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"Potato Leaf Disease Detection Using Deep Learning Approach"

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CERTIFICATE

Certified that the Mini-Project work entitled **"POTATO LEAF DISEASE DETECTION USING DEEP LEARNING"** carried out by **Pavan Kumar Yadav K [1JB19EC064], Sabari Krishnan A[1JB19EC078]** are bonafide students of **SJB INSTITUTE OF TECHNOLOGY** in partial fulfillment for the award of "**BACHELOR OF ENGINEERING**" in **ELECTRONICS AND COMMUNICATION ENGINEERING** as prescribed by **VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELAGAVI** during the academic year **2021-2022**. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the department library. The report has been approved as it satisfies the academic requirements in respect of Mini-Project work prescribed the said degree.

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DECLARATION

We hereby declare that the entire work embodied in this **Mini-project report** has been carried out under the supervision of **Mrs. Pushpalatha G , Assistant Professor** in partial fulfilment for the award of “BACHELOR OF ENGINEERING” in ELECTRONICS AND COMMUNICATION ENGINEERING as prescribed by VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELAGAVI during the academic year 2021 - 2022.

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Abstract

The transmission of diseases from unhealthy to healthy plants is one of the most disastrous threats to the agriculture industry. Diseases transferred spread like wild fire and have the potential to infest the whole farm if not detected early.

Plant disease detection methods aid in identifying infected plants in their very early stages and also help the user in scaling the identification of plant diseases to a variety of plants in a cost-effective manner. And Potato being staple food in everyday diet, and they are the fourth most consumed vegetable crop in the world.

So In this project, we are going to use Deep Learning to diagnose Potato plant diseases and build an application interface so that users can easily identify disease and provide a suitable treatment for the specify type of disease.

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LIST OF ABBREVIATIONS

Abbreviations	Meaning
CNNs	computational Neural Networks
ML	Machine learning
API	Application Programming Interface
ReLU	Rectified Linear Unit
MLP	Multi-layer Perceptron
ResNet-50	Residential Energy Services Network-convolutional neural network that is 50 layers deep
VGG-n	Visual Geometry Group-convolutional neural network that is ‘n’ layers deep
SVM	support-vector machines
R-CNN	Region-based Convolutional Neural Network
AI	Artificial Intelligence
ANN	Artificial Neural Network
DL	Deep learning
CRNN	Convolutional Recurrent Neural Network
RNN	Recurrent Neural Network
DeconvNet	DeConvolutional Neural Network
DNN	Deep Neural Network
BRNN	Bidirectional Recurrent Neural Network
ARNN	Anticipation Recurrent Neural Network
VPNN	Vector Product Neural Network

CHAPTER 1

INTRODUCTION

Agriculture is considered an important pillar of the world's economy and also satisfies one of the basic need of human being i.e. food. In most of the countries it is considered the major source of employment. Many countries like India still use the traditional way of farming, farmers are reluctant to use advanced technologies while farming because of either the lack of knowledge, heavy cost or because they are unaware about the advantages of these technologies. Lack of knowledge of soil types, yields, crops, weather, and improper use of pesticides, problems in irrigation, incorrect harvesting and lack of information about market trend led to the loss of farmers or adds to additional cost. Lack of knowledge in each stage of agriculture leads to new problems or increases the old problems and add the cost to farming

Agricultural technology and the use of artificial intelligence in diagnosing plant diseases, it becomes important to make pertinent research to sustainable agricultural development. Various diseases like early blight and late blight immensely influence the quality and quantity of the potatoes and manual interpretation of these leaf diseases is quite time-taking and cumbersome. Also, the world demand for potato is increasing significant. As it requires tremendously a good level of expertise, efficient and automated detection of these diseases in the budding phase can assist in ameliorating the potato crop production.

The presence of disease during this growth period can reduce the quality and quantity of agricultural products. Also, it can lead to harvest premature and harvest failure. These problems are mostly caused by the late identification of diseases in potato plants and mistakes in disease diagnosis. The identification of diseases in potato plants quickly and accurately is highly essential to reduce the impact of diseases on plants. Manual monitoring activities carried out by farmers become difficult and impractical because it takes a long time and in-depth knowledge. Identification of plants diseases types that are slow will trigger the spread of diseases in plants uncontrollably. Besides, farmers generally identify diseases in plants in a way that is approximately and assumptions that allow inaccurate identification results because the symptoms on the leaves appear to have similarities that are difficult to describe at a glance.

Agricultural productivity is something on which economy highly depends. This is the one of the reasons that disease detection in plants plays an important role in agriculture field. Potato is one of the staple foods that is widely consumed, becoming the 4th staple food consumed throughout the world,

Thus, we can use certain techniques to make productivity of the crop more.

Fortunately, several diseases in potato plants can be identified based on leaf conditions. Therefore, in this project, we are going to use Convolutional Neural Network – Deep Learning to diagnose plant diseases.

1.1 Facts and important of potato

- Potatoes are rich in nutrients, most notably vitamins C and B6 and the minerals, potassium, magnesium, and iron.
- The Inca Indians in Peru were the first to cultivate potatoes around 8,000 BC to 5,000 BC.
- In a partnership between NASA and the University of Wisconsin, seed potatoes were first tested in space in 1995 aboard the Space Shuttle Columbia. Potatoes were the first vegetable grown in space.
- Fourth staple food consumed throughout the world

CHAPTER 2

LITERATURE SURVEY

2.1 R. Sujatha et al.[1] ,performed the comparison of deep learning and machine learning technique for the detection of Grape plant leaf disease. The disease dataset comprises Black Spot, Canker, Greening, Melanose, and Healthy plant leaves. This data set is then subjected to both ML and DL models. The performance of ML models like SVM, RF, and SGD are compared with DL models like VGG#16, Inception-V3, and VGG#19. The comparison result shows, that the DL models outperform the ML models. The accuracy achieved for DL Models is: - VGG-16 gives an accuracy of 89.5%, VGG-19 gives an accuracy of 87.4%, and Inception –V3 gives an accuracy of 89%. The accuracy achieved for Machine Learning Models is:- Stochastic Gradient Descent gives an accuracy of 86.5%, Rainforest gives an accuracy of 76.8%, and Support Vector Machine gives an accuracy of 87%. As a Future Enhancement, the author aimed to improve computational accuracy even for the small-sized dataset by using Fuzzy Logic and Bio-Inspired methods

2.2 Miaomiao Ji, Lei Zhang, Qiufeng Wu [2], Theauthors worked on various Grape Leaf diseases. The collected dataset comprises various images of leaf diseases like black rot, ESCA, leaf spot, and Isariopsis. A combined model having both InceptionV3 and Resnet50 was proposed as the CNN model by Author. The proposed model distinguishes a healthy leaf from a diseased leaf by achieving a training accuracy of 99.17% and a test accuracy of 98.57%.

2.3 Ashraf Darwish, Dalia Ezzat, Aboul Ella Hassanien [3] , presented a model for plant disease diagnosis based on Convolutional Neural Network and Orthogonal Learning Particle Swarm Optimization. In the proposed model, the authors used two CNNs, namely VGG16 and VGG 19. These models were pre-trained for plant leaf disease diagnosis by classifying the images of leaves as healthy and unhealthy. CNN in combination with Orthogonal Learning Particle Swarm Optimization is used due to its ability to optimize various hyper parameters and these parameters are used for the classification of plant disease. CNN has different hyper parameters, thus, it becomes a challenge to identify and manually optimize these hyper parameters. The optimization problem is resolved using „Orthogonal Learning Particle Swarm Optimization, where it searches for the optimal value that has an impact on the classification.

2.4 Uday Pratap Singh et al [4] , The author designed a model for the classification of Mango leaves with Anthracnose disease using a multilayer CNN. For this author used an Alex Net architecture for mango leaves classification and obtained an accuracy of 97.13%.

2.5 Parul Sharmaa et al [5] ,developed a unique solution for classification, where a Convolutional Neural Network (CNN) model is trained on the segmented images. In this paper, a comparison of two CNN models was performed. The first technique is, F-CNN on the image without segmentation and S-CNN for the segmented image. When the comparison is performed, S-CNN doubles the performance as compared to F-CNN and gives the accuracy of 98.6% even when tested with previously unseen data of 10 disease classes.

2.6 J. Sun et al [6] , Author worked on the Maize plant with Northern Maize Leaf blight disease. The paper comprises three steps of data processing. The first step includes data processing by improved retinex which handles the problem of poor detection caused by a high-intensity light. An improved Region Proposal Network (RPN) network is used to adjust the anchor box of diseased leaves as the second step and this network reduces the search space of the classifier by deleting negative anchors and thereby creating a repository of the better initial information.

2.7 Ümit ATİLA, [7]. They worked on multiple plants and their diseases. The model used for plant leaf disease detection is the Efficient Net Deep learning model and its performance was compared with Deep Learning Models. The authors considered the images of apples, Grapes, Tomato, Cherry, Peach, and Potato. A disease that was targeted is Cedar Apple Rust of Apple Fruit, Powdery Mildew of Cherry, Black Measles of Grape Plant, Late Blight of Potato Plant, Bacterial Spot of Peach Fruit, Late Blight of Tomato. The augmented and original datasets of 55,448 and 61486 respectively are used to train the models. The Efficient Net Architecture was trained by the Transfer Learning approach in which all the layers of the model are trained with some weights. Both original and augmented dataset was used to test the Efficient Net model and Deep Learning model. The Efficient Net model showed the highest accuracy and precision. As a future enhancement, the author’s focus was to increase the number of classes and also to expand the current plant leaf dataset. This helps the models to get trained on a huge data set and also to enhance the model performance.

2.8 G. Sambasivam, G.D. Opiyo [8] , The author worked on leaf disease detection in Cassava Plant. The author proposed the CNN model which comprises three convolutional layers and four fully connected layers. For extracting richer features, the author stacked the convolution and batch normalization layer of two sets before max pooling. Max Pooling layer reduces the spatial dimensions of the input images. The network consists of 4 fully connected layers with 512 neurons in the first layer, 1024 neurons in the second and third layers, and lastly 256 neurons in the fourth layer and a neuron per category in the output layer corresponding to five different classes. After hyperparameter tuning and optimization with grid search. Drop out was used in the fully connected layers which reduces the generalization error and over-fitting problems by encouraging the neural network to learn sparse features out of raw observations that always yields good performance by empowering the model"s ability to generalize to new data. In general, the convolutional layers extract key features from the images and the fully connected layers focus uses the extracted features to classify images of cassava leaves into five different categories. Input image attributes take an order of 3 tensors. Example: an image with H rows, w columns, and 3 channels (R, G, B color channels) on the input layer and a neuron for every category in the output layer corresponds to five different classes: Bacteria Blight of Cassava, Green Mite infection, and healthy. The ReLU (Rectifier Linear Unit) activation function was used in the convolutional and hidden layers and SoftMax (for a multi-class case) is used in the output layer. The proposed model achieved an accuracy of 93%

2.9 A. Khattak et al. [9] , worked on citrus leaves and fruit diseases like Cankers, black spots, and melanoses. The dataset comprises 2293 images of all the classes. Pixel scaling and data normalization are used as preprocessing techniques. Two layers of convolution are used, where the task of the first layer is to collect images of low-level features, and the task of the second layer is to collect high-level features. After each convolution layer, max-pooling is used to reduce the size of the feature map. The fourth step is flattening where the feature vector of three-dimension is converted to one dimension. The last step is classification in which the output of the flattening layer is used to predict the class with the help of the SoftMax activation function. An accuracy of 95.65% is obtained for the proposed model. In the future, the author planned to add more numbers of plant images to other deep learning models: RNN, LSTM, Bi-LSTM, and hybrid models.

2.10 S.C.K. et al [10] ,This paper focuses author‟s works on the Cardamom (Colletotrichum Blight, Phyllosticta Leaf Spot diseases) and Grapes plant (Black Rot, ESCA, isariopsis Leaf Spot diseases).The disease of cardamom is identified with the help of 1724 real-time images.These images are affected by noise, light illumination, and different angles. 4026 images of grapes leaf are taken as an input. Cardamom images are not directly subjected to the models because they contain background, light illumination, and a lot of noises. These images reduce the accuracy of the model. Hence, for removal of background noise U2–Net is used. U2-Net has three parts, the six-layer encoder comes under the first part which creates the Residual U-Block. The second part contains a five-stage decoder and the third part creates Saliency Probability Maps. Saliency maps find the difference between the background and interested part of the leaf. CNN, Efficient-Net, Efficient-Net V2-S, Efficient-Net V2-M, and Efficient-Net V2-L are the different classification models considered in this work. The Efficient-Net V2-L model gives the highest accuracy of 98.26% for cardamom and Efficient-Net gives the highest accuracy of 97.81 for grapes.

2.11 Z. Zinonos et al [11], In this paper, authors focus on grapes plant leaf diseases like Black rot, Esca, and Leaf blight disease were identified by using LoRa(Low-Power Wide Area Networks) and deep learning technology which uses low-resolution images. Low-Power Wide-Area Networks are used to transmit Grapes leaf images from grape fields. Low-Power Wide-Area Networks convert images into packets. Bandwidth, Spreading Factor, Coding Rate, and Transmission Power are parameters of Low-Power Wide Area Networks. Bandwith is responsible for long-distance transmission. The spreading factor is responsible for deciding the length of packets. A coding rate is a code that corrects the packet errors before transmission. The last parameter is transmission power, which is the power consumed by transmitting a package of data. CNN models MobileNetV2 and ResNet50 are the deep learning models considered by the author. This results in the highest accuracy of 99.77% for the ResNet model with a 100% Packet Reception Ratio. And 99.65% accuracy is obtained for ResNet without augmentation with a 100% Packet Reception Ratio.

2.12 K.K. Chakraborty et al.[12] , The author worked on the Potato plant by optically recognizing Potato Leaf blight disease. The author collected the Potato leaf dataset from

Plant Village Dataset. This dataset is augmented using label-preserving transformations, reducing overfitting and artificially increasing the number of data/samples. The author incorporated image pre-processing techniques such as resizing and scaling techniques. Resizing alters the size of the image to 224px height and 224px width which is also the input size for the first layer of the CNN model and rescaling standardizes each pixel value in the range of 0-1 and this helps to prevent the model to slow down. The processed image is then fed as an input to the CNN model. In this, the output of each layer acts as input forevery corresponding layer. Then the author tested the dataset on different models such as VGG16, VGG19, MobileNet, and ResNet50. However, VGG16 turned out to be the model with the highest efficiency 97.89%. VGG19 achieved 80.39%. Mobile net achieved 78.84%. ResNet 50 achieved 73.75% accuracy. The final output layer of VGG16 is fine-tuned with a sparse Adam optimizer and Binary Cross-Entropy loss function

2.13 M. Ahmad et al [13] ,The author Pepper a dataset from two different sources is considered and compared the efficiency of various models on the considered dataset. The author has taken the first dataset from the National Institute of Horticultural and Herbal Science, Republic of Korea, and another one from the Plant Village dataset. The dataset comprises 99507 images belonging to 24 different classes of diseases. Among these 24 classes, 6 are related to pulp and stem respectively, 9 are related to leaf, 2 are related to larva, and 1 class of healthy images for pulp, leaf, and larva. The imbalance dataset is handled by employing it to the different approaches such as the Adaptive Synthetic Sampling Approach and Synthetic Minority Oversampling Technique. These two techniques decrease the count of overrepresented classes and augment the class of underrepresented classes. After data processing, it is fed to different CNN models. Random Initialization, Fine Tuning, Feature Extraction using Random Initialization, and Feature Extraction using Fine-tuning are the different parameters considered for improving the performance of the model. InceptionV3 with Random Initiation and Fine-tuning achieved the highest efficiency 99.57% and 99.56% respectively.

2.14 S. M. Hassan, A. K. Maji [14] ,The author used three different datasets of different plants. The author has used the Rice Plant dataset, Cassava Plant dataset, and Plant Village dataset. From the Plant Village dataset, the author has used a Corn, Potato, and Tomato plant disease image set. The rice plant dataset consists of 5932 images and the Cassava plant dataset consists of 5656 images. These images are resized to 256 x 256 pixels and rescaled before subjecting them to the CNN model. The Plant Village dataset comprises images that are uniform with most of the pictures taken from a uniform background. Class balancing is performed on both datasets. Class balancing is done on both the dataset was resized, and rescaled before being fed to the CNN model. To check the stability of the proposed CNN model, k-fold cross-validation was used. After running the model for 50 epochs, the author obtained an accuracy of 99.81% for the Plant Village dataset. An accuracy of 99.94% and 98.17% is obtained for Rice and Cassava plant images. As a future enhancement, the author planned to use the model for weed detection and pest identification

2.15 Z. Zinonos et al [15] , The collection of leaf datasets for early-stage disease and rare diseases is a complicated task. A very smaller number of images are available for these types of plant diseases. This smaller number of images affects the efficiency of the DL model because of overfitting. Therefore the author proposed grained-GAN for data pre-processing. The grained-GAN works in two stages: first is to identifythe leaf spot location and after that segmentation is applied on the spot part. The second is the data augmentation stage. Four detection boxes of different sizes (32∗32, 64∗64, 96∗96, and 128∗128) were selected to find the ratio of area intersected to the area of candidate bounding boxes. The 64*64 have the largest ratio sample, so it is selected for segmentation. Generative Adversarial Networks (GAN) help in the synthesis of images that have the same feature as original images. Thus, Data Augmentation isperformed by Generative models (DCGAN, Info-GAN, WANG, LRGAN, original, Leaf GAN, WGAN-GP, CAVE-GAN, fine Gradient GAN). Then the original and generated dataset is subjected to the five CNN (AlexNet, ResNet-50, DenseNet-121, X-ception, VGG-16) models for the classification of images is used. The best accuracy of 96.7%is obtained by using fine gradient GAN with ResNet-50.

CHAPTER 3

METHODOLOGY

3.1 Problem description

Different types of leaf disease

- Late blight
- Early blight

3.1.1 Late Blight

- caused by the water mold Phytophthora infestan
- The disease occurs in humid regions with temperatures ranging between 4 and 29 °C
- When plants have become infected, lesions appear on the leaves, petioles, and stems.

Fig 3.1 Late Blight Potato leaf disease

3.1.2 Early Blight

- Early blight of potato is caused by the fungal pathogen Alternaria Solani
- The disease affects leaves, stems and tubers and can reduce yield.
- Symptoms appear first on the oldest foliage. Affected leaves develop circular to angular dark brown lesions

Fig 3.2 Early Bright Potato leaf disease

3.2 Proposed methodology

3.2.1 Data Acquisition

Different image resolutions and sizes were obtained from several sources.

3.2.2 Data preprocessing

The first step is to minimize the noise in the image by cutting the part of the image that is not the region of interest. If there is excessive noise in the image, it will not be used. Images collected from multiple sources of different sizes must be resized to 224x224 pixels to standardize input images in the dataset.

3.2.3 Data Augmentation

Data augmentation in data analysis are techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularize and helps reduce overfitting when training a machine learning model

3.2.4 Data Analyzing

Convolutional Neural Network is one of the popular classes. Some studies use the convolutional neural network method to detect diseases in plants based on leaf conditions.

A convolutional neural network is a class of artificial neural network, most commonly applied to analyze visual imagery.

The CNN learning architecture is both monitored and unmonitored. It is possible to use them to forecast something or classification. But CNN mainly used a monitored process. CNN classifies pictures according to their characteristics.

Convolutional Neural Networks generally consist of one or more convolutional layers that are grouped by function. Often the subsampling layer is followed by one or more layers that are fully connected as a standard neural network. Each feature layer receives input from a feature set located in a small area on the previous layer.

The processed results are then mapped and output is generated.

CHAPTER 4

PROPOSED MODEL

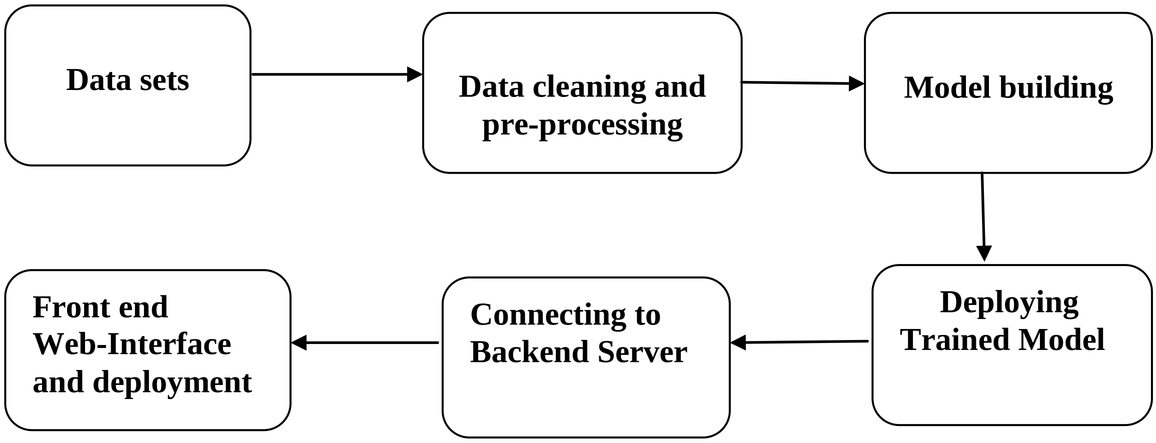

Table 4.1 Model 0f Potato Leaf Detection Using Deep Learning

4.1 Data sets

The dataset chosen for this paper contains 10,000 images of potato leaves with 2 different categories. Each category contains the same number of images. The images of plant diseases are of the size 256x256 and the dataset does not contain any missing images. The dataset is commonly referred to as the plant village dataset and can be found on the Kaggle website.

4.2 Data cleaning and pre-processing

The data cleaning process detects and removes the errors and inconsistencies present in the data and improve its quality. Data quality problems occur due to misspellings during data entry, missing values or any other invalid data. Basically, "dirty" data is transformed into clean data. "Dirty" data does not produce the accurate and good results. Garbage data gives garbage out. So it becomes very important to handle this data.

In this step resizing and rescaling of data , data augmentation through random flip and random rotation is done.

Data augmentation is technique used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularizer and helps reduce overfitting when training a machine learning model. It is closely related to oversampling in data engineering

4.3 Model building

4.3.1 Machine learning (ML)

Machine learning (ML) is the study of algorithms and mathematical models that computer systems use to progressively improve their performance on a specific task. Machine learning algorithms build a mathematical model of sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task.

Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a field of study within machine learning, and focuses on exploratory data analysis through unsupervised learning. Machine learning tasks are classified into several broad categories. In supervised learning, the algorithm builds a mathematical model of a set of data that contains both the inputs and the desired outputs. For example, if the task were determining whether an image contained a certain object, the training data for a supervised learning algorithm would include images with and without that object (the input), and each image would have a label (the output) designating whether it contained the object. In special cases, the input may be only partially available, or restricted to special feedback. Semi- supervised learning algorithms develop mathematical models from incomplete training data, where portions of the sample inputs are missing the desired output.

Plant disease identification by visual way is more laborious task and at the same time, less accurate and can be done only in limited areas. Whereas if automatic detection technique is used it will take less efforts, less time and become more accurate. In plants, some general diseases seen are brown and yellow spots, early and late scorch, and others are fungal, viral and bacterial diseases. Image processing is used for measuring affected area of disease and to determine the difference in the color of the affected area.

Image segmentation is the process of separating or grouping an image into different parts. There are currently many different ways of performing image segmentation, ranging from the simple thresholding method to advanced color image segmentation methods. These parts normally correspond to something that humans can easily separate and view as individual objects. Computers have no means of intelligently recognizing objects, and so many different methods have been developed in order to segment images. The segmentation process is based on various features found in the image. This might be color information, boundaries or segment of an image.

Image is processed using Batches, Repeat , Shuffle , Prefetching techniques. Then unnecessary part (green area) within leaf area is removed. Finally, the extracted features are passed through a pre-trained neural network

4.3.2 Convolutional Neural Networks

Regular Neural Networks such as the Multi-layer Perceptron (MLP), in the past were used for image classification purposes however as the resolution of the images being used to classify became higher and higher the networks became computationally hard to deal with and the number of total parameters used for classification would be far too many.

Convolutional Neural Networks are very similar in working to regular neural networks such as the MLP, however, what changes in Convolutional Neural Networks is that the layers of a CNN have three-dimensional arrangement (width, height and depth) of neurons instead of the standard two-dimensional array and for this simple reason CNNs are widely used on image data for the purpose of classification as the architecture of a CNN is designed to take advantage of the 3d form of an image.

A simple Convolutional Neural Network's architecture consists of three main layers, namely, Convolutional layer, Pooling layer and the Fully connected layer. The Convolutional layer is regarded as the main building block of a CNN, it consists of learnable parameters known as filters/kernels. The filter is responsible for finding patterns (textures, edges, shapes, objects, etc) in the input image. Each filter slides/convolves over the height and width of the input image, computing the dot product between the filter and the pixels present in the input image.

The resultant of a Convolutional layer is a feature map that summarizes all the features found in the input image .

The Pooling layer is another building block of a CNN that is used to perform down sampling in order to reduce the spatial size of the feature map. This is done to reduce the number of parameters, computations in the network and also to make sure overfitting is controlled. There are two different types of pooling in CNN namely, Max Pooling and Average Pooling. Max Pooling returns the maximum value that is present in the portion of the image convolved by the kernel and Average Pooling returns the average of all the values present in the portion of the image convolved by the kernel.

This layer is often followed only after non-linearity is introduced into the network using a Rectified Linear Unit (ReLU) activation function, this layer is used to turn all the negative values present in the feature map into zeros. The addition of ReLU is very important in a CNN as it helps increase the non-linearity in the images. Images as such are known to contain non-linear features such as different objects or the boundaries between those objects, however, when imposing an image through a Convolutional layer to create a feature map, there might be some linearity introduced in the image and in order to bring back the non-linearity in the image the ReLU activation function is used .

After adding multiple Convolutional layers and Pooling layers, the fully connected layers are introduced in the architecture. The input coming to the fully connected layer is the flattened output from the final convolutional and pooling layer. The flattening is done to convert the 3d matrix data from the last pooling layer into a 1d array of vectors so that it can be used by the fully connected layers which perform the same operations to an ANN to carry out the final classification and compute the class scores. And in this way, a simple Convolutional Neural network is structured to read and classify images.

4.4 Deploying Trained Model

Deployment is the method by which you integrate a machine learning model into an existing production environment to make practical business decisions based on data. It is one of the last stages in the machine learning life cycle and can be one of the most cumbersome.

In order to start using a model for practical decision-making, it needs to be effectively deployed into production. If you cannot reliably get practical insights from your model, then the impact of the model is severely limited.

In this project Docker is used to deploy the trained models. Docker is a tool for developing and deploying applications using containers. A container is built on the concept that you may bundle your code together with its dependencies into one deployable unit. Containers have been in use for a long time now .

Where Docker uses Container deployment method. Container deployment is a method for quickly building and releasing complex applications. Docker container deployment is a popular technology that gives developers the ability to construct application environments with speed at scale . Container deployment is the action of putting containers to use. The deployment of containers uses management software that simplifies the launch and updates of applications. Container deployment provides fast access to environments and speeds up development because secure containers can be quickly downloaded and put to use. Container deployment also minimizes errors because it reduces the number of moving parts in development.
Applications are deployed with a combination of manual procedures and automated scripts. Security can be a concern when containers run at a root level, which increases vulnerability.

4.5 Connecting to Backend Server

The back-end, also called the server-side, consists of the server which provides data on request, the application that channels it, and the database which organizes the information.

In this project we are using FastAPI . An API, or application programming interface, is a set of rules that define how applications or devices can connect to and communicate with each other. A REST API is an API that conforms to the design principles of the REST, or representational state transfer architectural style. For this reason, REST APIs are sometimes referred to RESTful APIs

FastAPI is a Python -web framework that allows you to write backend server in a matter of minutes. It can be used as a general backend for any website or a way to deploy machine learning model in form of a REST api server.

4.6 Front end Web-Interface and deployment

The front-end of a website is the part that users interact with. Everything that you see when you're navigating around the Internet, from fonts and colors to dropdown menus and sliders, is a combo of HTML, CSS, and JavaScript being controlled by your computer's browser.

In this project we are using React JS. ReactJS is a declarative, efficient, and flexible JavaScript library for building reusable UI components. It is an open-source, component-based front end library which is responsible only for the view layer of the application. The main objective of ReactJS is to develop User Interfaces (UI) that improves the speed of the apps. It uses virtual DOM (JavaScript object), which improves the performance of the app. The JavaScript virtual DOM is faster than the regular DOM. We can use ReactJS on the client and server-side as well as with other frameworks. It uses component and data patterns that improve readability and helps to maintain larger apps.

CHAPTER 5

RESULTS

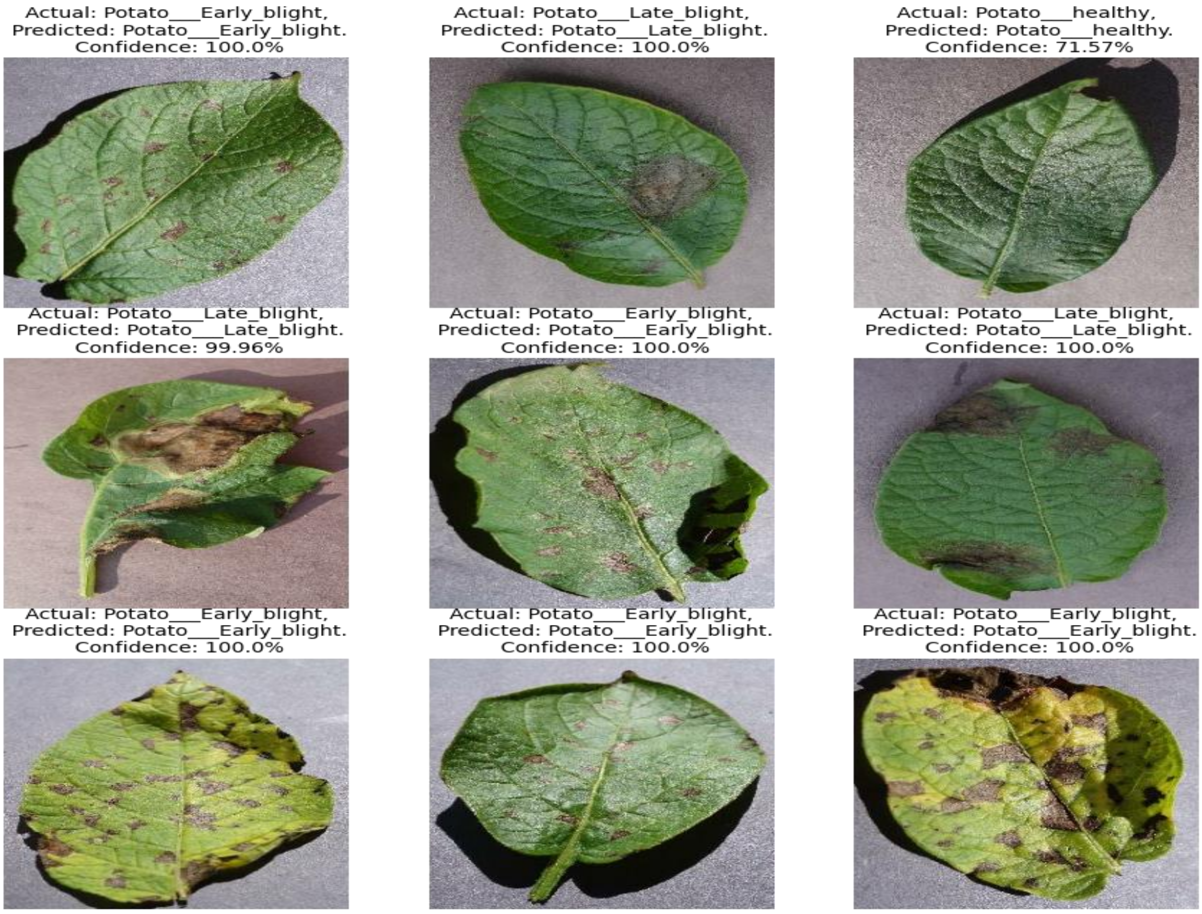

Fig 5.1 Inputs and their corresponding output of trained model is shown in the figure above

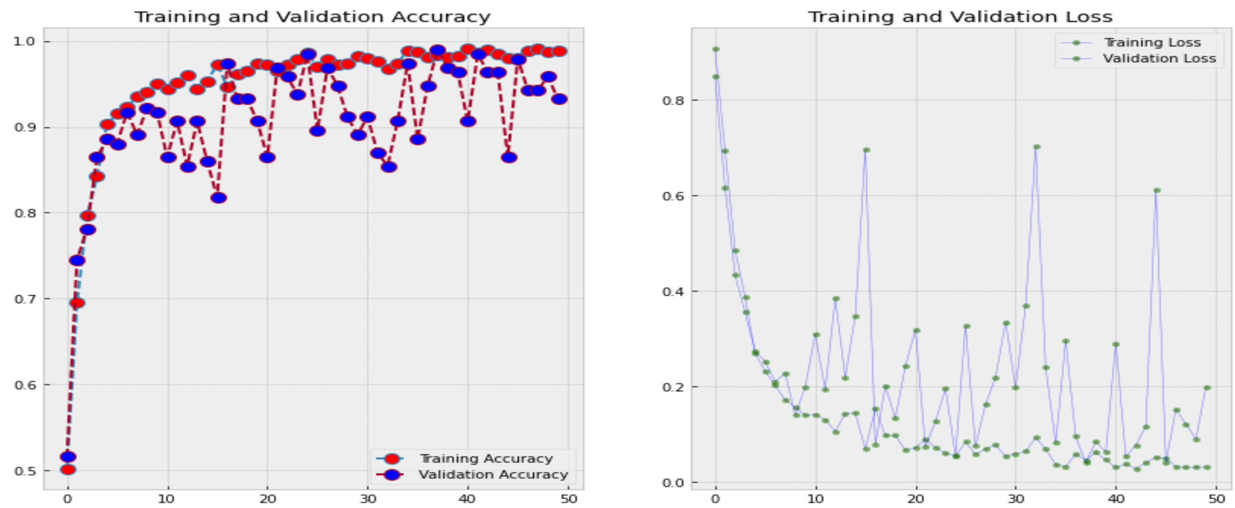

Fig 5.2 Training , validation data sets Accuracy and Loss of model shown using Scatter Plot

The output was formulated , this indicates to the proof that the machine learnt to identify the image through algorithms and neural networks and classify it into different types of leaf diseases.

Machine learning , datasets allowed the machine to learn certain patterns and produce a peculiar output.

In the fig 5.1 shows that the model takes the training data as input and labelled as “Actual” in the first column of label where as in the second column of the label the model is predicting the name of image as in which disease it is, and at the last column of the label the model says how much percentage it has that what it has given the result is true based on its training and it is labelled as “Confidence”

The model is build and trained under the test data set and called as Training data set, the real world pictures that are apart from test data set are called as Validation data set , the model predicting the correct image is called as accuracy and the model prediction the wrong image is called as loss

In the fig 5.2 shows the model Training , Validation data sets verses the Accuracy and Loss of model in Scatter Plot

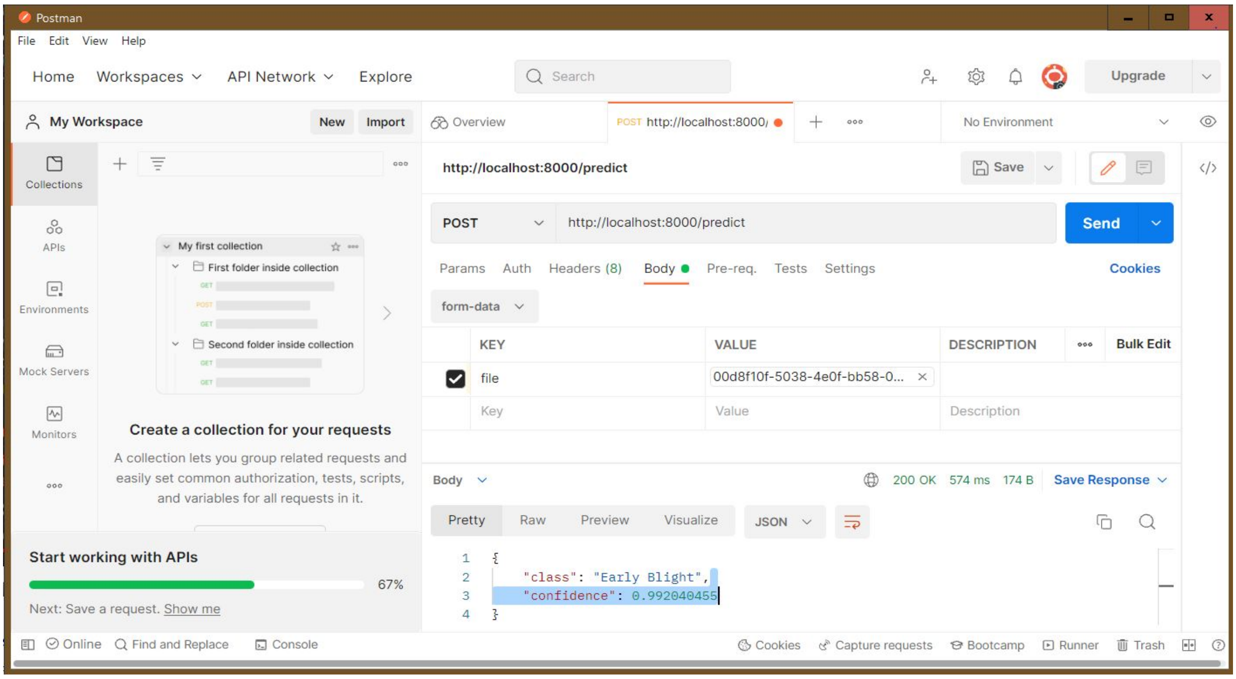

Fig 5.3 TF serving and Fast-API outcomes

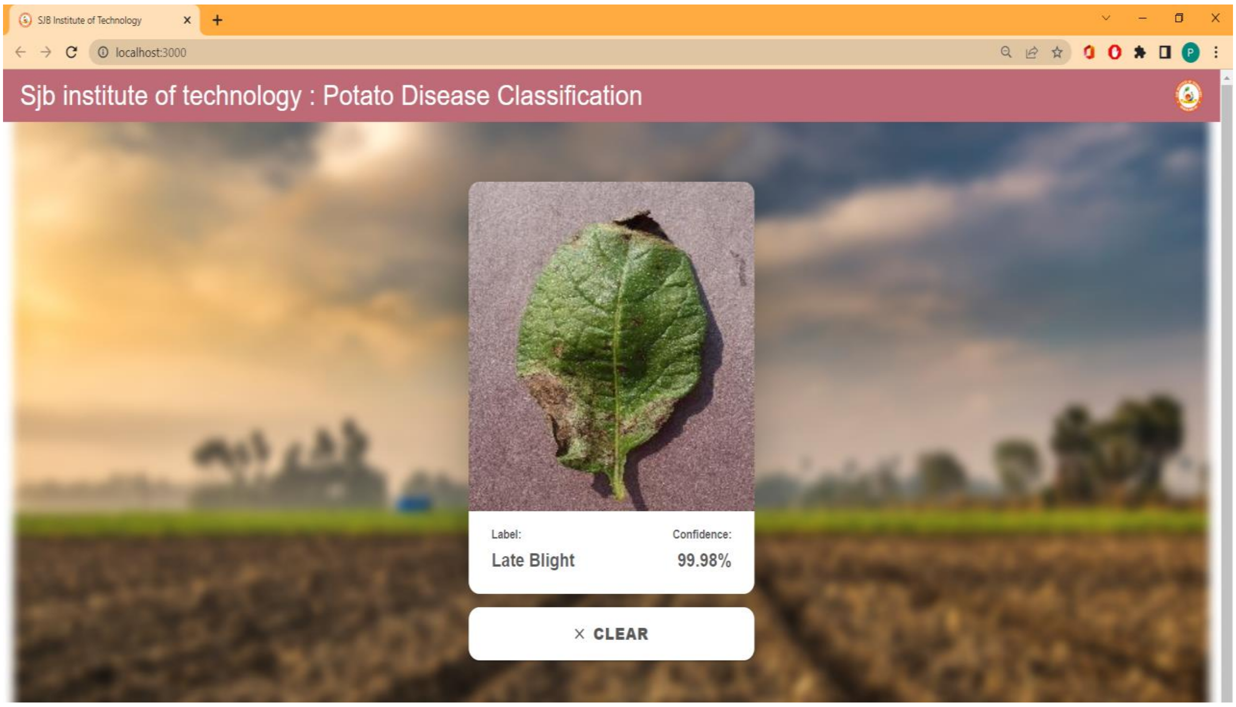

Fig 5.4 React JS outcomes

The client is sending the image as input to the server and response of server to the client request is shown in the Fig 5.3 using Postman software.

The output from the server is displayed using the front-end using software React JS and is shown in the Fig 5.4 .

CONCLUSION AND FUTURE ENHANCEMENT

There are number of ways by which we can detect disease of plants and suggest remedies for them. Each has some pros as well as limitations .On one hand visual analysis is least expensive and simple method, it is not as efficient and reliable.

The applications of convolutional Neural Networks (CNNs) have been formulated for classification of diseases that effect on plant leaves. Recognizing the disease accurately and efficiently is mainly the purpose of the proposed approach.

In this project, we even made use of postman and docker , we used postman as it makes it easy for developers to create, share, test and document APIs. we used docker as the platform makes it easier, simpler, and safer to build, deploy and manage programs and models.

These days, a lot of research related to images is happening based on CNN methodologies to obtain better and reliable accuracy. The concept of activation functions, batch normalizations, convolutional layers, and fully connected layers are playing a key role in CNN architectures to attain better accuracy.

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