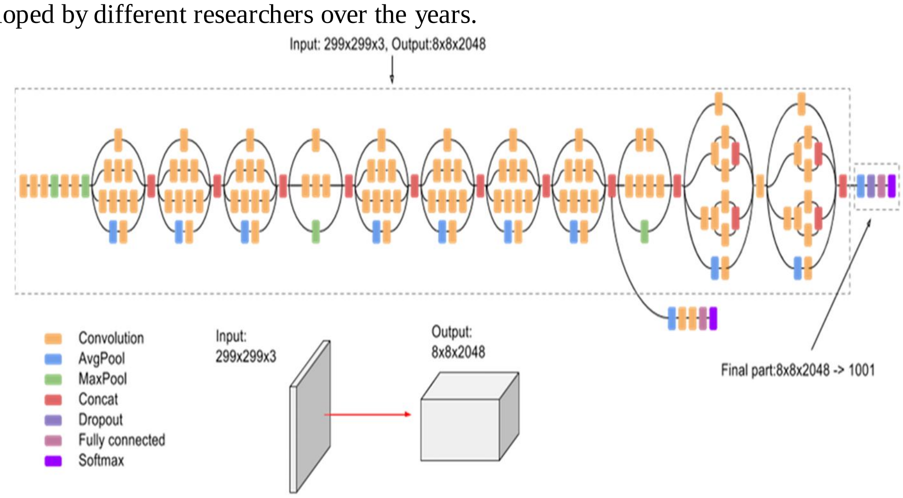

Fig 3.3.6 Inception V3 Architecture

4) VGG-16

VGG16 grew to become out to be an essential second in humankind's bid to make it viable for computer systems to" see" the sector. The subject of pc vision(CV) has finished terrific improvements in this location several decades in the past. VGG16 is one of the main innovations that paved the manner for different enhancements in this assiduity.

At the University of Oxford, Andrew Zisserman and Karen Simonyan advanced a convolutional neural network(CNN) model. The idea for the version turned into introduced in 2013, but the genuine version changed into unveiled as a part of the ILSVRC ImageNet challenge in 2014.On every occasion, ways for huge-scale photograph categorization have been envisioned as part of the ImageNet huge Scalevisible recognition competition(ILSVRC)(and object recognition).

VGG16 changed into set up to be the model with the stylish overall performance for the ImageNet dataset out of all of the settings. let's examine the actual armature of this arrangement.Any of the network configurations are purported to have a fixed 224 × 224 photos with R, G, and B channels as they enter. The only pre-processing executed is to homogenize the RGB values of every pixel. To negotiate this, the suggested price is removed from each pixel.

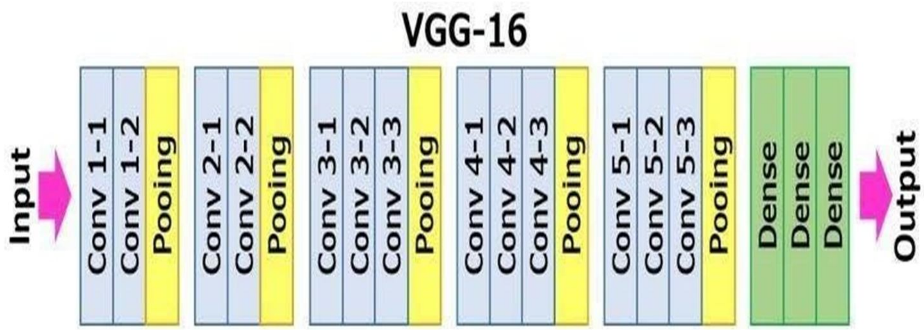

Fig 3.3.8 VGG-16 Architecture

5) Resnet

2015 noticed the introduction of ResNet using Microsoft studies experts, who also categorized it as a unique structure.

Residual Blocks were an idea that this design evolved to solve the vanishing/exploding gradient hassle. in this community, we use a method referred to as pass connections. To attach layer activations to the following layers, the bypass connection skips over some intermediate degrees. A block is created due to this. To build inns, theseleftover blocks are piled. alternatively, of having layers learn the underlying mapping, the technique used by this community is to let the community fit the residual mapping. consequently, as opposed to the usage of, for instance, the preliminary mapping of H, let the network healthy (x),

$F(x) := H(x) - x$ which gives $H(x) := F(x) + x$.

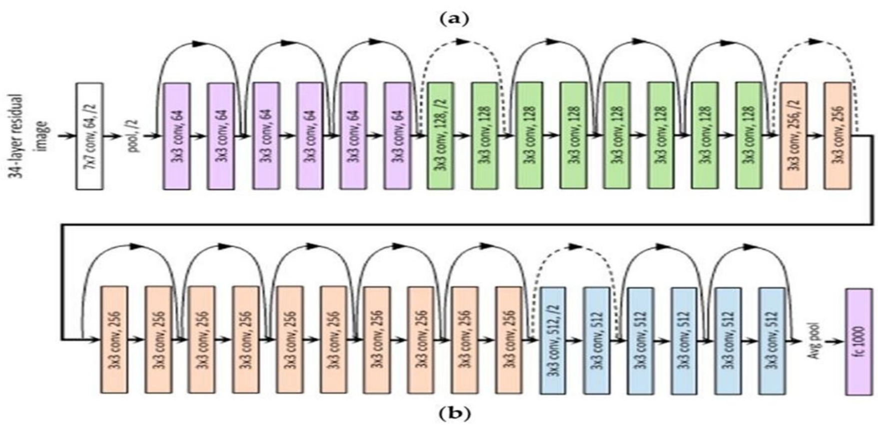

Fig 3.3.10 ResNet Architecture

IV. IMPLEMENTATION

A. Module description

1) Dataset Use

Dataset Collection

For this classification, a real-time dataset must be acquired to overcomeevery weakness in the current systems. In the older systems, the photographs of the plants were the sole data. The only categories recognized at the time were "plants sick" and "plants well". There are now only 56,725 photos of plant diseases available in the systems.

Data is therefore gathered from the "New plant disease dataset" for plant diseases to address the shortcomings of the dataset used in the current system. Both datasets were assembled through Kaggle.

https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

2) Dataset Description

Many plant disease pictures that have been improved with their names can be found in the updated plant disease dataset. This collection is divided into 38 classes and contains about 87K RGB images of healthy and diseased crop leaves. The training and validation sets are divided into training and validation sets in an 80/20 ratio while maintaining the directory structure.

Fig 4.1.1.1:Various plant leaves afftected by diseases

Fig 4.1.2 Images of New Plant disease dataset

3) Pre-Processing The Data

Learning how to pre-process incoming image data into usable floating-point tensors for Convolutional Neural Networks is the goal. Tensors can be thought of as multidimensional arrays simply because they are meant to hold knowledge rather than actual data.

Load the dataset after importing the required libraries. Every data analysis procedure must include this step. Pictures come in a variety of sizes and shapes.

Data preprocessing starts with uniformly sizing all of the photographs. With the help of ImageDataGenerator in Keras, several enhancement algorithms are applied to the collected photos, creating new images with a resolution of 256*256 pixels as a result.

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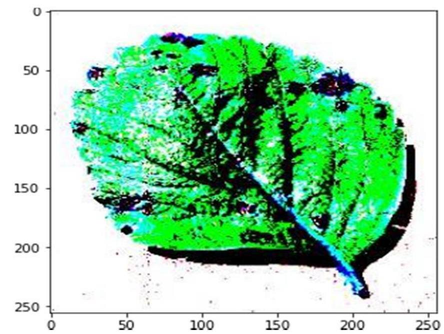

Fig 4.1.4 Pre-processed image

4) CNN Model

The loaded picture data set needs to be used for both training and testing. Images and class labels are stored separately in arrays for training purposes. The train-test split strategy utilizes 70% of the information for preparing and 30% for testing. After 30 percent of the data is used for validation, another 70 percent is separated.

The class labels are converted to integers with the help of a dictionary. Keras is delinked of the fully linked layers. changes to the system that can't be taught. After flattening the output of a SoftMax feature extractor, it applies the SoftMax filter.

A model was constructed from the ground up using the Adam optimizerand category cross entropy as the loss function to classify plant disease identification. After fifty iterations, there was no change in the outcomes. The model was trained using VGG-19, Sequential, VGG-19 with Early Stopping, and Mobile Net models. The VGG-19 model performed well and produced better results than any of these approaches.

5) Databases and Connection to Model

For each disease of the plant, organic methods of control have been gathered. The authoritative Google pages, books on plant care, and manuals for organic farming were used to compile these organic remedies. For each plant disease, several organic remedies are gathered.

MYSQL databases were used to create an entry in the database for eachof these organic solutions. Two tables were created with two columns—one for the name of the disease and another for an organic remedy—to identify plant diseases.

A connection to the databases and previously trained models was established by utilizing the Python MySQL Connector. Python is used to connect the model for identifying plant diseases.

V. RESULTS AND DISCUSSION

Python is used to combine the plant disease identification model, and the databases for plant disease organic remedies are linked to thisintegrated model using Python's MYSQL connector package.

To determine whether a plant is contaminated, a picture of the plant must be uploaded. Organic solutions are not offered if healthy. Otherwise, the disease's name and natural treatments are offered.

Five alternative algorithms, including VGG-19, Inception, MobileNet, ResNet, and VGG-16, were used to train a model of plant disease. The MobileNet model out of these five has the highest accuracy and outperforms the others in terms of performance.

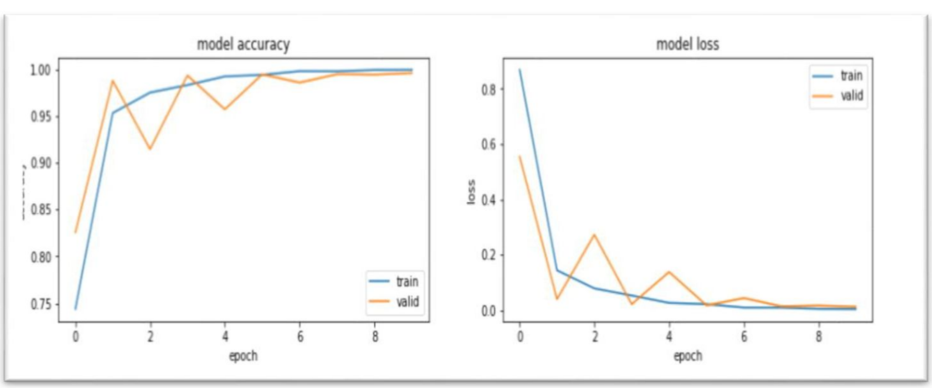

Fig. 5.1. Accuracy and loss graphs for MobileNet

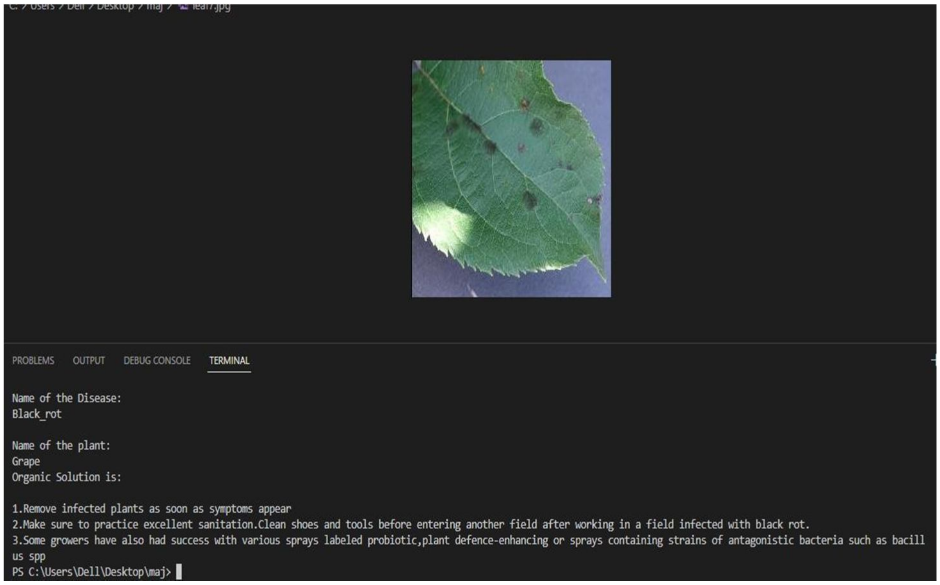

Fig. 5.2 Detected Black_rot on grape plant with its Organic Solutions

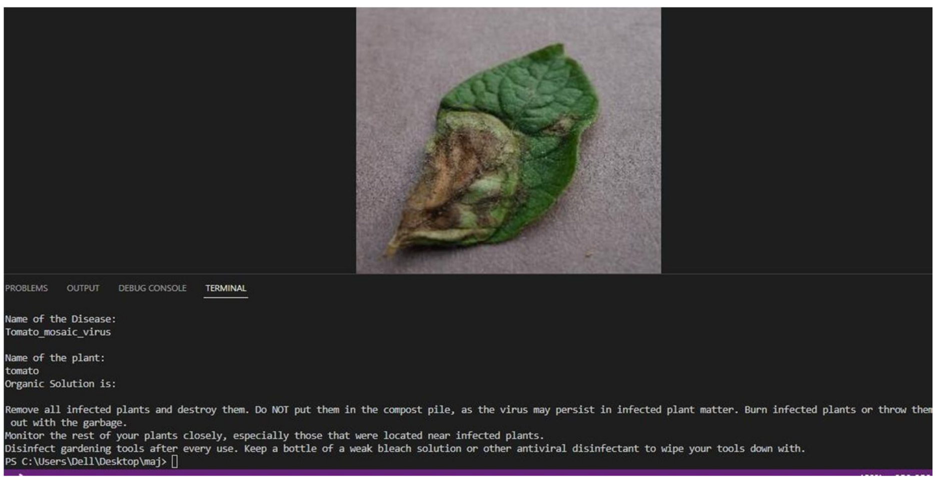

Fig. 5.3 Detected Tomato_mosaic_virus on Tomato plant with itsOrganic Solutions

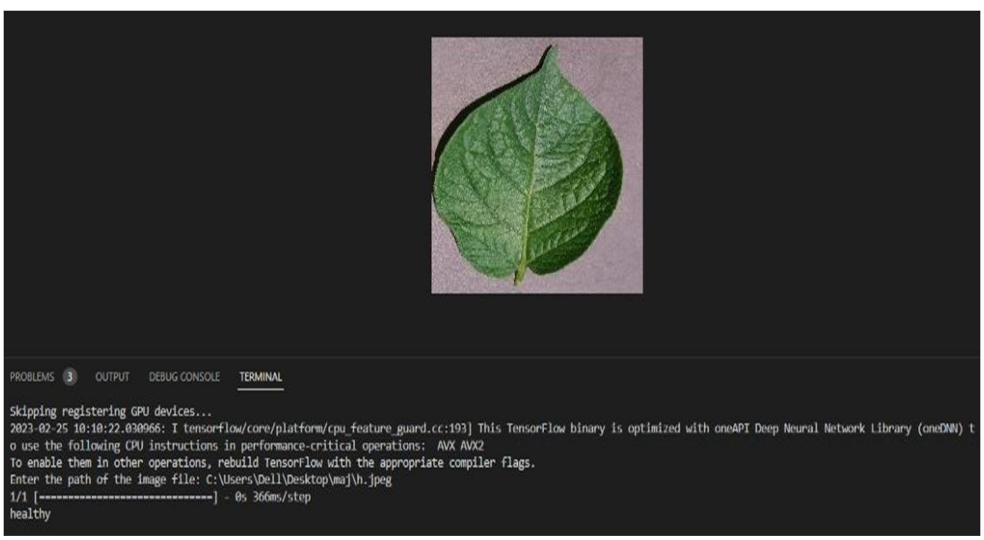

Fig 5.4. Healthy Plant

Table 5.5 Comparative analysis of different algorithms for plantdisease identification

Model	Accuracy
VGG-19	87%
Inception V3	91%
ResNet	99%(Overfitting)
MobileNet	97%
VGG-16	92%

VI. CONCLUSION AND FUTURE SCOPE

This model makes use of a deep learning model to recognize plant ailments and then suggests natural remedies fit for the general care of the plants. The dataset has over 80K images of plant diseases. Several pre-trained models, including VGG-19, VGG-16, Mobile Net, and Inception, were used to build the CNN model, with MobileNet emerging as the top performer.

For each plant and insect, organic remedies are gathered and entered into MySQL databases. After combining both datasets and CNN models, the user is shown the results.

The aim is to give farmers detailed information on how to manage various plant diseases. The accuracy of the results must be improved bythe use of real-time data. Giving farmers detailed information on how to manage various plant diseases is the aim. The accuracy of the results must be improved by the use of real-time data. This can be expanded to offer some DIY gardening solutions to home gardeners. This can also be applied to a mobile application, where the services could be offered via NLP in more languages.

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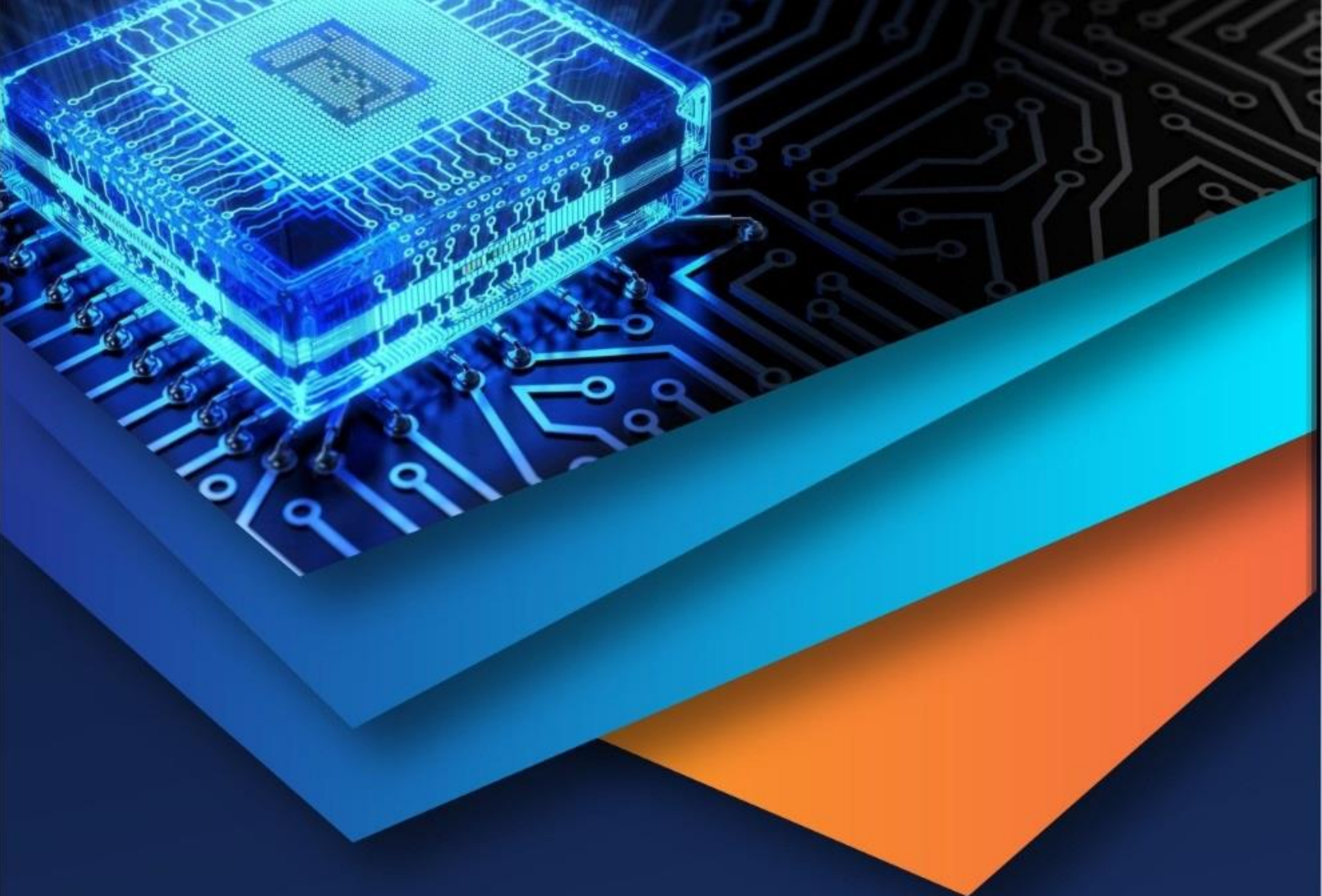

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