Leaf Disease Detection Using Convolutional Neural Network

By

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This is to certify that the research work embodied in this dissertation entitled "***Leaf Disease Detection using Convolutional Neural Network*** " was carried out by ***18CP812*:*Sneha Patel***, at Birla Vishvakarma Mahavidyalaya (Engineering College) An Autonomous Institution for partial fulfillment of Master of Technology (***Computer Engineering***) with Specialization in ***Software Engineering*** degree to be awarded by Gujarat Technological University. she has complied to the comments given by the Dissertation phase – II as well as Mid Semester Dissertation Reviewer to my / our satisfaction

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Abstract

Agriculture field has a high impact on our life. Agriculture is the most important sector of our Economy. Proper management leads to a profit in agricultural products. Farmers do not expertise in leaf disease so they produce less production. Plant leaf diseases detection is the important because profit and loss are depends on production. CNN is the solution for leaf disease detection and classification. Main aim of this research is to detect the apple, grape, corn, potato and tomato plants leaf diseases. Plant leaf diseases are monitoring of large fields of crops disease detection, and thus automatically detected the some feature of diseases as per that provide medical treatment. Proposed Deep CNN model has been compared with popular transfer learning approach such as VGG16. Plant leaf disease detection has wide range of applications available in various fields such as Biological Research and in Agriculture Institute. Plant leaf disease detection is the one of the required research topic as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves.

Acknowledgments

This thesis is based on research work conducted for"Leaf Disease Detection using Convolutional Neural Network". This work would not be possible without two people whose contributions can't be ignored.

I consider it an honor to work under my guides Dr. U.K Jaliya and Prof. Pranay Patel. This thesis is fruit of their valuable guidelines and directions. They were always available to monitor me for this work. I specially acknowledge Dr. U.K Jaliya for guide me in leaf disease detection research work and always support me. and thanks to Prof. Pranay Patel for always solve the coding problem in my dissertation work.

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Chapter 1: Introduction

1.1 Introduction of Leaf Disease Detection

The most important sector of our Economy is Agriculture. Various types of disease damages the plant leaves and effects the production of crop there for Leaf disease detection is important. Regular maintenance of plant leaves is the profit in agricultural products. Farmers do not expertise in leaf disease so they producing lack of production. Leaf disease detection is important because profit and loss depend on production. So that here use deep learning techniques to detect apple, grape, corn [11], potato, and tomato plant leaves diseases. That contains twenty-four types of leaf diseases and twenty-four thousand leaves images are used [13].

Apple, grape, corn, potato, and tomato plant leaves which are categorized total 24types of labels apple label namely: Apple scab, Black rot, apple rust, and healthy. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Corn label namely: Corn Cercospora spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight[11][13]. Potato label namely: Early blight, healthy, and Late blight. Tomato label namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, mosaic virus[11][13].

The dataset consist of 31,119 images of apple, grape, potato and tomato, all Images are resized into 256 x 256,that images divided into two parts training and testing dataset[11][13].

1. Apple scab 2. Grape Esca 3.Corn leaf spot 4.potato Early Blight 5.Tomato Bacterial Spot

Fig.1 Leaves with Disease part [11]

In fig.1 we can see vegetable and fruit leaves like potato, tomato, corn, apple, grape with diseased part this disease can be easily detected using deep learning techniques [13].

This disease detected using convolutional neural network (CNN), and also this model is compared with VGG16. Images are resized into 224 x 224[13].

1.2 Applications

- Biological research
- Plant leaf disease detection also useful in agriculture institute.
- Some plant leaf disease detection automatic techniques are beneficial for large work of monitoring in farm of crops disease detection.

1.3 Objectives

- The objective of this research is to concentrate based on potato, tomato, corn, grapes, and apple leaf disease detection using CNN.
- CNN is used for examine the healthy and diseased plants leaves.

1.4 Motivation

- Identifying and recognition of leaves disease is the solution for saving the reduction of large farm in crop disease detection and profit in productivity, it is beneficial in agricultural institute, Biological research [13].

1.5 Organization of Report

Chapter 1 gives the brief introduction of leaf disease detection using convolutional neural network, its applications, objective of the system and motivation.

Chapter 2 contains literature survey that provide summary of individual paper.

Chapter 3 provide overview of existing work for leaf disease detection using CNN that has been done using done using feature based approach.

Chapter 4 presents Implementation and its results, tools and technology used to achieve this and dataset detail.

Chapter 5 contains conclusion about leaf disease detection using CNN and future work about what you are wanted to do in future.

Chapter 2: Literature Survey

1. Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition[1].

Publication Year: 2019

Author: Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala [1].

Journal Name: International Conference on Advances in Big Data, Computing and Data Communication Systems

Summary: Smart farming system using necessary infrastructure is an innovative technology that helps improve the quality and quantity of agricultural production in the country including tomato. Since tomato plant farming take considerations from various variables such as environment, soil, and amount of sunlight, existence of diseases cannot be avoided. The current advance computer system innovation made possible by deep learning that have cover the way for camera captured tomato leaf disease. This study developed the innovative solution that provides efficient disease detection in tomato plants. A motor-controlled image capturing box was made to capture four sides of every tomato plant to detect and recognize leaf diseases. A specific breed of tomato which is Diamante Max was used as the test subject. The system was designed to identify the diseases namely Phroma Rot, Leaf Miner, and Target Spot. Dataset leaves contain diseased and healthy plant leaves are collected. Then train a deep convolution neural network to identify three diseases. The system used Convolution Neural Network to identify which of the tomato diseases is present on the monitored tomato plants. The F-RCNN trained anomaly detection model produced a confidence score of 80% while the Transfer Learning disease recognition model achieves an accuracy of 95.75%. The automated image capturing system was implemented in actual and registered 91.67% accuracy in the recognition of the tomato plant leaf diseases [1].

2. CNN based Leaf Disease Identification and Remedy Recommendation System[2].

Publication Year: 2019

Author: Sunku Rohan , Triveni S Pujar ,Suma VR Amog Shetty, Rishabh F Tated [2].

Journal Name: IEEE conference paper

Summary: Agriculture field has a high impact on our life. Agriculture is the most important sector of our Economy. Farmers are difficult to identify the leaf disease so they produce less production. Though, videos and images of leaves provide better view for agricultural scientists can provide a better solution. So that can solve the problem of related to crop disease [2]. It is required to note that if the productivity of the crop is diseased then, it has high risk of providing good nutrition [2]. Due to the improvement and development in technology where devices are smart enough to recognize and detect plant diseases. Acknowledge diseases faster treatment in order to lessen the negative impacts on harvest [2]. In this paper focus on plant disease detection using image processing techniques [2]. This paper access open dataset images that consist 5000 images of healthy and diseased plant leaves, and there used semi supervised techniques for crop types and detect the disease of four classes[2].

3. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolution Neural Networks [3].

Publication Year: 2019

Author: Bin Liu , Peng Jiang, Yuehan Chen, Dongjian He, Chunquan Liang [3].

Journal Name: IEEE ACCESS

Summary: This paper contains five types of apple leaf disease that are, aria leaf spot, Brown spot, Mosaic, Grey spot, and Rust. That is affected in apple [3]. This paper used deep learning techniques to improved convolution neural networks (CNNs) for detection in apple leaf diseases [3]. In this paper, the apple leaf disease dataset (ALDD) is used, which consist complex images and laboratory images, and rest constructed via data augmentation and image annotation technologies to create new apple leaf disease detection model that uses deep-CNNs is by using Rainbow concatenation and Google Net Inception structure[3]. In testing dataset used 26,377 images of apple leaves disease, the proposed INAR- model is trained and then detect five common apple leaf diseases [3]. In the experimental results show that the INAR- SSD model realizes 78.80% detection performance, with a high-detection speed of 23.13 FPS [3]. The results demonstrate that the novel INAR-SSD model provides a high- performance solution for the early diagnosis of apple leaf diseases that can perform real-time detection of these diseases with higher accuracy and faster detection speed than previous methods [3].

4. Identification of plant leaf diseases using a nine-layer deep convolution neural network [4]

Publication Year: 2019

Author: Geetharamani G. , Arun Pandian J.

Journal Name: Computers and Electrical Engineering 76 (2019)

Summary: In this paper, plant leaf disease identification using deep learning technique in convolution neural network (CNN). The Convolutional neural network model is trained using an than 39 different classes of open dataset of plant leaves diseases, and background images [4]. That contain six types of data augmentation methods and that are used for gamma correction, image flipping, principal component analysis (PCA) color augmentation, rotation, noise injection, and scaling[4]. Whole are notice that using data augmentation. That can increase the performance of the model. The model was trained using different training range of epochs, batch sizes and dropouts [4]. Then CNN is compared with transfer learning approaches, the proposed model achieves better result. When using the validation data [4]. Though simulation proposed model achieves 96.46% classification accuracy [4]. Accuracy of the CNN is better than the accuracy of transfer learning approaches [4].

5. A Segmentation Improved Robust PNN Model for Disease Identification in Different Leaf [14]

Publication Year: 2016

Author: Rekha Chahar, Priyanka Soni [14]

Journal Name: IEEE International Conference.

Summary: this paper contains vegetable, fruit, crops and flowers Agricultural Images, and that leaf disease [14]. The agricultural product type associated disease identification [14]. These diseases are specific to the product component which can be root, seed, and leaf [14]. This is helpful into the provide identification of disease from remote lab [14]. The work is here divided in two steps. In first step, the ring project based segmentation model is defined to explore the features of leaf images [14]. Once the features are identified then work is apply for PNN classifier to identify the existence disease [14]. The work is about to identify the health and infected disease based on featured region identification [14]. The work is applied on randomly collected leaf images from web for different plants [14].

6. Crop Disease Detection Using Deep Learning

Publication Year: 2018

Author: Omkar Kulkarni

Journal Name: IEEE access

Summary: In recent times, drastic climate changes and lack of immunity in crops has caused substantial increase in growth of crop diseases. This causes large scale demolition of crops, decreases cultivation and eventually leads to financial loss of farmers. Due to rapid growth in variety of diseases and adequate knowledge of farmer, identification and treatment of the disease has become a major challenge. The leaves have texture and visual similarities which attributes for identification of disease type. Hence, computer vision employed with deep learning provides the way to solve this problem. This paper proposes a deep learning-based model which is trained using public dataset containing images of healthy and diseased crop leaves. The model serves its objective by classifying images of leaves into diseased category based on the pattern of defect[6].

7. Identification of Plant Disease using Image Processing Technique [7]

Publication Year: 2019

Author: Karunya Rathan, Abirami Devaraj, K Indira and Sarvepalli Jaahnavi [7].

Journal Name: International Conference on Communication and Signal Processing, IEEE

Summary: Agriculture has become far more than simply a method to feed ever growing populations [7]. It's important wherever in additional than seventieth population of an Asian country is depends on agriculture [7]. Which means it feeds nice range of individuals [7]. The foremost necessary consider less amount crop of quality because of disease. Leaf disease detection may be stop agricultural losses. The aim of this is to develop a software system answer that mechanically find and classify disease [7]. That consist steps like image acquisition, pre-Processing, Segmentation, extraction and classification are involves disease detection [7]. The leaves images are used for detecting the plant diseases. Therefore use of image process technique to find and classify diseases in agricultural [7].

8. GUI based Detection of Unhealthy Leaves using Image Processing Techniques [8]

Publication Year: 2019

Author: Vellanki Krishna Vamsi, Velamakanni Sahithya, Brahmadevara Saivihari, Parvathreddy Sandeep Reddy and Karthigha Balamurugan [8]

Journal Name: International Conference on Communication and Signal Processing,

Summary: Increasing the agricultural productivity improves the Indian economy. Keeping this as objective, in order to achieve an efficient and smart farming system, identification of unhealthy leaf using image processing techniques is contributed in this paper. For this, ladies finger plant leaves are chosen and examined to find an early stage of various diseases such as yellow mosaic vein, leaf spot, powdery mildew etc. Leaf images are captured, processed, segmented, features extracted, and classified to know if they are healthy or unhealthy. Due to practical limitations in climatic conditions and other terrain regions, noisy image data sets are also created and taken into consideration. K-Means clustering is used for segmentation and for classification, SVM and ANN are used. This work uses PCA to reduce the feature set. Results show that, the average accuracy of detection in SVM and ANN are 85% and 97% respectively. Without noise they are observed to be 92% and 98% respectively. This work paves the way to reach complete automation in agricultural industries[8].

9. Tomato Plant Leaves Disease Classification Using KNN and PNN

Publication Year: 2019

Author: Balakrishna K Mahesh Rao

Journal Name: International Journal of Computer Vision and Image Processing

Summary: Plant diseases are a important in the crops production, which affects food security and reduces the profit of farmers[9]. Identifying the diseases in plants is the key to avoiding losses by proper feeding measures to cure the diseases early and avoiding the reduce in production.[9] In this paper, the authors used two methods for identification and classification of healthy and diseased tomato leaves[9]. In the first technique, the tomato leaf is classified as healthy or unhealthy using the k-nearest neighbor approach. Later, in the second technique, they classify the unhealthy tomato leaf using probabilistic neural network and the k-nearest neighbor approach[9]. The features are like GLCM, Gabor, and color are used for classification purposes[9]. Experimentation is conducted on the authors used that own dataset[9]. That consist 600 healthy and diseased leaves. The experimentation reveals that the fusion approach with PNN classifier outperforms than other methods[9].

10. Automatic Disease Symptoms Segmentation Optimized for Dissimilarity Feature Extraction in Digital Photographs of Plant Leaves

Publication Year: 2019

Author: Masum Aliyu Muhammad Abdu, Musa Mohd Mokji, Usman Ullah Sheikh, Kamal

Journal Name: IEEE 15th International Colloquium on Signal Processing & its Applications

Summary: Segmentation of diseased symptom regions in images of plant leaves is a crucial stage in the application of machine learning for plant diseases detection. This process also known as Region of Interest (ROI) segmentation involves separating purely color variant symptom lesions from surrounding green tissue from which discriminant features are later extracted.

However, investigations have shown that vivid anatomy of a disease symptom progression right from inception to manifestation through which finer disease characterization dissimilarity features can be fostered are not captured in a segmented ROI. Furthermore, the typical ROI segmentation process is often plagued by challenges ranging from intrinsic factors such as image capture conditions to extrinsic factors such as disease anatomy where symptoms fade into healthy green tissue the separation boundary to become impalpable. This adds further complexity to the process or produce erroneous result. This research proposes an automatic extended region of interest (EROI) segmentation to incorporate symptom progression information by extending the border region to cover some part of healthy tissue using color homogeneity thresholding. To produce a ground truth, the typical ROI segmentation alongside a reduced ROI were implemented on a well-known Plant Village dataset from which separate textural and color features were extracted and used to build a linear classifier. A comparison between the classification results further reinforced the advantages of the proposed approach for dissimilarity features extraction. Through this research, finer characterization features can be extracted for the classification and severity estimation of plant diseases[10].

11. Deep Learning Based on NAS Net for Plant Disease Recognition Using Leave Images

Publication Year: 2018

Author: Adedamola Adedoja & Pius Adewale Owolawi & Temitope Mapayi

Journal Name: Proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3)

Summary: Global food security has become a very important research focus. This is due to the fact that food is a basic need of human beings and its adequate supply to meet the need of humans must be ensured [16]. Plant diseases have, however, been one of the major problems threatening the adequate supply of food to humans [16]. The early detection of these diseases can assist in their efficient management, thus making huge differences between survival and destruction of crops in farmlands affected by these plant diseases[16]. Deep neural networks have been successfully applied in the field of artificial intelligence. This has inspired an increased research into the use of deep learning in the domains of image processing and computer vision. This paper present a study on the use of deep learning-based approach to identify diseased plants using leaf images by transfer learning [16]. The study uses NAS-Net architecture for the convolution neural networks (CNN). The model is then trained and tested using a publicly available Plant Village project dataset that contains varied images of plant leaves with multiple variations in infection status and location in the plants. Using the model, an accuracy rate of 93.82% was achieved [16].

12.Tomato Leaf Disease Detection using Convolutional Neural Networks [17].

Publication Year: 2019

Author: Prajwala TM, Alla Pranathi, Kandiraju Sai Ashritha, Nagaratna B. Chittaragi, Shashidhar G. Koolagudi [17]

Journal Name: Proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3).

Summary: Tomato is the most common vegetable is used in an India. Tomato provide very important mineral for good health [17]. India the third largest county of the tomato producer in the world. Disease affected so the plant's production in 10-30% of the total loss [17]. Identification of such diseases in the plant is very important in preventing any heavy losses [17]. Proposed methodology that aims to accurately detect and classify diseases in the tomato crop. In the paper contains to the most common diseases found in the tomato plant like, Bacterial leaf spot and Septorial leaf spot, Yellow Leaf Curl among many others [17]. that are used Plant Village dataset in 54,306 images of 14 crops infested with 26 diseases[17]. The subset includes around18160 images of tomato leaf diseases. Broadly, the proposed methodology consists of three major steps: data acquisition, pre-processing and classification[17].The images used for the implementation of the proposed methodology were acquired from a publicly available dataset called Plant Village[17]. In the next step, the images were re-sized to a standard size before feeding it into the classification model [17].The final step is the classification of the input images with the use of a slight variation of the deep learning convolutional neural network (CNN) standard model called the LeNet which consists of the convolutional, activation, pooling and fully connected layers [17]. This proposed system has achieved accuracy of 95% [17].

Chapter 3: Existing Work & Implementation work

3.1 Overview of Existing Work

Existing work related to leaf disease detection using CNN show to detect and classify leaf disease using image processing techniques that follow steps like

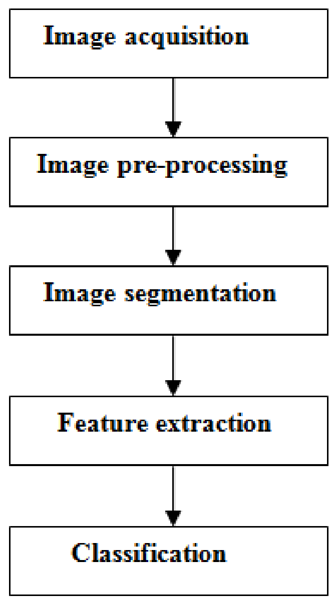

Fig.2 General Block Diagram of Feature Based Approach [13]

Image Acquisition: image acquisition in the first load the image in digital picture process and that consist capturing the image through digital camera and stores it in digital media for additional MATLAB operations [13][7].

B. Image Preprocessing: The main aim of image pre-processing is to enhance the image information contained unwanted distortions or to reinforce some image features for any processing [7][13]. Preprocessing technique uses various techniques like dynamic image size and form, filtering of noise, image conversion, enhancing image and morphological operations[7][13].

C. Image Segmentation: In image segmentation is used K-means cluster technique for partitioning of pictures into clusters during which a minimum of one part of cluster contain image with major space of unhealthy part [7][13]. The k means cluster algorithmic rule is applied to classify the objects into K variety of categories per set of features [13][7].

D. Feature extraction: After clusters are formed texture features are extracted using GLCM [13].

(Gray-Level Co-occurrence Matrix).

E. Classification: In classification is used for testing the leaf disease. The Random forest classifier is used for classification.[7][13]

3.2 Implementation work

Apple, grape, potato, and tomato plant leaves which are categorized total 24 types of labels apple label namely: Apple scab, Black rot, Apple rust, and healthy. Corn label namely: Corn Cercospora Gray spot, Corn rust, Corn healthy, Corn Blight [11][13]. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Potato label namely: Early blight, healthy, and Late blight. Tomato label namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, mosaic virus, and yellow leaf curl virus[11][13].

The dataset consist of 31,119 images of apple, corn, grape, potato and tomato, out of 31,119 images 24000 images are used. all Images are resized into 256 x 256,that images divided into two parts training and testing dataset, the whole range of the train test split using 80-20 (80% of the whole dataset used for the training and 20% for the testing)[11][13]. Then train CNN model.

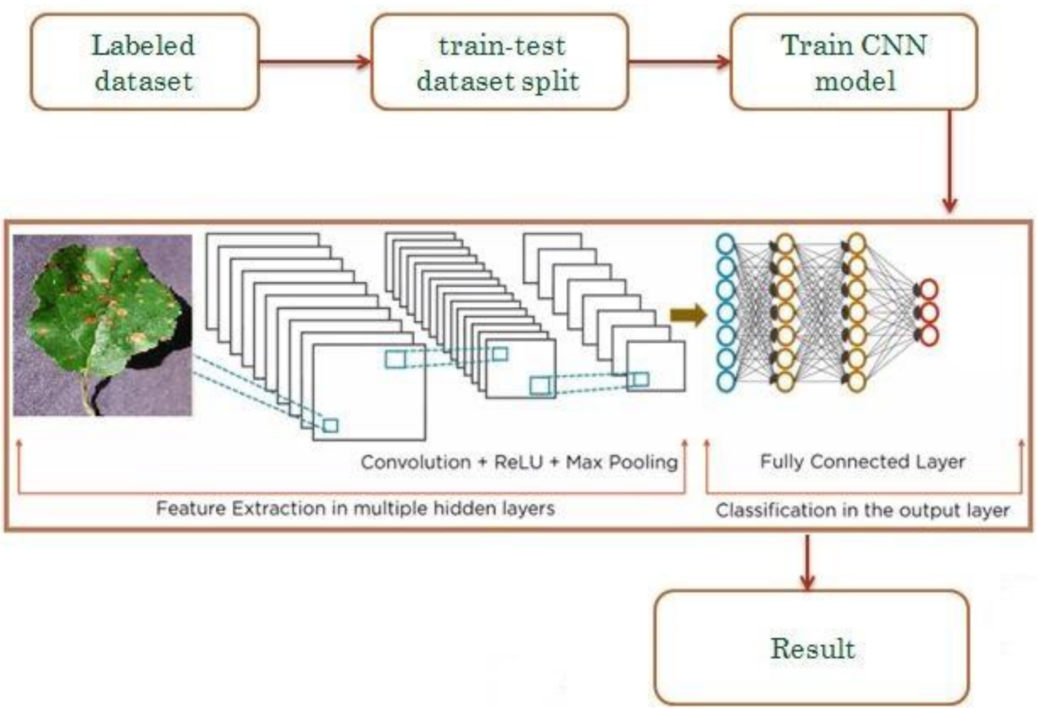

Fig 3: Proposed workflow [13]

Convolutional neural networks (CNN) can be used for the computational model creation that works on the unstructured image inputs and converts to output labels of corresponding classification[13]. They belong to the category of multi-layer neural networks which can be trained to learn the required features for classification purposes [13].

Less pre-processing is required in comparison to traditional approaches and automatic feature extraction is performed for better performance. For the purpose of leaf disease detection, the best results could be seen with the use of a variation of the LeNet architecture [13].

LeNet consists of convolutional, activation, max-pooling and fully connected layer also LeNet is simple CNN model. This architecture used for the classification of the leaf diseases in LeNet model [13]. It consists of an additional block of convolution, activation and pooling layers in comparison to the original LeNet architecture. The model used in this paper been shown in Fig. 2.Each block consists of a convolution, activation and a max pooling layer. Three such blocks followed by fully connected layers and soft-max activation are used in this architecture. Convolution and pooling layers are used for feature extraction whereas the fully connected layers are used for classification. Activation layers are used for introducing non-linearity into the network [13].

Convolution layer applies convolution operation for extraction of features. With the increase in depth, the complexity of the extracted features increases. The size of the filter is fixed to 5 × 5 whereas number of filters is increased progressively as we move from one block to another. The number of filters is 20 in the first convolution block while it is increased to 50 in the second and 80 in the third. This increase in the number of filters is necessary to compensate for the reduction in the size of the feature maps caused by the use of pooling layers in each of the blocks. After the application of the convolution operation feature maps are zero padded, in order to preserve the size of the image. The max pooling layer is used for reduction in size of the feature maps, speeding up the training process, and making the model less variant to minor changes in input. The kernel size for max pooling is 2×2. Re-LU activation layer is used in each of the blocks for the introduction of non-linearity. Also, Dropout regularization technique has been used with a keep probability of 0.5 to avoid over-fitting the train set. Dropout regularization randomly drops neurons in the network during iteration of training in order to reduce the variance of the model and simplify the network which aids in prevention of over fitting. Finally, the classification block consists of two sets fully connected neural network layers each with 500 and 10 neurons respectively. The second dense layer is followed by a soft max activation function to compute the probability scores for the ten classes [13].

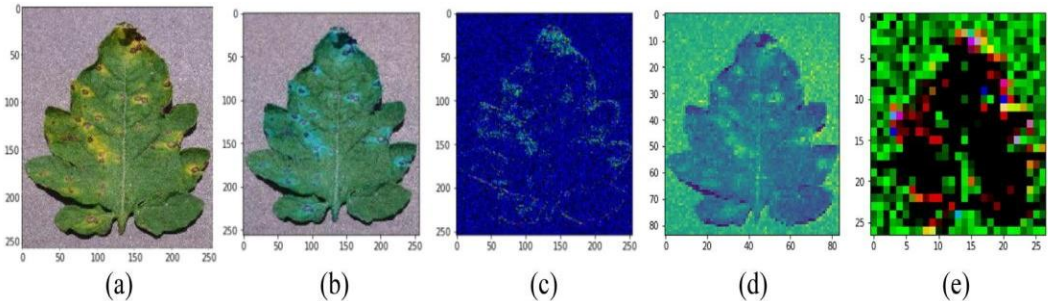

Fig.4 Experimental result(a)input image(b)convolution layer-1(c) convolution layer-2 (d) convolution layer-3 (e)flatting layer [3].

Further, in every experiment, the overall accuracy over the whole period of training and testing regular intervals (for every epoch) will be computed. The overall accuracy score will be used for performance evaluation [3].

Transfer learning is a knowledge- sharing method that reduces the size of the training data, contains 224*224 image fix size. To transfer the learning of a pre-trained model to a new model Transfer learning is useful. Transfer learning has been used in various applications, such as plant classification, software defect prediction, activity recognition and sentiment classification [3]. In this, the performance of the proposed Deep CNN model has been compared with popular transfer learning approach VGG16.

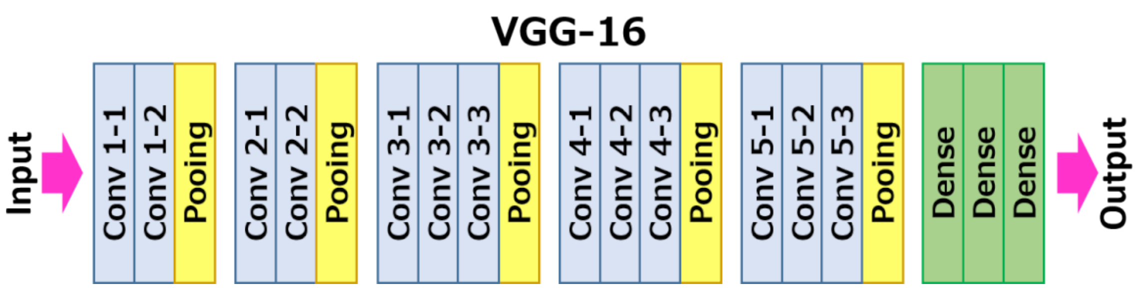

Fig .5 VGG16 layered architecture [18]

VGG16 is a convolutional neural network. The input to convolution layer size is 224 x 224 RGB fixed image size. The image is passed to convolutional layers, where the filters used with a very small receptive field which is the smallest size to capture the notion of left, right, up, and down, center: 3×3 [18]. Some of the configurations, it utilizes 1×1 convolution filters, which can be linear transformation followed by non-linearity of the input channels [18]. The convolution stride is fixed that is one pixel the spatial padding of convolution layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1 pixel for 3×3 convolution layers. Five max-pooling layers carried out spatial pooling, which follow some of the convolution layers (not all the conv. layers are followed by max-pooling).

Over a 2×2 pixel Max-pooling is performed [18].

Three layers follow a stack of convolutional layers. The first two have 4096 channels and third performs 1000-way ILSVRC classification and thus contains 1000 channels. The last layer is the soft-max layer. The configuration of the fully connected layers is the identify the leaf disease [18].

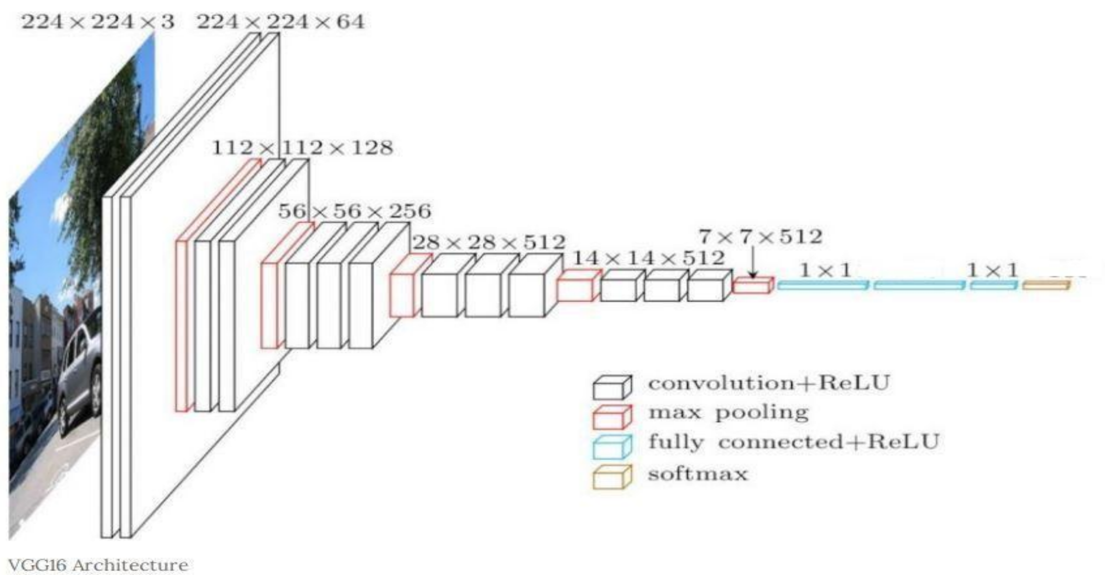

Fig 6.VGG16 architecture [18]

All hidden layers are equipped with the rectification Re-Lu Is rectified linear unit is contain non- linearity on network, and Also noted that none of the networks contain Local Response Normalization (LRN), such LRN does not improve the performance on the dataset [18].

Chapter 4: Dataset, Implementation and Result

4.1 Dataset Detail

The Plant leaf diseases dataset with augmentation data-set, 39 different classes of plant leaf and background images are available. The data-set containing 61,486 images. We used six different augmentation techniques for increasing the data-set size. These techniques are 1)image flipping, 2) Gamma correction, 3) noise injection, 4) PCA color augmentation, 5) rotation, and 6) Scaling [11][13].

We use The Plant leaf diseases dataset with augmentation dataset only 30,052 images with 24 labels. The apple label namely: Apple scab, Black rot, apple rust, and healthy. Corn label namely: Corn Cercospora spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight[13][11]. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Potato label namely: Early blight, healthy, and Late blight. Tomato label namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, mosaic virus, yellow leaf curl virus[13][11].

Classes	no. of images	used images
Apple_scab	1000	1000
Apple_black_rot	1000	1000
Apple_cedar_apple_rust	1000	1000
Apple_healthy	1645	1000
Corn_gray_leaf_spot	1000	1000
Corn_common_rust	1192	1000
Corn_northern_leaf_blight	1000	1000
Corn_healthy	1162	1000
Grape_black_rot	1180	1000
Grape_black_measles	1383	1000
Grape_leaf_blight	1076	1000
Grape_healthy	1000	1000
Potato_early_blight	1000	1000
Potato_healthy	1000	1000
Potato_late_blight	1000	1000
Tomato_bacterial_spot	2127	1000
Tomato_early_blight	1591	1000
Tomato_healthy	1909	1000
Tomato_late_blight	1000	1000
Tomato_leaf_mold	1000	1000
Tomato_septoria_leaf_spot	1707	1000
Tomato_spider_mites_two-spotted_spider_mite	1676	1000
Tomato_target_spot	1404	1000
Tomato_mosaic_virus	1000	1000
Total images	30052	24000

TABLE 2.LEAF DISEASE DATASET

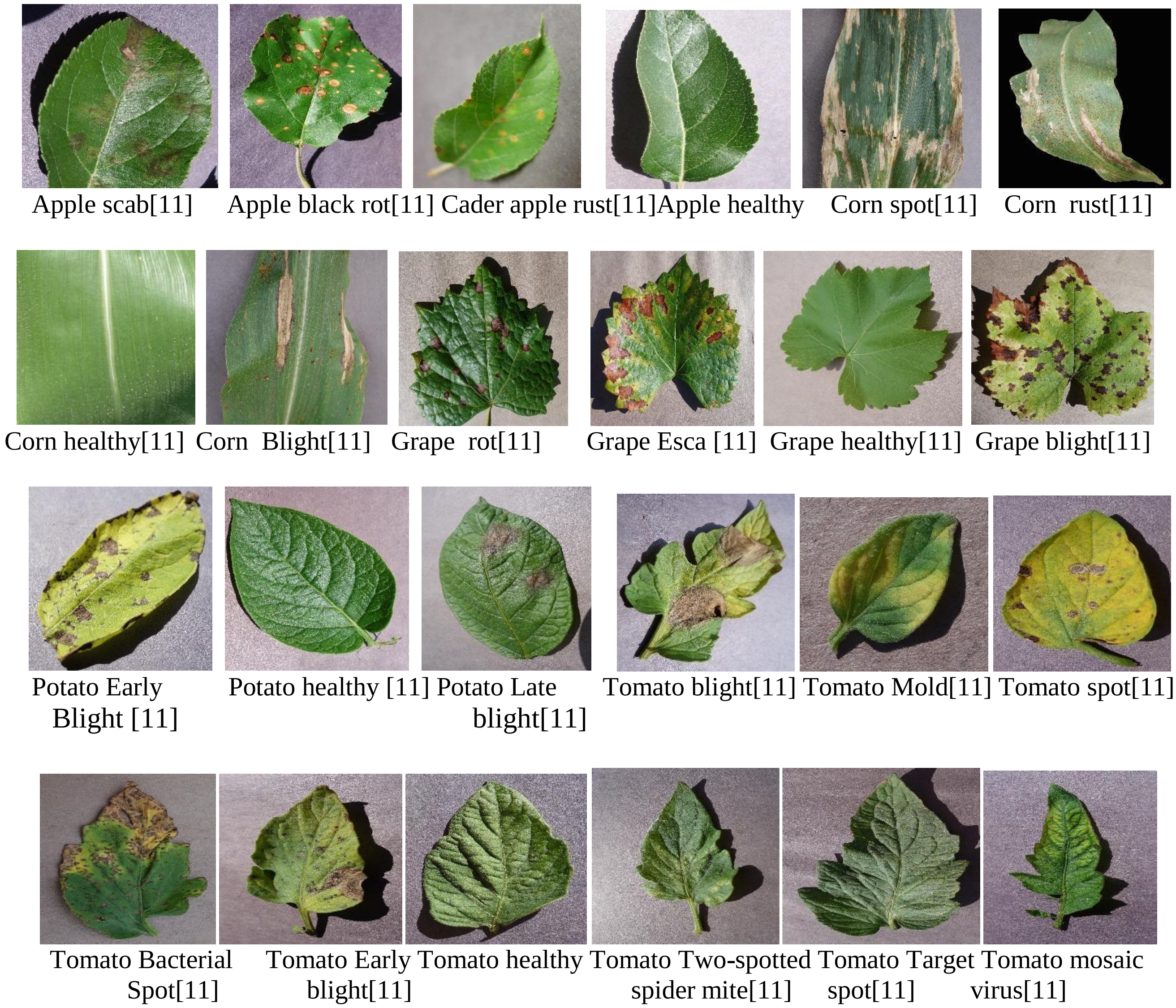

Fig.7 vegetable and fruits leaves with diseases [11] [13].

4.2 Tools & Technologies

4.2.1 PYTHON

Python as a language has a vast community behind it. Any problem which may be faced is simply resolved with a visit to Stack Overflow. Python is among the foremost standard language on the positioning that makes it very likely there will be straight answer to any question

Python has an abundance of powerful tools prepared for scientific computing Packages like NumPy, Pandas and SciPy area unit freely available and well documented. Packages like these will dramatically scale back, and change the code required to write a given program. This makes iteration fast.

Python as a language is forgiving and permits for program that appear as if pseudo code. This can be helpful once pseudo code given in tutorial papers must be enforced and tested. Using python this step is sometimes fairly trivial.

However, Python is not without its errors. The language is dynamically written and packages are area unit infamous for Duck writing. This may be frustrating once a package technique returns one thing that, for instance, looks like an array instead of being an actual array. Plus the actual fact that standard Python documentation does not clearly state the return type of a method, this can lead to a lot of trials and error testing that will not otherwise happen in a powerfully written language. This is a problem that produces learning to use a replacement Python package or library more difficult than it otherwise may be.

4.2.2 NUMPY

Numpy is python package which provide scientific and higher level mathematical abstractions wrapped in python. It is [19] the core library for scientific computing, that contains a strong n-dimensional array object, provide tools for integrating C, C++ etc. It is additionally useful in linear algebra, random number capability etc.

Numpy's array type augments the Python language with an efficient data structure used for numerical work. Numpy additionally provides basic numerical routines, like tools for locating Eigenvector.

4.2.3 SCIKIT LEARN

Scikit-learn [21] could be a free machine learning library for Python. It features numerous classification, regression and clustering algorithms like support vector machine, random forests, and k-neighbors', and it additionally supports Python numerical and scientific libraries like NumPy and SciPy. Scikit-learn is especially written in Python, with some core algorithms written in Python to get performance. Support vector machines are enforced by a python wrapper around LIBSVM .i.e., logistic regression and linear support vector machines by a similar wrapper around LIBLINEAR.

4.2.4 TENSORFLOW

TensorFlow [22] is an open source software library for numerical computation using data flow graphs. Nodes inside the graph represent mathematical formula, whereas the graph edges represent the multidimensional knowledge arrays (tensors) communicated between them. The versatile architecture permits you to deploy computation to at least one or more CPUs or GPUs in a desktop, server, or mobile device with a single API. Tensor Flow was originally developed by researchers and engineers acting on the Google Brain Team at intervals Google's Machine Intelligence analysis organization for the needs of conducting machine learning and deep neural networks research, however, the system are general enough to be applicable in a wide range of alternative domains as well.

4.2.5 KERAS

Keras is[20] a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with attention on enabling quick experimentation. Having the ability to travel from plan to result with the smallest amount doable delay is key to doing great research. Keras permits for straightforward and quick prototyping (through user-friendliness, modularity, and extensibility).Supports each convolutional networks and recurrent networks, furthermore as combinations of the two Runs seamlessly on CPU and GPU. The library contains numerous implementations of usually used neural network building blocks like layers, objectives, activation functions, optimizers, and a number of tools to create operating with image and text data easier. The code is hosted on GitHub, and community support forums embody the GitHub issues page, a Glitter channel and a Slack channel.

4.2.6. COMPILER OPTION

Anaconda is also a premium open-source distribution of the Python and R programming languages for large-scale process, predictive analytics, and scientific computing, that aims to modify package managing and deployment.

4.2.7. JUPITER NOTEBOOK

The Jupyter Notebook is an open-source web application that enables you to make and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more [23].

4.3 Results

```
/content/drive/My Drive/leafdisease dataset/Apple___Apple_scab
/content/drive/My Drive/leafdisease dataset/Apple___Black_rot
/content/drive/My Drive/leafdisease dataset/Apple___Cedar_apple_rust
/content/drive/My Drive/leafdisease dataset/Apple___healthy
/content/drive/My Drive/leafdisease dataset/Grape___Black_rot
/content/drive/My Drive/leafdisease dataset/Grape___Esca_(Black_Measles)
/content/drive/My Drive/leafdisease dataset/Grape___healthy
/content/drive/My Drive/leafdisease dataset/Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
/content/drive/My Drive/leafdisease dataset/Corn___Cercospora_leaf_spot Gray_leaf_spot
/content/drive/My Drive/leafdisease dataset/Corn___Common_rust
/content/drive/My Drive/leafdisease dataset/Corn___healthy
/content/drive/My Drive/leafdisease dataset/Corn___Northern_Leaf_Blight
/content/drive/My Drive/leafdisease dataset/Potato___Early_blight
/content/drive/My Drive/leafdisease dataset/Potato___healthy
/content/drive/My Drive/leafdisease dataset/Potato___Late_blight
/content/drive/My Drive/leafdisease dataset/Tomato___Bacterial_spot
/content/drive/My Drive/leafdisease dataset/Tomato___Early_blight
/content/drive/My Drive/leafdisease dataset/Tomato___healthy
/content/drive/My Drive/leafdisease dataset/Tomato___Late_blight
/content/drive/My Drive/leafdisease dataset/Tomato___Leaf_Mold
/content/drive/My Drive/leafdisease dataset/Tomato___Septoria_leaf_spot
/content/drive/My Drive/leafdisease dataset/Tomato___Spider_mites Two-spotted_spider_mite
/content/drive/My Drive/leafdisease dataset/Tomato___Target_Spot
/content/drive/My Drive/leafdisease dataset/Tomato___Tomato_mosaic_virus
X_data shape: (24000, 256, 256, 3)
y_data shape: (24000,)
```

Fig 8. Labled images

4.4 This output in images are resized and gives label name to all images.

```
X_train shape: (19200, 256, 256, 3)
X_test shape: (4800, 256, 256, 3)
Y_train shape: (19200,)
Y_test shape: (4800,)
```

Fig 9. Split dataset images

4.5 Fig 9. Contain Total 1500 dataset images are divided into two parts 1200 are in training part and 300 is the testing part.

```
Epoch 138/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0016 - accuracy: 1.0000 - val_loss: 0.4220 - val_accuracy: 0.8958
Epoch 139/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0015 - accuracy: 1.0000 - val_loss: 0.4293 - val_accuracy: 0.8964
Epoch 140/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0015 - accuracy: 1.0000 - val_loss: 0.4233 - val_accuracy: 0.8995
Epoch 141/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0015 - accuracy: 1.0000 - val_loss: 0.4267 - val_accuracy: 0.8974
Epoch 142/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.4367 - val_accuracy: 0.8995
Epoch 143/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.4282 - val_accuracy: 0.8995
Epoch 144/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.4326 - val_accuracy: 0.8984
Epoch 145/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.4363 - val_accuracy: 0.8969
Epoch 146/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.4301 - val_accuracy: 0.9005
Epoch 147/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.7371 - accuracy: 0.8725 - val_loss: 0.7075 - val_accuracy: 0.8307
Epoch 148/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.1158 - accuracy: 0.9592 - val_loss: 0.4037 - val_accuracy: 0.8896
Epoch 149/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0253 - accuracy: 0.9957 - val_loss: 0.3917 - val_accuracy: 0.8932
Epoch 150/150
17280/17280 [==============================] - 28s 2ms/step - loss: 0.0155 - accuracy: 0.9987 - val_loss: 0.3777 - val_accuracy: 0.9000
```

Fig.10 Train CNN model

4.6 Fig . 10. Consist output of train the convolutional neural network. Train 1080 samples and validate on 120 samples

```
4800/4800 [==============================] - 5s 943us/step
accuracy: 90.229166%
```

Fig .11. Test CNN model

4.7 Fig 11. Consist output of convolutional neural network testing accurancy score 90.23%

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 254, 254, 32)	896
activation_1 (Activation)	(None, 254, 254, 32)	0
max_pooling2d_1 (MaxPooling2	(None, 127, 127, 32)	0
conv2d_2 (Conv2D)	(None, 125, 125, 64)	18496
activation_2 (Activation)	(None, 125, 125, 64)	0
max_pooling2d_2 (MaxPooling2	(None, 62, 62, 64)	0
conv2d_3 (Conv2D)	(None, 60, 60, 128)	73856
activation_3 (Activation)	(None, 60, 60, 128)	0
max_pooling2d_3 (MaxPooling2	(None, 30, 30, 128)	0
conv2d_4 (Conv2D)	(None, 28, 28, 256)	295168
activation_4 (Activation)	(None, 28, 28, 256)	0
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 256)	0
conv2d_5 (Conv2D)	(None, 12, 12, 512)	1180160
activation_5 (Activation)	(None, 12, 12, 512)	0
max_pooling2d_5 (MaxPooling2	(None, 6, 6, 512)	0
flatten_1 (Flatten)	(None, 18432)	0
dense_1 (Dense)	(None, 128)	2359424
dense_2 (Dense)	(None, 256)	33024
dense_3 (Dense)	(None, 20)	5140
activation_6 (Activation)	(None, 20)	0

Total params: 3,966,164
Trainable params: 3,966,164
Non-trainable params: 0

Table.3. CNN model summary table

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_2 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 112, 112, 64)	0
conv2d_3 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_4 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 56, 56, 128)	0
conv2d_5 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_7 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 28, 28, 256)	0
conv2d_8 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_10 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 512)	0
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_13 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 4096)	102764544
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 2)	8194

Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0

Table. 4. VGG16 model summary table

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dropout_1 (Dropout)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None,   )                752670
=================================================================
Total params: 15,467,358
Trainable params: 752,670
Non-trainable params: 14,714,688
```

Table. 4. Transfer learning VGG16 model summary

Epochs	CNN Accuracy	VGG16 Accuracy
150	**90.229166 %**	**51.166334 %**
120	**86. 666667%**	**50.140005 %**
90	**86.133333 %**	**47.157776 %**
60	**85.085556 %**	**46.872223 %**
30	**84.166664 %**	**45.708333 %**

TABLE 5. comparison table of CNN vs. VGG16

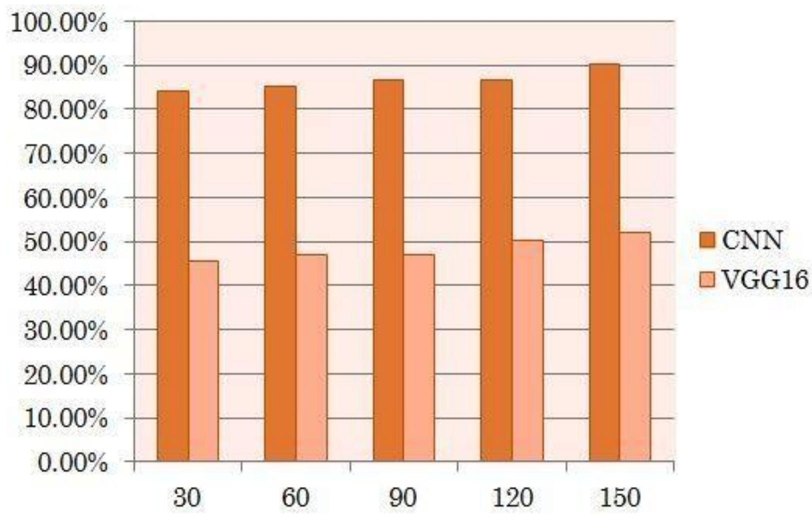

Fig 12. Chart of CNN vs. VGG16

Chapter 5: Conclusion and Future work

5.1 Conclusion

We have studied about existing system feature based approach. It's done by image processing technique in this we have studied steps like image Acquisition, image pre-processing, Image Segmentation, features extraction, classification.

Proposed system to achieve this purpose, we have use CNN and get accuracy is 90.23%. We have also use VGG16 model to detect leaf disease but in our case CNN has better result than VGG16.

In future we can add more classes of leaves and disease type.

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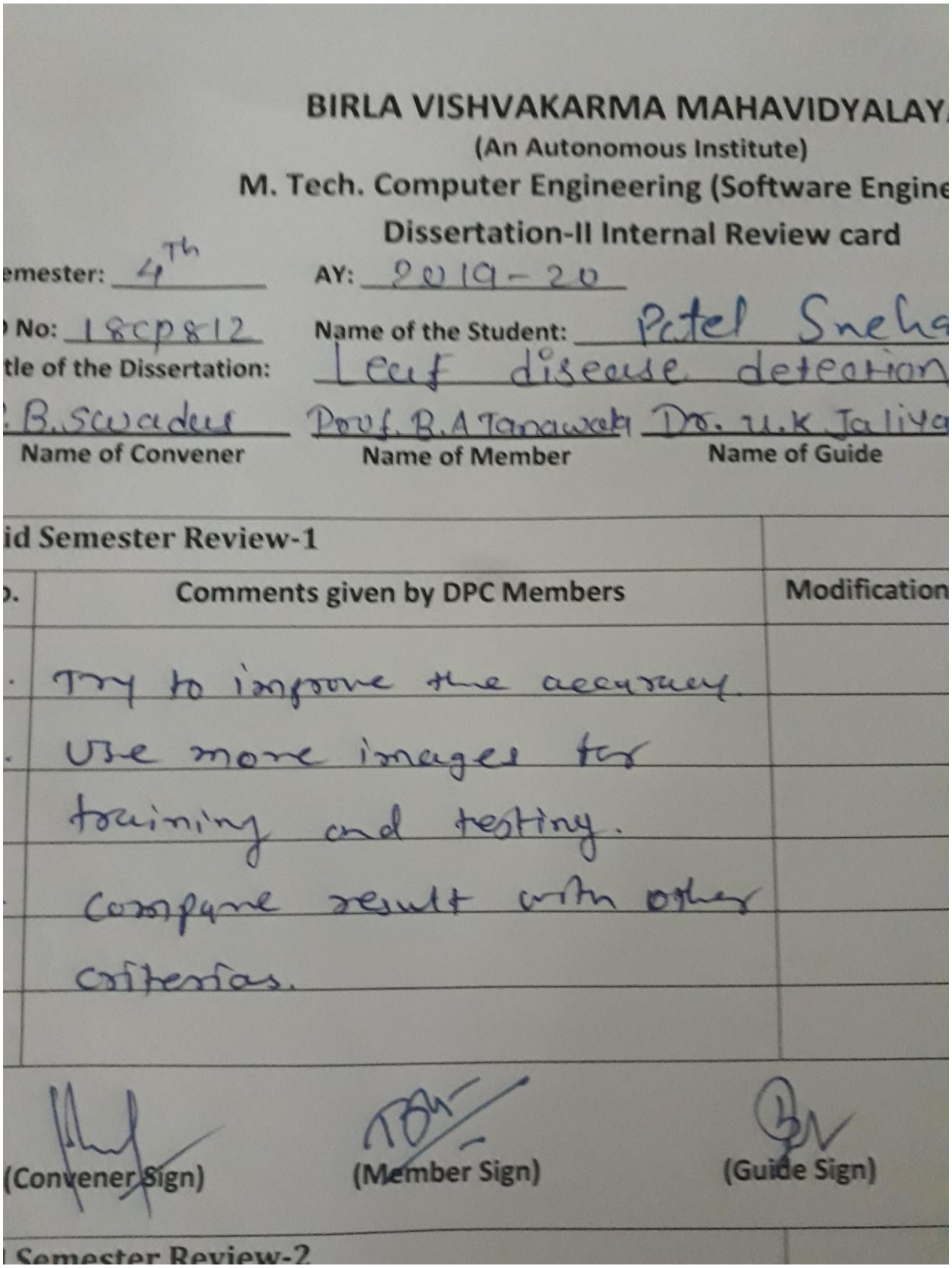
APPENDIX A

ABBRAVIATION

Sr. No.	Abbreviation	Meaning
1	CNN	Convolutional Neural Network
2	R-CNN	Region based Convolutional Neural Network
3	Fast RCNN	Fast Region based Convolutional Neural Network
4	Faster RCNN	Faster Region based Convolutional Neural Network
5	VGG16	Visual Geometry Group
6	ROI	Region Of Interest
7	SVM	Support Vector Machine
8	KNN	K Nearest Neighbor
9	PNN	Probabilistic Neural Network
10	GLCM	Gray-Level Co-occurrence Matrix

APPENDIX B

REVIEW CARD



BIRLA VISHVAKARMA MAHAVIDYALAY

(An Autonomous Institute)

M. Tech. Computer Engineering (Software Engine

Dissertation-II Internal Review card

emester: 4th AY: 2019-20

No: 18CP812 Name of the Student: Patel Sneha

tle of the Dissertation: Leaf disease detection

B. Swadia | Prof. B.A Tanawala | Dr. U.K Jaliya
Name of Convener | Name of Member | Name of Guide

id Semester Review-1

o.	Comments given by DPC Members	Modification
.	Try to improve the accuracy.	
.	Use more images for training and testing.	
.	compare result with other criterias.	

(Convener Sign) (Member Sign) (Guide Sign)

Semester Review-2

APPENDIX C

PLAGARISM REPORT

URKUND

Document Information

Analyzed document	18CP812_thesis.pdf (D76394546)
Submitted	7/15/2020 1:20:00 PM
Submitted by	BVM Engineering College
Submitter email	mec008owner@gtu.edu.in
Similarity	7%
Analysis address	mec008owner.gtuni@analysis.urkund.com

Sources included in the report

W	URL: https://github.com/zafir-stojanovski/tomato-leaf-disease-detection Fetched: 7/15/2020 1:22:00 PM	3
W	URL: https://www.scirp.org/journal/paperinformation.aspx?paperid=100100 Fetched: 5/28/2020 7:04:12 AM	1
W	URL: https://www.frontiersin.org/articles/10.3389/fpls.2016.01419/full Fetched: 7/15/2020 1:22:00 PM	1

APPENDIX D

PAPER PUBLICATION CERTIFICATE