

SUGARCANE DISEASE IDENTIFICATION AND QUALITY CHECK USING IMAGE PROCESSING

A Project Report Phase - II

Submitted in partial fulfillment of the requirements for the award of Bachelor
of Engineering Degree in Electronics and Communication Engineering

By

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**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **SATHISH KUMAR G (39130404)** who carried out the project entitled "**SUGAR CANE DISEASE IDENTIFICATION AND QUALITY CHECK USING IMAGE PROCESSING**" under our supervision from January 2023 to April 2023.

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ABSTRACT

Harvest infection acknowledgment is one of the extensive concerns looked by the sugarcane farming business. Notwithstanding, late advancement in visual registering with improved computational equipment has cleared the path for computerized illness recognition. Results on openly accessible datasets utilizing Convolutional Neural Network (CNN) models have exhibited its suitability. To research how flow cutting edge order models would act in uncontrolled conditions as would be seen nearby, we gained a dataset of five infections of sugarcane plants taken from fields across various districts of Uttarakhand and Bihar, India, caught by camera gadgets under various goals and lighting conditions. Image processing is one of the main tools in finding diseases in sugarcane and checking the quality of sugarcane. It undergoes many processes like image acquisition, image preprocessing, image segmentation, image classification, feature extraction disease detection. We use convolutional neural networks to get more accuracy. so disease can be detected accurately.

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LIST OF ABBREVIATION

CNN	CONVOLUTIONAL NEURAL NETWORK
POOL	POOLING LAYER
FC	FULLY CONNECTED LAYER
CONV	CONVOLUTIONAL LAYER
RGB	RED GREEN BLUE
ReLU	RECTIFIED LINEAR UNIT
HSV	HUE SATURATION VALUE
DND	DEEP NETWORK DESIGN
VGG	VISUAL GEOMETRY GROUP

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Sugar cane disease identification through unaided eye perception of the indications on plant leaves, consolidate quickly expanding intricacy. Because of this intricacy and to the enormous number of developed Crops and their current phytopathology issues, indeed, even experienced agrarian specialists and plant pathologists may frequently neglect to effectively analyze explicit sicknesses, and are thus prompted mixed up ends and concern arrangements. A robotized framework intended to help distinguish plant infections by the plant's appearance and visual manifestations could be of incredible assistance to novices in the horticultural cycle.

This will be demonstrated as a valuable strategy for ranchers and will alarm them at the correct time prior to spreading of the sickness over a huge zone. Deep learning comprises a new, current strategy for picture handling and information examination, with precise outcomes and huge potential. As Deep learning has been effectively applied in different areas, it has as of late entered the space of agribusiness. So we will apply profoundly figuring out how to make a calculation for robotized recognition and characterization of plant leaf infections.

These days, Convolutional Neural Networks are considered as the main strategy for object location. In this paper, we considered locators in particular Faster Region-Based Convolutional Neural Network (Faster R-CNN), Region-based Completely Convolutional Networks (R-FCN) and Single Shot Multibox Detector (SSD). Every one of the designs ought to be ready to be converged with any component extractor relying upon the application or need.

1.2 PROBLEM STATEMENT

Agriculture is the pillar of the Indian economy. Huge commercialization of agriculture has made a really negative impact on our current circumstance. The application of substance fungicides has encouraged gigantic degrees of synthetic development in our current circumstance, insoll, water, air in brutes and unexpectedly on our own bodies.

Fake manures give on a temporary impact on profitability still a more extended term negative impact on the climate, where they stay for quite a long time posterior to filtering and running out, tainting ground water. Another negative impact of this pattern has been on the fortunes of the cultivating networks around the world.

In malignancy of this purported expanded effectiveness, drovers in for all intents and purposes each country around the world have seen a decline in their fortunes. This is the place where natural cultivation comes from. Natural Cultivating has the capability to deal with every one of these issues.

Automatic detection of plant diseases is an essential 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.

Plant diseases and pests detection is a very important research content in the field of machine vision. It is a technology that uses machine vision equipment to acquire images to judge whether there are diseases and pests in the collected plant images.

Image processing algorithms are developed to detect the plant infection or disease by identifying the color feature of the leaf area. The K mean algorithm is used for color segmentation and GLCM is used for disease classification.

1.3 DEEP LEARNING

Deep learning uses an artificial neural network architecture and usually contains many layers to process compared to the traditional neural network architectures. Deep learning has transformed the areas of image detection , image classification acoustics , etc. that requires huge data to process. The integration of deep learning in plant disease diagnosis has paved the way on how the experts analyze and make decisions .

In this study, the researchers used the Convolutional Neural Networks (CNNs) as the basic deep learning method [9]. CNN is one of the most prevailing methods in demonstrating complex methods and uses a large amount of data to perform pattern recognition applications. The study of Lee et al. is one example of CNN that automatically recognizes a plant based on the plant leaf images [13]. Our study will train a dataset of 13, 842 sugarcane images. The data contains 7 classes (6 types of sugarcane leaf diseases and a healthy class of sugarcane leaf).

Deep Learning plays an essential part in developing artificial human intelligence and automated systems. Deep Learning is composed of a huge number of neural networks and uses the processor or the embedded video processor of the computer to control each neuron in a neural network which is characterized as a single node. Deep learning has been integrated in many applications such as crop variety detection and classification , plant identification and classification , and fruit grading of images . Images captured using mobile cameras or any camera devices mounted in a robot also have gained popularity.

Convolutional Neural Network or CNN is now popular for researchers who do research in computer vision and it executes different layers of processing through several stages of execution. Shows the components of a CNN model that includes an input image, convolutional layers, pooling layers, fully connected layers, activation functions, and an output.

1.4 SUGARCANE DISEASES

The spindle leaves (3rd & 14th)) display drying. At a later stage, stalks become discolored and hollow. Acervuli (black fruiting bodies) develop on rind and nodes. After splitting open the diseased stalk, a sour smell emanates. The internal tissues are reddened with intermingled transverse white spots.

Sugarcane is a major commercial crop grown in tropical and subtropical regions of the country. During the last 100 years, the country has witnessed epidemics of various diseases like red rot, smut, wilt, rust, leaf scald and yellow leaf (YLD). The damage caused to sugarcane during each epidemic would vary depending upon the nature of disease and spread of the affected varieties. Many sugarcane varieties were replaced due to their breakdown to a new disease or to a new pathogenic strain. Still, red rot remains to be the major disease of sugarcane in the country and wilt and smut are the other major diseases seriously affecting cane production in India. In addition, the new disease YLD causes serious damage to cane productivity in many states. Severity of grassy shoot disease, pokkah boeng and rust is also growing in many parts of the country. Propagation of sugarcane through vegetative cuttings favors spread of diseases through planting materials. Primary transmission of different diseases through seed canes poses a serious threat to sugarcane growth and performance. Disease resistant varieties play a crucial role in managing many of the diseases in sugarcane and several varieties have been developed to manage the diseases in the past. In addition, different agronomic approaches and physical methods like heat therapy are being effectively used to manage the diseases in sugarcane. Recently, multiplication of sugarcane through tissue culture is being advocated to produce virus and phytoplasma disease-free planting materials.

finally we can take three types of disease, they are

1. Red rot.
2. Red rust.
3. Healthy.

1.5 DATA SET

This data set contains three catalog classes: Red Rot, Red Rust, and Healthy. I visited and collected sugar cane mold and collection methods through Google lectures on kaggle.com. The red Rot has 74 images, the red rust has 74 images, and finally the healthy one has 76 images. You can then finally split it into two sets: training and testing.

112 images are tested and 112 images are also trained. Then, finally, this image can be used to identify sugar cane diseases.

1.6 RED ROT

The spindle leaves (3rd & 14th)) display drying. At a later stage, stalks become discolored and hollow. Acervuli (black fruiting bodies) develop on rind and nodes. After splitting open the diseased stalk, a sour smell emanates. The internal tissues are reddened with intermingled transverse white spots. Sugarcane is a major commercial crop grown in tropical and subtropical regions of the country. During the last 100 years,



Fig: 1.1: Red Rot

1.7 RED RUST

The earliest symptoms of common rust on the leaves are small, elongated yellowish spots which are visible on both the surfaces. These spots increase in size, mainly in length, and turn red-brown to brown in color. A narrow, pale yellow-green halo develops around the lesions.

When the common rust is severe, numerous lesions occur on individual leaves giving them an overall brown or rusty appearance. These lesions coalesce to form large, irregular necrotic areas that usually result in premature death of the leaf. In such cases, the number of live leaves per plant can be seriously reduced.



Fig:1.2 : Red Rust

1.8 HEALTHY

Sugarcane is a good source of vitamin C and antioxidants that may boost your immunity. Presence flavonoids – help the body stave off cancerous cells, especially prostate and breast cancer. Sugarcane juice works excellent for digestive and liver problems.

Natural sugarcane also contains substances called antioxidants. Antioxidants help combat free radicals (molecules that cause damage to cells) that can worsen several medical problems like diabetes, malaria, myocardial infarction, and skin cancer. It helps to prevent cancer if consumed regularly and also improves the normal functioning of the kidneys and helps lose weight. Additionally drinking sugarcane juice helps to keep the skin healthy, acts as an energy booster, helps during pregnancy and prevents tooth decay of sugarcane diseases.



Fig:1.3 Healthy

CHAPTER 2

LITERATURE SURVEY AND OBJECTIVES

2.1 LITERATURE SURVEY

Saradhambal .G , Dhivya. R, Latha. S, R. Rajesh “Plant Disease -884 Detection and Its Solution using Image Classification” International Journal of Pure and Applied Mathematics. Volume 119 No. 14 -0913232018, 879. Crop cultivation plays an essential role in the field. Presently, the loss of food is mainly due to infected crops, which reflexively reduces the production rate. To identify the plant diseases at an untimely phase is not yet explored. The main challenge is to reduce the usage of pesticides in the agricultural field and to increase the quality and quantity of the production rate. Our paper is used to explore the leaf disease prediction at an untimely action.

We propose an enhanced k-mean clustering algorithm to predict the infected area of the leaves. A color based segmentation model is defined to segment the infected region and place it to its relevant classes. Experimental analyses were done on sample images in terms of time complexity and the area of the infected region. Plant diseases can be detected by image processing techniques. Disease detection involves steps like image acquisition, image pre-processing, image segmentation, feature extraction and classification. Our project is used to detect the plant diseases and provide solutions to recover from the disease. It shows the affected part of the leaf in percentage. We planned to design our project with a voice navigation system, so a person with lesser expertise in software should also be able to use it easily.

Pallavi.S. Marathe“ Plant Disease Detection using Digital Image Processing and GSM” International Journal of Engineering Science and Computing, April 2017, Website:<http://ijesc.org/>. In India, 70% of its people are in the sector. The remaining 30% of people are an inseparable part of this field. Because from agriculture, we get various raw materials.

And especially crops, which serve as a staple food for people. But The Crops and plantations get destroyed mainly due to two major reasons, first reason is destruction by natural calamities such as flood, earthquake, drought, famine, etc. and second reason is the destruction by the pathogens. 98% of the destruction is caused by the pathogens and 2% of the destruction happens due to natural calamities. So the need for plant disease detection was felt. The traditional methods were inaccurate and not effective. So various researches in this field lead to inclusion of image processing for accurate detection of disease by using plant leaves. Various spots, patterns on plant leaves are useful in detecting the disease. Further advancement was the use of digital image processing for more accurate results. On referring various reputed IEEE, international conference and international journal papers regarding this field, it was found that none of these suggest a remedy for curing the plant disease.

RakeshChaware, RohitKarpe, PrithviPakhale, Prof.SmitaDesai“ Detection and Recognition of Leaf Disease Using Image Processing” International Journal of Engineering Science and Computing, May 2017, Website: <http://ijesc.org/> It's important wherever the seventieth population of an Asian country is dependent on agriculture. Which means it feeds a nice range of individuals. The foremost necessity is to consider less crop quality because of disease. Detecting disease may be a key to stopping agricultural losses. The aim of this project is to develop a software system that Mechanically finds and classifies disease. The steps like loading an image, preProcessing, Segmentation, extraction and classification involve illness detection. The leaf pictures are used for detecting plant diseases. Therefore use of image process techniques to find and classify diseases in agricultural applications is useful. This paper discussed various techniques to segment the disease part of the plant. This paper also discussed some Feature extraction and classification techniques to extract the features of infected leaves and the classification of plant diseases. The use of ANN methods for classification of disease in plants such as self-organizing feature map, back propagation algorithm, SVMs etc. can be efficiently used. From these methods, we can accurately identify and classify various plant diseases using image processing techniques.

Amandeep Singh, Maninder Lal Singh” The most significant challenge faced during the work was capturing the quality images with maximum detail of the leaf color”It is a very typical task to get the image with all the details within a procesable memory. Such images are formed through high resolution and thus are of 6-10 MB of size. This was handled by using a Nikon made D5200 camera which served the task very well. Second challenge faced was to get rid of illumination conditions as from the start to the end of paddy crop season, illumination varies a lot even when the image acquiring time is fixed. However the solution to this is variable user defined thresholding and making necessary adjustments to the shades of LCC.

Sachin D. Khirade “Identification of the plant diseases is the key to preventing the losses in the yield and quantity of the agricultural product.”It requires a tremendous amount of work, expertise in the plant diseases, and also requires excessive processing time. Hence, image processing is used for the detection of plant diseases. Disease detection involves the steps like image acquisition, image pre-processing, image segmentation, feature extraction and classification. This paper discussed the methods used for the detection of plant diseases using their leaves images. This paper discussed various techniques to segment the disease part of the plant. This paper also discussed some Feature extraction and classification techniques to extract the features of infected leaves and the classification of plant diseases. The accurate detection and classification of the plant disease is very important for the successful cultivation of crops and this can be done using image processing. This paper discussed various techniques to segment the disease part of the plant. This paper also discussed some Feature extraction and classification techniques to extract the features of infected leaves and the classification of plant diseases. The use of ANN methods for classification of disease in plants such as self-organizing feature map, back propagation algorithm, SVMs etc. can be efficiently used. From these methods, we can accurately identify and classify various plant diseases using image processing techniques.

Mr. Pramod S. Landge, Sushil A. Patil& et al"In "this propose and experimentally evaluate a software solution for automatic detection and classification of plant diseases through Image Processing."Farmers in rural India have minimal access to agricultural experts, who can inspect crop images and render advice. Delayed expert responses to queries often reach farmers too late. This paper addresses this problem with the objective of developing image processing algorithms that can recognize problems in crops from images, based on color, texture and shape to automatically detect diseases or other conditions that might affect crops and give the fast and accurate solutions to the farmer with the help of SMS. The design and implementation of these technologies will greatly aid in selective chemical application, reducing costs and thus leading to improved productivity, as well as improved produce.

Bhumika S.Prajapati, Vipul K.Dabhi& et al..."In this detection and classification of cotton leaf disease using image processing and machine learning techniques was carried out "Also The survey on background removal and segmentation techniques was discussed. Through this survey, we concluded that for background removal color space conversion from RGB to HSV is useful. We also found that the thresholding technique gives good results compared to other background removal techniques. We performed color segmentation by masking green pixels in the background removed image and then applying thresholding on the obtained masked image to get a binary image. This is useful to extract accurate features of disease. We found that SVM gives good results, in terms of accuracy, for classification of diseases. There are five major steps in our proposed work, out of which three steps have been implemented: Image Acquisition, Image pre-processing, and Image segmentation.

Oppenheim and G. Shani, "Potato disease classification using convolutional neural networks," in Proc. 11th Eur. Conf. Precis. Agriculture (ECPA), 2017, pp. 244–249.The algorithm uses a deep convolutional neural network training it to classify the tubers into five classes, four disease classes and a healthy potato class. The database of images used in this study, containing potatoes of different shapes, sizes and diseases, was acquired, classified, and labeled manually by experts.

so that the system benefited from this effect. However, even when we used only one network's heat maps in the third stage, we still observed significant improvement over the initial, baseline network, which took as input scaled-down versions of the full images. Therefore, the three-stage system's improved performance was primarily due to other factors. Neural network performance is greatly affected by the amount of data available for training. Because we trained the first stage on small sections of the images instead of the full image, the training set size was effectively increased, at least for the networks in stage.

S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers Plant Sci.*, vol. 7, p. 1419, Sep. 2016. so that the system benefited from this effect. However, even when we used only one network's heat maps in the third stage, we still observed significant improvement over the initial, baseline network, which took as input scaled-down versions of the full images. Therefore, the three-stage system's improved performance was primarily due to other factors. Neural network performance is greatly affected by the amount of data available for training. Because we trained the first stage on small sections of the images instead of the full image, the training set size was effectively increased, at least for the networks in stage Ensemble methods that combine the output of different classifiers often show improved performance over a single classifier. We achieved the best result with a combination of three of the stage 1 networks, so that the system benefited from this effect. However, even when we used only one network's heat maps in the third stage, we still observed significant improvement over the initial, baseline network, which took as input scaled-down versions of the full images. Therefore, the three-stage

Dechant et al., "Automated identification of northern leaf blight infected maize plants from field imagery using deep learning," *Phytopathology*, vol. 107, no. 11, pp. 1426–1432, 2017. Ensemble methods that combine the output of different classifiers often show improved performance over a single classifier. We achieved the best result with a combination of three of the stage 1 networks, so that the system benefited from this effect. However, even when we used only one network's heat maps in the third stage,

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Pheeraphat Sarikabuta and Siriporn Supratid presented a paper. Their work investigates impacts of large, medium and small size ResNets: ResNet50, ResNet35 and ResNet17 on sugarcane image dataset with distinct number of classes: 10, 50 and 102 Sugarcane classes. Within the scope of this study, ResNet50, ResNet35 and ResNet17 yield close accuracy results in very narrow ranges: [0.991, 0.998], [0.9975, 0.9996] and [0.9985, 0.9992] relying on 10, 50 and 102 classes of Oxford-102 sugarcane disease image set, respectively. Even though ResNet35 produces a few bit better results than those two others for all cases, a large increasing rate in classification performance is pointed by ResNet17 relative to ResNet50 and ResNet35, when expanding the sugarcane dataset from 10 to 50 classes. Moreover, the increase in accuracy performance rate can be maintained based on such ResNet17, compared to ResNet50 and ResNet35 when enlarging the sugarcane data from 50 to 102 classes. It can be noticed that even if ResNet35 yields the best results over others; less than 0.71% higher classification performance is indicated for ResNet35 than ResNet17 for all cases of 10-, 50- and 102-class sugarcane data. Such insignificant superior performance, compared to approximately 33% higher amounts of parameters used in ResNet35 than ResNet17 may cause ResNet17 to be preferred to ResNet35.

2.2 LITERATURE SUMMARY

We have studied different papers on disease detection and we decided to use the Hidden Markov Model, Anisotropic Diffusion Algorithm and Convolutional Neural Network. Using the system, the user is able to detect the disease in 2 approaches - select symptoms by comparing sugarcane (static approach) and select image from gallery or capture an image directly using a camera (dynamic approach). The basic equation of anisotropic diffusion equation is presented as: We have studied different papers on disease detection and we decided to use the Hidden Markov Model, Anisotropic Diffusion Algorithm and Convolutional Neural Network. Using the system, the user is able to detect the disease in 2 approaches - select symptoms by comparing sugarcane (static approach) and select image from gallery or capture an image directly using a camera (dynamic approach). It helps to remove noise from the digital image without blurring edges. Using edge seeking diffusion coefficient for a certain number of iterations it detects the edges. Anisotropic diffusion is regularly executed by methods for a guess of the summed up dispersion condition: each new picture in the family is processed by applying this condition to the last picture. Hence, anisotropic diffusion is an iterative procedure where a moderately basic arrangement of calculations are utilized to figure each progressive picture in the family and this procedure proceeds until an adequate level of smoothing is obtained. The Hidden Markov Model is used for image segmentation. It works pixel by pixel for selecting the pixel from the digital image for processing. After selecting the necessary part i.e diseased part, we mask the green part of a leaf. It results in an enhanced image of a leaf . A concealed Markov model can be viewed as speculation of a blended display where the shrouded factors.

CHAPTER 3

RESEARCH DATABASE

3.1 DATA TYPES

This dataset contains 3 directories/ classes, Red Rot, Red Rust and Healthy. These have been collected by visiting a sugarcane farm and method of collection is through Google Teachable. <https://www.kaggle.com/datasets/pungliyavithika/sugarcane-leaf-disease-classification>. Total summary image is 224 we can divided into 2 section test and train. test data types having 112 images and train having 112 images so we can take this type of data set is suitable for our project.

In India, production of sugarcane has increased from 241 million tonnes in TE 1992-93 to 346.5 million tonnes in TE 2012-13. The production of sugar has increased from 12.0 million tonnes in TE 1992-93 to 25.0 million tonnes in TE 2012-13. It is interesting to note from the chart that sugar and cane production have a cyclical behavior with two-three years upswing followed by two years downswing.

This has happened in the past despite the fact that this sector has been heavily regulated by the government in terms of levy of sugar, monthly releases of non-levy sugar, imports and exports, and pricing of cane, etc. This causes uncertainty to farmers and millers alike with an adverse effect on fresh investments in the sector.



FIG:3.1: DATA TYPES IMAGES

3.2 IMAGE ACQUISITION

It is the first method of image processing. It is described as capturing an image through a digital camera and stores it in digital media for further matlab operations.

Image acquisition can be defined as the act of procuring an image from sources. This can be done via hardware systems such as samaras, des sensors, etc. Irrefutably, it is the most crucial step in the MV workflow because an inaccurate image will render the entire workflow in Since machine vision systems don't analyze the acquired digital image of the object and not the object itself, gaining an image with the night clarity and contrast is paramount.

In the image acquisition step, the incoming light wave from an object is converted into an electrical signal by a combination of photo-sensitive sensors These small subsystems fulfill the role of providing your machine vision algorithms with an accurate description of the object.

3.3 PRE-PROCESSING

The main purpose of image pre-processing is to improve the image data containing unwanted distortion. Preprocessing utilizes different systems for example changing image size and shape, filtering of noise, image conversion, and morphological operations.

As a Machine Learning Engineer, data pre-processing or data cleansing is a crucial stop and most of the ML engineers spend a good amount of time in data preprocessing before building the model. Some examples for data pre-processing include outlier detection, missing value treatments and remove the unwanted or noisy data.

Similarly, Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances same image features relevant for further processing and analysis tasks. The modification makes use of various unsupervised clustering

techniques as an alternative to the GrabCut initialization phase.

There are 4 different types of image Pre-Processing techniques and they are listed.

below

1. Peel brightness transformations/ Brightness corrections.

2. Geometric Transformations.

3 image Filtering and Segmentation 4 Fourier transform and image restoration.

3.4 RESIZING

Image resizing is necessary when you need to increase or decrease the total number of pixels, whereas remapping can occur when you are correcting for lens distortion or rotating an image. Zooming refers to increasing the quantity of pixels, so that when you zoom an image, you will see more detail. When you resize an image and do not resample it, you change the image's size without changing the amount of data in that image. Resizing without resampling changes the image's physical size without changing the pixel dimensions in the image.

3.5 BINARY IMAGE

The main reason binary images are particularly useful in the field of Image Processing is because they allow easy separation of an object from the background. The process of segmentation allows to label each pixel as 'background' or 'object' and assigns corresponding black and white colors.

3.6 FILTERING

Filtering is a technique for modifying or enhancing an image. For example, you can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement.

3.7 IMAGE SEGMENTATION

In this project we used segmentation technique so the input image is divided into three clusters for good segmentation results.

1. Region based.
2. Edge based.
3. Threshold based.

Image segmentation is a method of dividing a digital image into subgroups called image segments, reducing the complexity of the image and enabling further processing or analysis of each image segment. Technically, segmentation is the assignment of labels to pixels to identify objects, people, or other important elements in the image.

A common use of image segmentation is in object detection. Instead of processing the entire image, a common practice is to first use an image segmentation algorithm to find objects of interest in the image. Then, the object detector can operate on a bounding box already defined by the segmentation algorithm. This prevents the detector from processing the entire image, improving accuracy and reducing inference time.

Image segmentation is a key building block of computer vision technologies and algorithms. It is used for many practical applications including medical image analysis, computer vision for autonomous vehicles, face recognition and detection, video surveillance, and satellite image analysis.

CHAPTER 4

EXISTING CNN ALGORITHM

4.1 GLCM METHOD FOR IMAGE PROCESSING

Here we are going to use the GLCM method for image processing. Feature Extraction: Gray-Level Co-occurrence Matrix (GLCM) with Python. Gray-Level Co-occurrence matrix (GLCM) is a texture analysis method in digital image processing. This method represents the relationship between two neighboring pixels that have gray intensity, distance, and angle GLCM is a second-order statistical texture analysis method. It examines the spatial relationship among pixels and defines how frequently a combination of pixels are present in an image in a given direction and distance.

Plants are defenseless to a few problems and assaults brought about by infections. There are a few reasons that can be characterizable to the impacts on the plants, messes because of the ecological conditions, like temperature, stickiness, nourishing overabundance or misfortunes, light and the most widely recognized. The authors focused The application of texture for detecting the sugarcane disease has been explained by the color transformation structure RGB is converted into HSV space because HSV is a good color descriptor. Masking and removing of green pixels with predefined threshold level and segmentation is done.

4.1.1 Disadvantages of CNN

These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. As the size of the image for which Texture features are extracted increases the values of all the features are also increased proportionally.

4.2 TYPES OF CNN

A convolutional neural network, ConvNets in short has three layers:

1. Input layer
2. Hidden layer
3. Output lay

Neural Networks are multi-layered networks consisting of neurons or nodes. These neurons are the core processing units of the neural network. They are designed to act like human brains. They take in data, train themselves to recognize the patterns in the data and then predict the output.

The input layers receive the input, the output layer predicts the output and the hidden layers do most of the calculations. The number of hidden layers can be modified according to the requirements. There should be at least one hidden layer in a neural network.

Let's consider an image, each pixel is fed as input to each neuron of the first layer, neurons of one layer are connected to neurons of the next layer through channels. Each of these channels is assigned a numerical value known as weight. The inputs are multiplied by the corresponding weights and this weighted sum is then fed as input to the hidden layers. The output from the hidden layers is passed through an activation function which will determine whether the particular neuron will be activated or not. The activated neurons transmit data to the next hidden layers. In this manner, data is propagated through the network, this is known as Forward Propagation.

In the output layer, the neuron with the highest value predicts the output. These outputs are the probability values. The predicted output is compared with the actual output to obtain the error. This information is then transferred back through the network, the process is known as Backpropagation. Based on this information, the weights are adjusted. This cycle of forward and backward propagation is done several times on multiple inputs until the network predicts the output correctly in most of the cases. This ends the training process of the neural network. The time taken to train the neural network may get high in some cases. Here are some guidelines to prepare data for image processing. More data needs to be fed to the model to get better results. Image dataset should be of high quality to get more clear information, but to process them you may require deeper neural networks. In many cases RGB images are converted to grayscale before feeding them into a neural network.

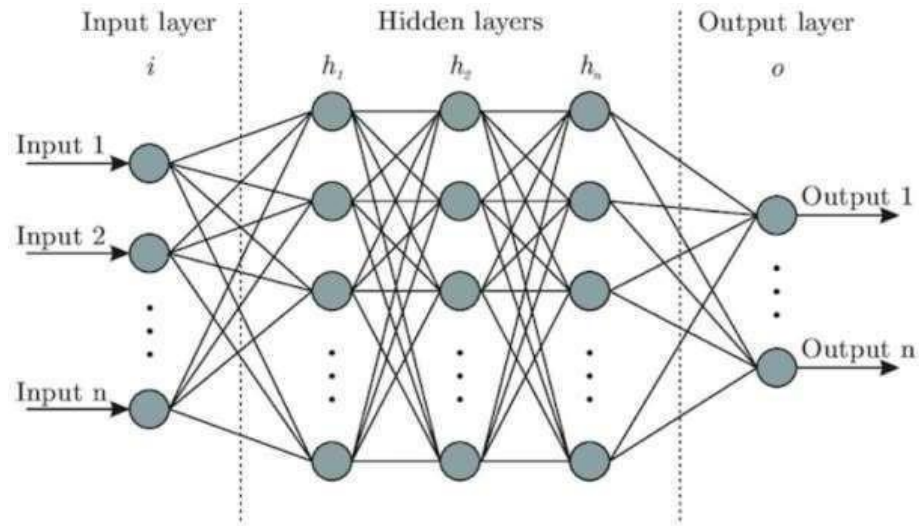


Fig: 4.1: Basic neural network

4.2.1 Convolutional Layer

They are the core building block of CNN, it is responsible for performing convolution operation. The element involved in carrying out the convolution operation in this layer is called the Kernel/Filter (matrix). The kernel makes horizontal and vertical shifts based on the stride rate until the full image is traversed.

The convolutional layer computes the convolutional operation of the input images using kernel filters to extract fundamental features. The kernel filters are of the same dimension but with smaller constant parameters as compared to the input images. As an example, for computing a $35 \times 35 \times 2$ 2D scalogram image, the acceptable filter size is $f \times f \times 2$, where $f = 3, 5, 7$, and so on. But the filter size needs to be smaller compared to that of the input image. The filter mask slides over the entire input image step by step and estimates the dot product between the weights of the kernel filters with the value of the input image, which results in producing a 2D activation map. Hence, CNN will learn a visual feature. Fig. 6.6 illustrates a simple example of the computing activation map. The equation of the generalized convolutional layer.

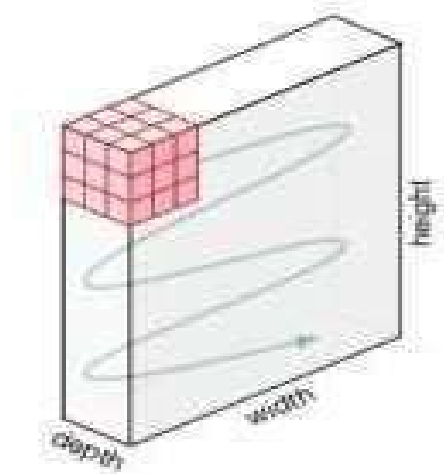


Fig:4.2: Movement of the kernel.

4.2.2 Pooling Layer

This layer is responsible for dimensionality reduction. It helps to decrease the computational power required to process the data. There are two types of Pooling: Max Pooling and Average Pooling. Max pooling returns the maximum value from the area covered by the kernel on the image. Average Pooling returns the average of all the values in the part of the image covered by the kernel.

Pooling layers are one of the building blocks of Convolutional Neural Networks, Where Convolutional layers extract features from images, Pooling layers consolidate the features learned by CNNs. Its purpose is to gradually shrink the representation's spatial dimension to minimize the number of parameters and computations in the network.

The feature map produced by the filters of Convolutional layers is location dependent. For example if an object in an image has shifted a bit it might not be recognizable by the Convolutional layer. So, it means that the feature map records the precise positions of features in the input "What pooling layers provide Is Translational invariance" which makes the CNN invariant to translations.co.even if the input of the CNN is tremitated the CNN will still be able to recognize.

4.2.3 Max Pooling

Create a MaxPool2D layer with pool_size=2 and strides 2. Apply the MaxPool2D layer to the matrix, and you will get the MaxPooled output in the tensor form. By applying it to the matrix, the Max pooling layer will go through the matrix by computing the max of each 2x2 pool with a jump of 2. Print the shape of the tensor. Use tf.squeeze to remove dimensions of size 1 from the shape of a tensor.

4.2.4 Average Pooling

Create an AveragePooling2D layer with the same 2 pool size and strides. Apply the AveragePooling2D layer to the matrix. By applying it to the matrix, the average pooling layer will go through the matrix by computing the average of 2x2 for each pool with a jump of 2. Print the shape of the matrix and Use tf.squeeze to convert the output into a readable form by removing all 1 size dimensions.

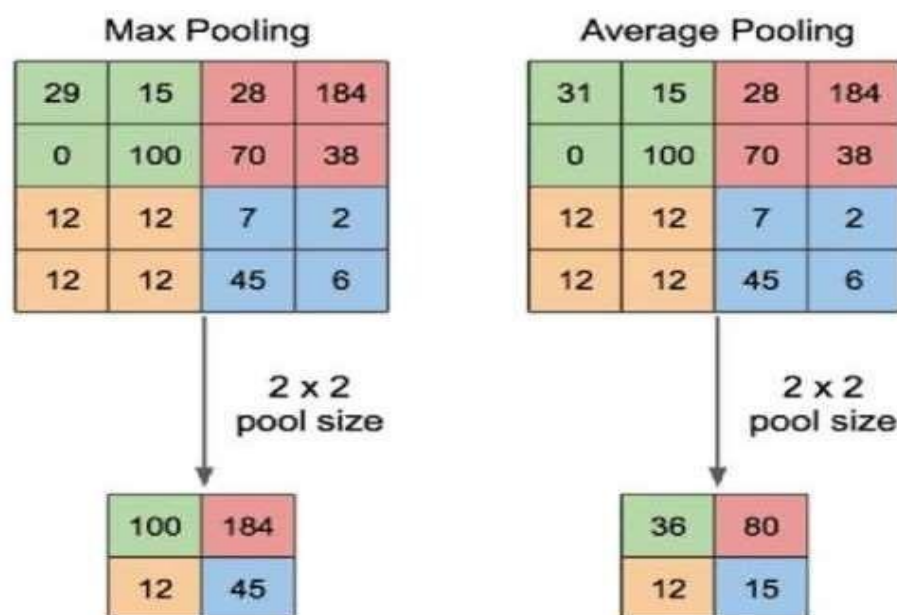


Fig:4.3: Pooling operation.

4.2.5 Fully Connected Layer

The fully connected layer (FC) operates on a flattened input where each input is connected to all neurons. If present, FC layers are usually found towards the end of CNN architectures.

Fully Connected layer takes input from Flatten Layer which is a one-dimensional layer (ID Layer) The data coming from Flatten Layer is passed first to Affine function and then to Non-Linear function. The combination of 1 Affine function and 1 Non-Linear Function is called 1 FC (Fully Connected) or 1 Hidden Layer. We can add multiple such layers based on the depth to which we want to take our classification model. Note that this entirely depends on the training dataset. Output from the final hidden layer is sent to Softmax or Sigmoid function for probability distribution over the final set of total number of classes.

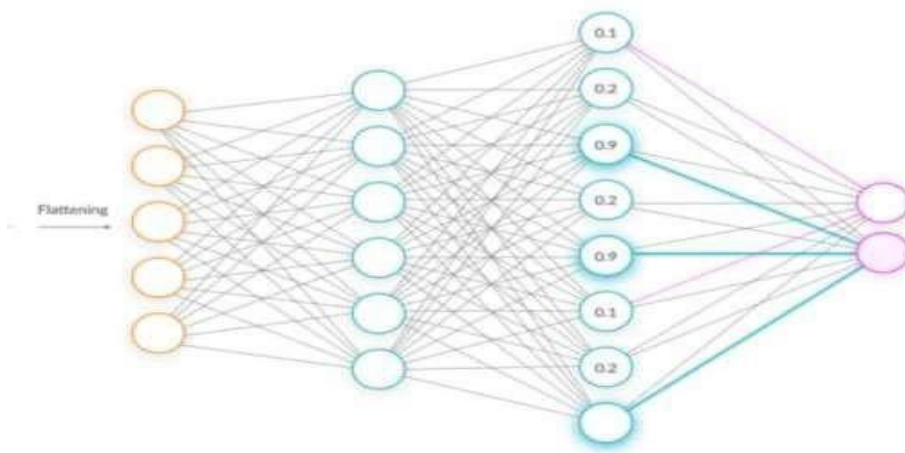


Fig:4.4: Fully connected layers.

4.3 CNN WORKING

A CNN can have multiple layers, each of which learns to detect the different features of an input image. A filter or kernel is applied to each image to produce an output that gets progressively better and more detailed after each layer. In the lower layers, the filters can start as simple features. At each successive layer, the filters increase in complexity to check and identify features that uniquely represent the input object. Thus, the output of each convolved image- the partially recognized image after each layer- becomes the input for the next layer in the last layer, which is an FC layer, the CNN recognizes the image or the object it represents.

With convolution, the input image goes through a set of these filters. As each filter activates certain features from the image, it does its work and passes on its output to the filter in the next layer. Each layer learns to identify different features and

the operations end up being repeated for dozens, hundreds or even thousands of layers. Finally, all the image data progressing through the CNN's multiple layers allow the CNN to identify the entire object.

4.3.1 CNNs vs neural networks

The biggest problem with regular neural networks (NNs) is a lack of scalability. For smaller images with fewer color channels, a regular NN may produce satisfactory results. But as the size and complexity of an image increases, the need for computational power and resources also increases which necessitates a larger and more expensive NN.

Moreover, the problem of overfitting also arises over time, wherein the NN tries to learn too many details in the training data. It may also end up learning the noise in the data, which affects its performance on test data sets. Ultimately, the NN fails to identify the features or patterns in the data set and thus the object itself.

In contrast, CNN uses parameter sharing. In each layer of the CNN, each node connects to another. A CNN also has an associated weight; as the layers' filters move across the image, the weights remain fixed-a condition known as parameter sharing. This makes the whole CNN system less computationally intensive than an NN system.

4.3.2 Benefits of using CNNs for deep learning

Deep learning is a subset of machine learning that uses neural networks with at least three layers. Compared to a network with just one layer, a network with multiple layers can deliver more accurate results. Both RNNs and CNNs are used in deep learning, depending on the application.

For image recognition, image classification and computer vision (CV) applications, CNNs are particularly useful because they provide highly accurate results, especially when a lot of data is involved. The CNN also learns the object's features in successive iterations as the object data moves through the CNN's many layers. This direct (and deep) learning eliminates the need for manual feature extraction (feature engineering).

CNNs can be retrained for new recognition tasks and built on pre existing networks. These advantages open up new opportunities to use CNNs for real-world applications without increasing computational complexities of costs.

4.3.3 Applications of convolutional neural networks

Convolutional neural networks are already used in a variety of CV and image recognition applications. Unlike simple image recognition applications, CV enables computing systems to also extract meaningful information from visual inputs (e.g., digital images) and then take appropriate action based on this information.

The most common applications of CV and CNNs are used in fields such as the following: Healthcare. CNNs can examine thousands of visual reports to detect any anomalous conditions in patients, such as the presence of malignant cancer cells. Automotive. CNN technology is powering research into autonomous vehicles and self-driving cars. Social media. Social media platforms use CNNs to identify people in a user's photograph and help the user tag their friends. Retail. E-commerce platforms that incorporate visual search allow brands to recommend items that are likely to appeal to a shopper. Facial recognition for law enforcement. Generative adversarial networks (GANs) are used to produce new images that can then be used to train deep learning models for facial recognition- Audio processing for virtual assistants. CNNs in virtual assistants learn and detect user-spoken keywords and process the input to guide their actions and respond to the user of CNN.

4.4 EXISTING CNN FOR VALIDATION

The pre-trained networks used for experimentation are mobilenetv2, Alexnet, Resnet101, Densenet201, Shufflenet, Resnet18, Xception and Darknet19.

4.4.1 DARKNET19

The Darknet19 classification model is to be used as the base of YOLOv2. The model builds off of prior work on network design as well as common knowledge in the field. Similar to the VGG models we use mostly 3×3 filters and double the number of channels after every pooling step. Following the work on Network in Network (NIN) we use global average pooling to make predictions as well as 1×1 filters to compress the feature representation between 3×3 convolutions. We use

batch normalization to stabilize training, speed up convergence, and regularize the model. Our final model, called Darknet-19, has 19 convolutional layers and 5 max-pooling layers.

Training for classification -The network is trained on the standard ImageNet 1000 class classification dataset for 160 epochs using stochastic gradient descent with a starting learning rate of 0.1, polynomial rate decay with a power of 4, weight decay of 0.0005 and momentum of 0.9 using the Darknet neural network framework. During training, we use standard data augmentation tricks including random crops, rotations, hue, saturation, and exposure shifts. As discussed above, after our initial training on images at 224×224 we fine tune our network at a larger size, 448. For this fine-tuning we train with the above parameters but for only 10 epochs and starting at a learning rate of 10^{-3} .

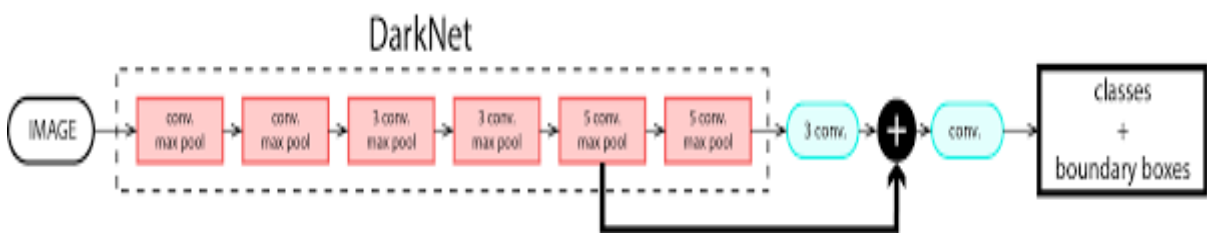


FIG:4.5: DARKNET19 ARCHITECTURE

4.4.2 ALEXNET

One thing to note here, since Alexnet is a deep architecture, the authors introduced padding to prevent the size of the feature maps from reducing drastically. The input to this model is the images of size $227 \times 227 \times 3$. The first convolution layer with 96 filters of size 11×11 with stride 4. The activation function used in this layer is relu. The output feature map is $55 \times 55 \times 96$. In case you are unaware of how to calculate the output size of a convolution layer, use, "Output= ((Input-filter)/stride)+1".

Also, the number of filters becomes the channel in the output feature map. Next, we have the first Max Pooling layer, of size 3X3 and stride 2. Then we get the resulting feature map with the size 27X27X96. After this, we apply the second convolution operation. This time the filter size is reduced to 5X5 and we have 256 such filters. The stride is 1 and padding 2. The activation function used is again relu. Now the output size we get is 27X27X256. Again, we applied a max-pooling layer of size 3X3 with stride 2. The resulting feature map is of shape 13X13X256. Now we apply the third convolution operation with 384 filters of size 3X3 stride 1 and also padding 1. Again, the activation function used is relu. The output feature map is of shape 13X13X384.

Then we have the fourth convolution operation with 384 filters of size 3X3. The stride along with the padding is 1. On top of that, the activation function used is relu. Now the output size remains unchanged i.e 13X13X384.

After this, we have the final convolution layer of size 3X3 with 256 such filters. The stride and padding are set to one also the activation function is relu. The resulting feature map is of shape 13X13X256. So if you look at the architecture till now, the number of filters is increasing as we are going deeper. Hence it is extracting more features as we move deeper into the architecture. Also, the filter size is reducing, which means the initial filter was larger and as we go ahead the filter size is decreasing, resulting in a decrease in the feature map shape. Next, we apply the third max-pooling layer of size 3X3 and stride 2. Resulting in the feature map of the shape 6X6X256. After this, we have our first dropout layer. The drop-out rate is set to be 0.5. Then we have the first fully connected layer with a relu activation function. The size of the output is 4096. Next comes another dropout layer with the dropout rate fixed at 0.5.

This followed by a second fully connected layer with 4096 neurons and relu activation. Finally, we have the last fully connected layer or output layer with 1000 neurons as we have 10000 classes in the data set. The activation function used at this layer is Softmax.

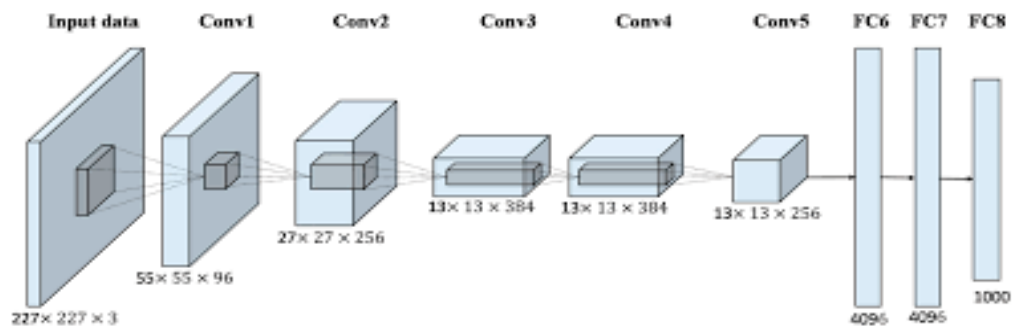


FIG:4.6: ALEXNET ARCHITECTURE.

4.4.3 RESNET101

ResNet-101 is a convolutional neural network that is 101 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. For more pretrained networks in MATLAB®, see Pre Trained Deep Neural Networks.

You can use `classify` to classify new images using the ResNet-101 model. Follow the steps of Classify Image Using GoogLeNet and replace GoogLeNet with ResNet-101.

To retrain the network on a new classification task, follow the steps of Train Deep Learning Network to Classify New Images and load ResNet-101 instead of GoogLeNet.

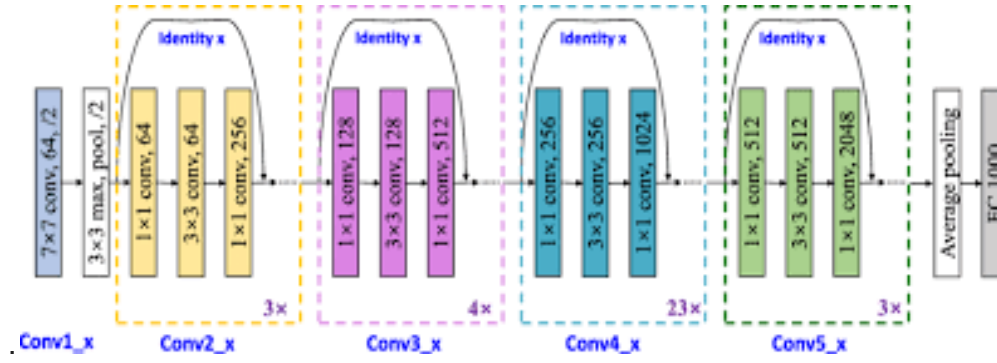


FIG:4.7: RESNET101 ARCHITECTURE

4.5.4 MOBILENETV2

In MobileNetV2, there are two types of blocks. One is residual block with stride of 1 and another one is block with stride of 2 for downsizing. There are 3 layers for both types of blocks. This time, the first layer is 1×1 convolution with ReLU6. The second layer is the depthwise convolution. The third layer is another 1×1 convolution but without any non-linearity. It is claimed that if ReLU is used again, the deep networks only have the power of a linear classifier on the non-zero volume part of the output domain. And there is an expansion factor t . And $t=6$ for all main experiments. If the input got 64 channels, the internal output would get $64 \times t = 64 \times 6 = 384$ channels.

where t : expansion factor, c : number of output channels, n : repeating number, s : stride. 3×3 kernels are used for spatial convolution. In typical, the primary network (width multiplier 1, 224×224), has a computational cost of 300 million multiply-adds and uses 3.4 million parameters. The performance trade offs are further explored, for input resolutions from 96 to 224, and width multipliers of 0.35 to

1.4. The network computational cost up to 585M MAdds, while the model size varies between 1.7M and 6.9M parameters. To train the network, 16 GPU is used with a batch size of 96.

Input	Operator	Output
$h \times w \times k$	1x1 conv2d, ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwconv s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

MobileNetV2 is a convolutional neural network architecture that seeks to perform well on mobile devices. It is based on an inverted residual structure where the residual connections are between the bottleneck layers.

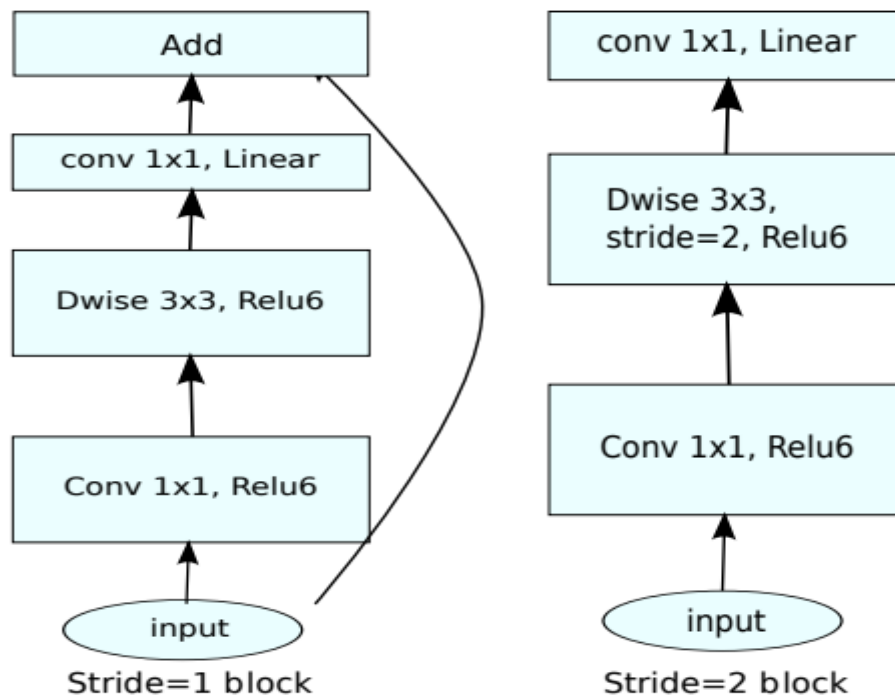


FIG:4.8: MOBILENETV2 ARCHITECTURE

4.5.5 SHUFFLENET

ShuffleNet is a convolutional neural network designed specially for mobile devices with very limited computing power. The architecture utilizes two new

operations, pointwise group convolution and channel shuffle, to reduce computation cost while maintaining accuracy. ShuffleNet is a convolutional neural network designed specially for mobile devices with very limited computing power. The architecture utilizes two new operations, pointwise group convolution and channel shuffle, to reduce computation cost while maintaining accuracy. Channel Shuffle is an operation to help information flow across feature channels in convolutional neural networks. It was used as part of the ShuffleNet architecture. If we allow a group convolution to obtain input data from different groups, the input and output channels will be fully related.

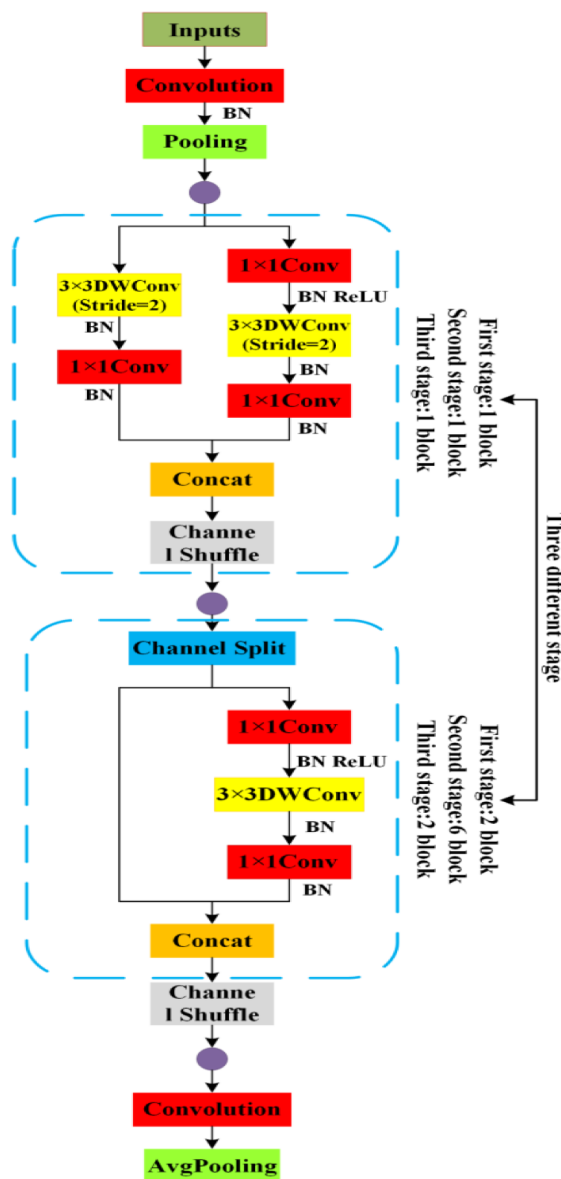


FIG:4.9:SHUFFLENET ARCHITECTURE

4.5 RESULTS FOR EXISTING NETWORKS

PRE-TRAINED NETWORK	ACCURACY
Alexnet	71.43
Resnet101	79.47
Densenet201	73.21
Shufflenet	78.57
Mobilenetv2	75.89
Resnet18	75
Darknet19	77.68
Xception	75

4.6 EXISTING NETWORKS

The highest level of accuracy is resnet101. The number of layers is 101 layers deep. You can load a pre-trained version of network trained on more than a million images from the imagenet database networks. fig:4.10 is represented as on specificity level and accuracy in Resnet 101.fig:4.11 is represented as on specificity level and accuracy in shufflenet.fig:4.12 is represented as on specificity level and accuracy in darknet19.

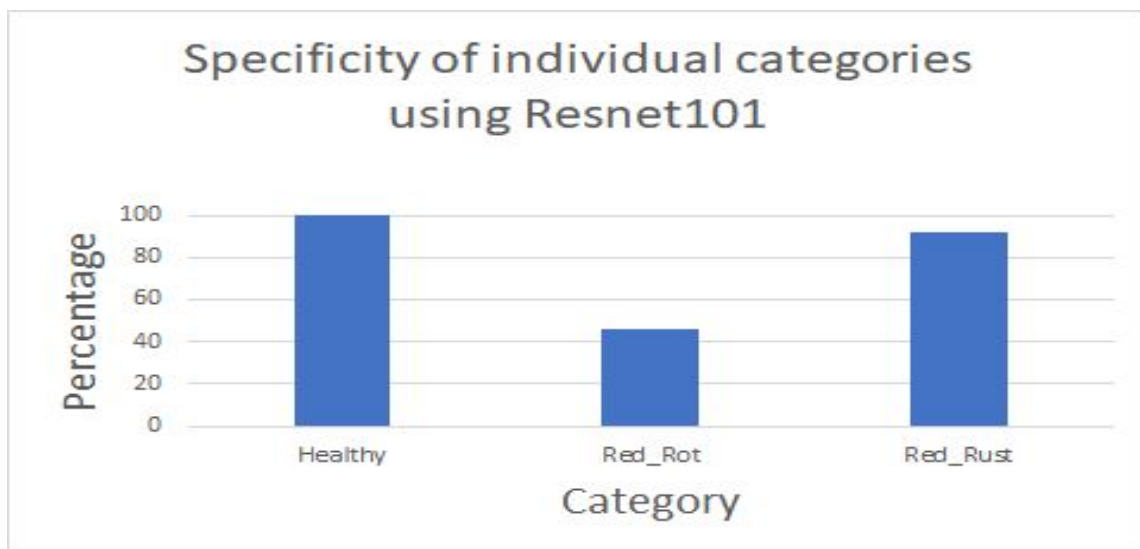


Fig:4.10: Resnet101 Graph

The image categories of the Resnet 101. Healthy is the highest percent of all the categories Healthy is 100 percent, Red_Rot is 44 percentage and Red_Rust is 86 percent.

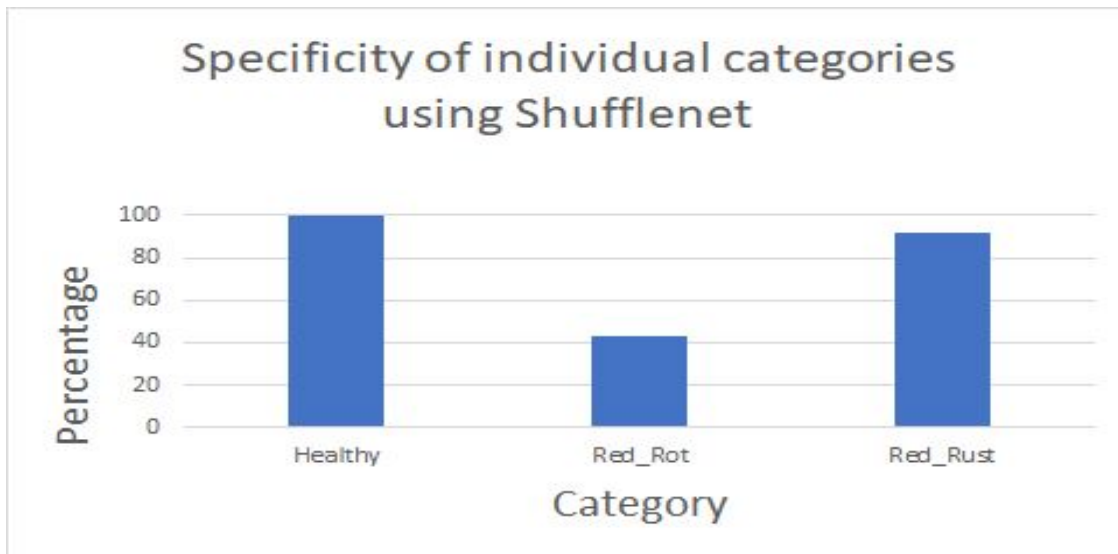


Fig:4.11: Shufflenet Graph

The image categories of the Shufflenet. Healthy is the highest percent of all the categories Healthy is 100 percent, Red_Rot is 42 percent and Red_Rust is 86 percent.

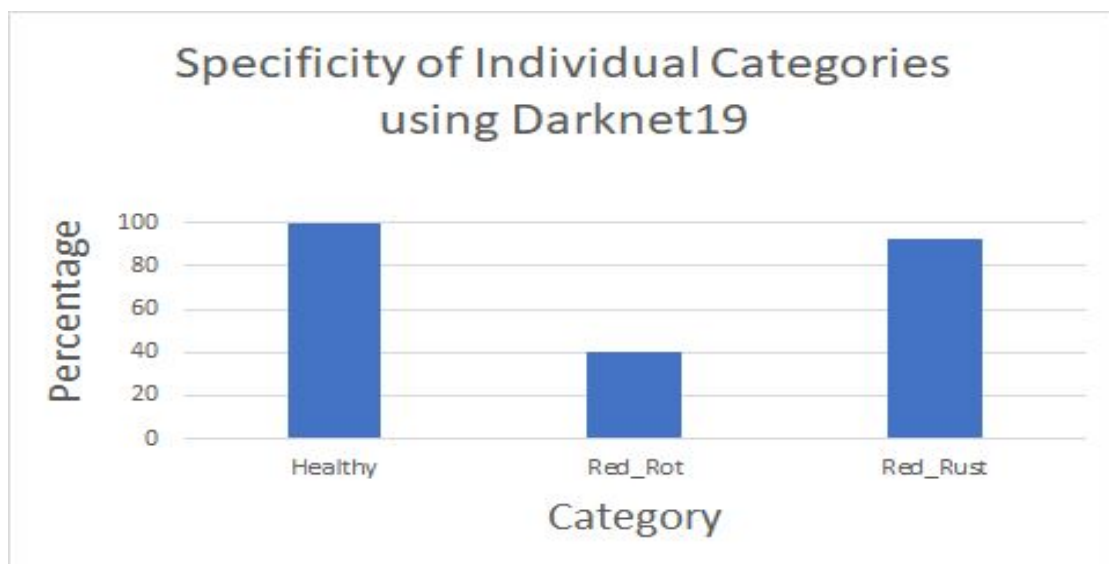


Fig:4.12: Darknet19 Graph.

The image categories of the Darknet19. Healthy is the highest percentage of all the categories Healthy is 100 percent, Red_Rot is 40 percent and Red_Rust is 86 percent.

CHAPTER 5

PROPOSED METHODOLOGY

5.1 TYPES OF LAYERS IN RESNET

Each ResNet block is either two layers deep (used in small networks like ResNet 18, 34) or 3 layers deep (ResNet 50, 101, 152). 50-layer ResNet: Each 2-layer block is replaced in the 34-layer net with this 3-layer bottleneck block, resulting in a 50-layer ResNet.

50-layer ResNet: Each 2-layer block is replaced in the 34-layer net with this 3-layer bottleneck block, resulting in a 50-layer ResNet (see above table). They use option 2 for increasing dimensions. This model has 3.8 billion FLOPs.

101-layer and 152-layer ResNets: they construct 101-layer and 152-layer ResNets by using more 3-layer blocks (above table). Even after the depth is increased, the 152-layer ResNet (11.3 billion FLOPs) has lower complexity than VGG-16/19 nets.

5.2 PROPOSED WORK OF REANET101

The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself. CNN is also computationally efficient.

The traditional neural networks that serve as the basis for many computer vision applications are called ResNets, short for Residual Networks. ResNet's major innovation allows us to successfully train very deep neural networks with over 150 layers. A convolutional neural network layer of 101 is called ResNet-101. The ImageNet database contains pretrained versions of networks trained on over a million images [1]. Thus, the network acquired rich feature representations for various images. The neural network accepts images with a resolution of 224 x 224. For other pre-trained neural networks in MATLAB®, see Pre Trained Deep Neural Networks. New photos can be classified using the ResNet-101 model. Classify the image using GoogLeNet instructions, but replace GoogLeNet with ResNet-101.

Finally, there are 32 sets in Resnet101 with 347 layers and 379 connections. Then you can add another set: 3 convolutions, 3 batch normalization, 3 leakyRel layers,

1 extra layer. con1 filter size is 1.1, filter number is 512, con2 filter size is 3.3, filter number is 512, con3 filter size is 1. 1. The filter number is 2048. Fixed in Resner 101. Forms a modified resnet101, so the result is 81.25.fig:5.1 is Architecture of modified Resnet101.fig:5.2 is specificity level of modified resnet101.

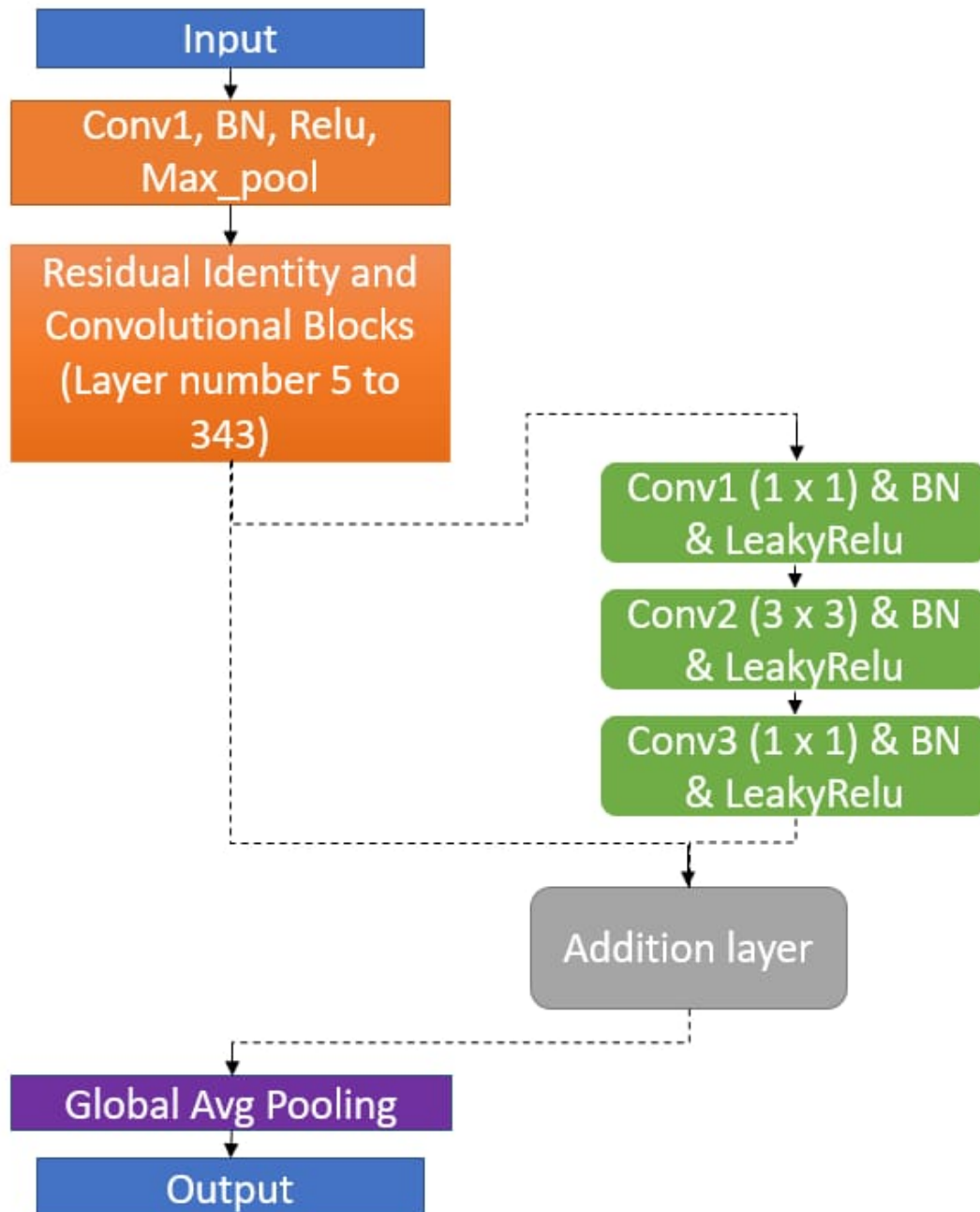


Fig: 5.1: Modified Resnet101 Architecture

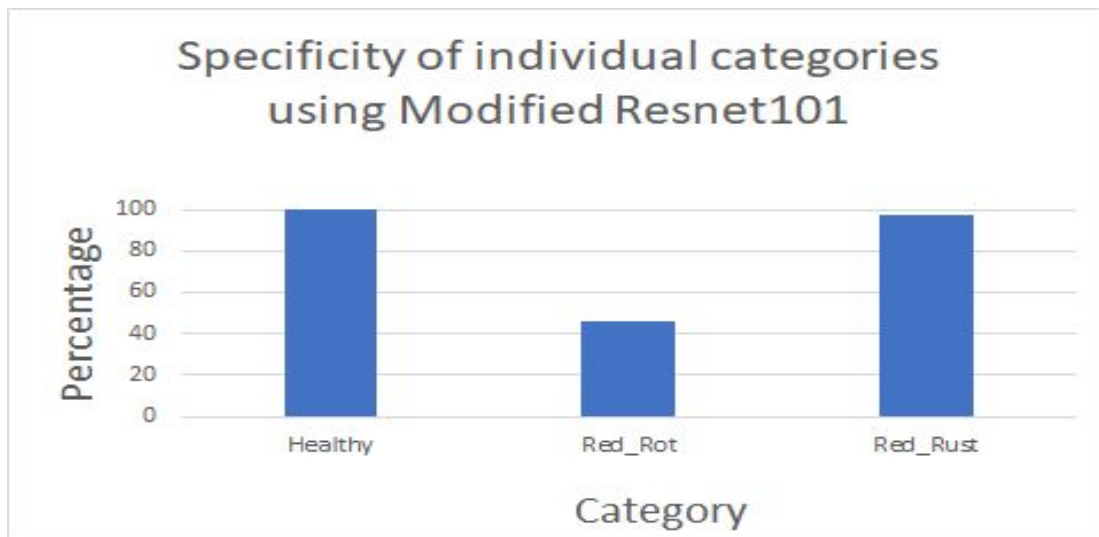


Fig:5.2: modified resnet101 Graph

5.3 PROPOSED METHOD CNN IN RESNET101

New photos can be classified using the ResNet-101 model. Classify the image using GoogLeNet instructions, but replace GoogLeNet with ResNet-101.

Now, I will briefly explain these models. The ResNet was introduced to solve the problems of increasing network depth. The main idea of the ResNet model is in utilizing Residual blocks. In this network, communication is considered outside the convolutional structure to move the input of the previous layer to the next layer without intermediaries. These connections are called Skip connections and this structure is called a Residual block.

NETWORKS	ACCURACY
Resnet101	79.47
Modified_Resnet101	81.25
Densenet201	73.21
Shufflenet	78.57
Mobilenetv2	75.89
Resnet18	75
Darknet19	77.68
Xception	75
Alexnet	71.43

CHAPTER 6

RESULT AND ANALYSIS

Then the highest validation accuracy is 79.47 obtained over 6 epochs of training section using resnet101. Then the shufflelet model achieves the rate of 77.68 and dark19 achieves the rate of 77.68. So we can modify the highest accuracy rate in Resnet 101.fig:6.1: show the Accuracy level of the pre-trained network.

ResNet-101 is a convolutional neural network that is 101 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

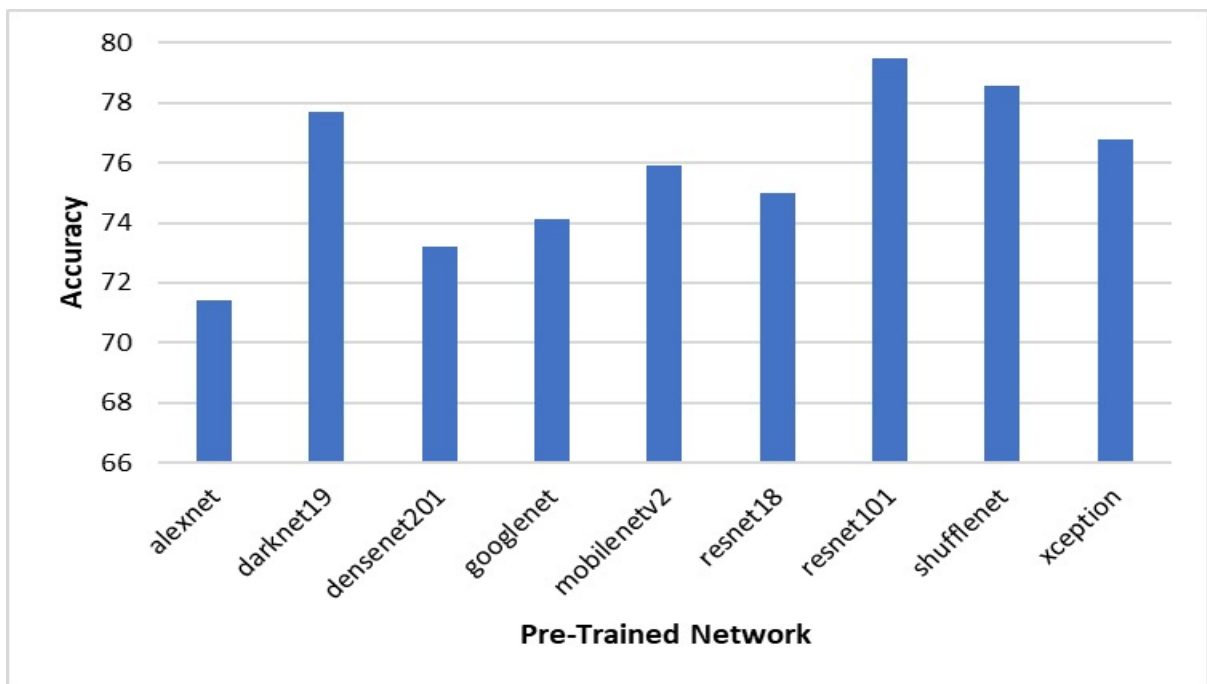


Fig:6.1 Accuracy of pre-Trained Networks

Then the results show the models perform well on the classification of sugarcane leaf disease. Then finally we can modify the highest accuracy rate in Resnet101. Fig 6.2 shows the comparison between actual resnet101 and modified resnet101.

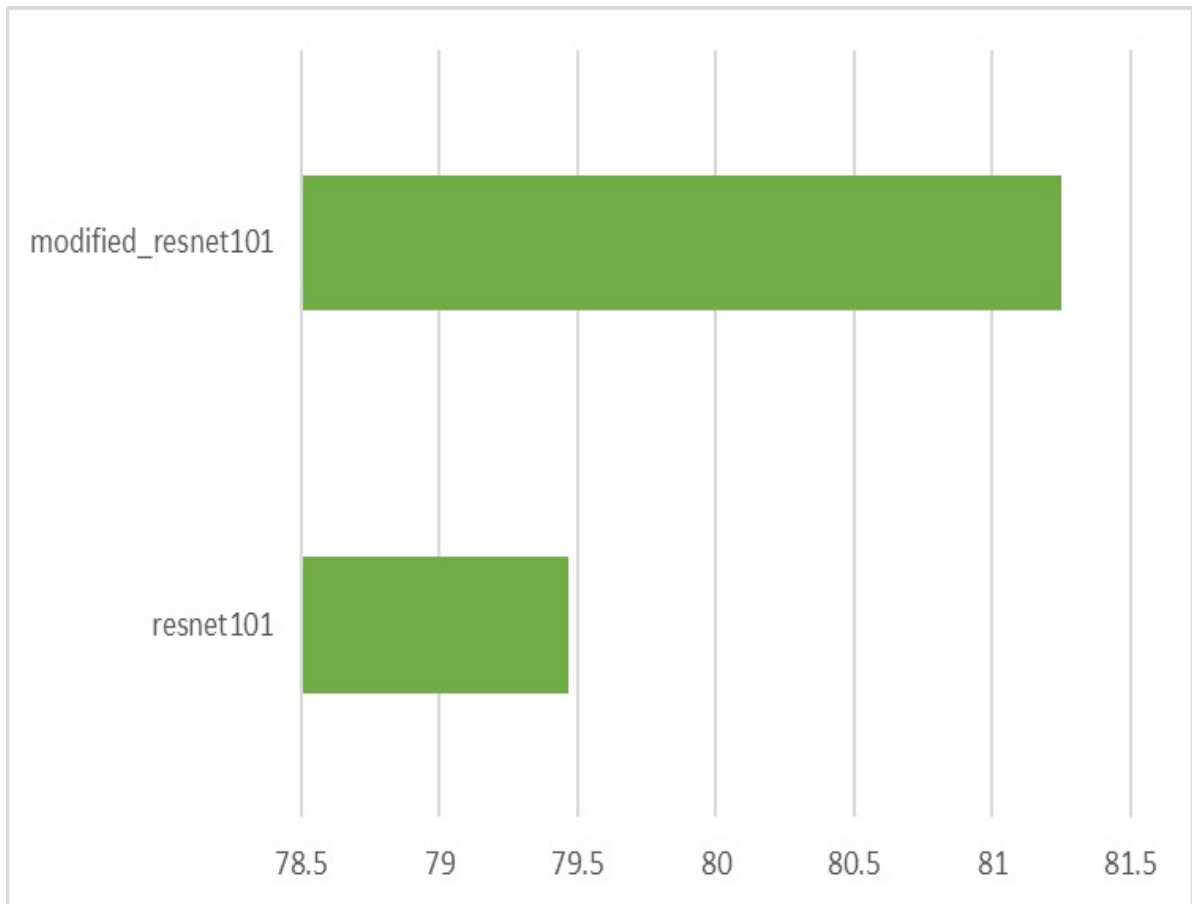


Fig:6.2: Resnet101 and modified-Resnet101 Graph.

CHAPTER 7

CONCLUSION AND FUTURE WORK

In order to identify and categorize leaves according to the diseases they carry, we used an approach in this paper that relies on image processing combined with deep learning (Convolutional Neural Networks). According to our test, the Resnet101 model has the highest rate accuracy for detecting sugarcane leaf disease. The lowest rate is achieved by Resnet 18 however. The modified resnet101 is 81.25, while the actual resnet101 is 79.46. For the upcoming work, we can expand the datasets to be used to verify, speed up learning, and optimize the models indicated above. This decision-making tool is intended to help farmers identify and recognise the sugarcane diseases that were discovered during the course of our project's research.

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APPENDIX

A. RESEARCH PAPER

SugarCane Disease Identification And Quality Check Using Image Processing

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Abstract—This work offers a quality control and illness detection method for sugarcane based on image processing. The suggested technique entails utilizing a digital camera to take pictures of sugarcane leaves, then preprocessing them to improve their quality. The sugarcane leaf is then separated from the backdrop using a segmentation algorithm, and attributes like color, texture, and shape are extracted using feature extraction techniques. Based on the retrieved features, a classification system divides the sugarcane leaf into various disease categories. The suggested method can also evaluate the sugarcane's quality by spotting flaws including splits, cracks, and bruising. The study's findings show how well the suggested approach works for precisely detecting sugarcane diseases and defects, offering a possible tool for early disease diagnosis and prevention as well as for maintaining sugarcane industry quality control.

Keywords—Convolutional Neural Network; sugarcane leaf disease recognition, deep learning, image classification.

I. INTRODUCTION

Identification of sugarcane diseases by unassisted eye detection of symptoms on plant leaves consolidates rapidly growing complexity. Even seasoned agricultural specialists and plant pathologists usually fail to accurately evaluate specific illnesses as a result of this complexity as well as the vast number of evolved Crops and their current phytopathology concerns, which leads to mixed-up ends and concern arrangements. Beginners in the horticultural cycle could benefit greatly from a robotized framework designed to help differentiate plant illnesses by the appearance and visual manifestations of the plant. This will be shown to be a useful tactic for ranchers and will alert them at the appropriate moment before the illness spreads across a wide area.

Deep learning is a cutting-edge method for managing images and analyzing data that produces exact results and has enormous potential. Deep learning has just entered the field of agribusiness because of its success in other applications. Thus, we will dedicate ourselves assiduously to determining how to calculate the recognition and characterisation of plant leaf illnesses by robots. Convolutional neural networks are now regarded as the primary approach for object localization. In this study, we

focused on three locators: Single Shot Multibox Detector, Region-Based Fully Convolutional Networks, and Faster Region-Based Convolutional Neural Network (Faster R-CNN) (SSD).

Depending on the application or necessity, each design should be prepared to be converged with any component extractor. Deep learning is a cutting-edge method for managing images and analyzing data that produces exact results and has enormous potential. Deep learning has just entered the field of agribusiness because of its success in other applications. Thus, we will dedicate ourselves assiduously to determining how to calculate the recognition and characterisation of plant leaf illnesses by robots. Convolutional neural networks are now regarded as the primary approach for object localization. In this study, we focused on three locators: Single Shot Multibox Detector, Region-Based Fully Convolutional Networks, and Faster Region-Based Convolutional Neural Network (Faster R-CNN) (SSD).

Every one of the designs ought to be ready to be converged with any component extractor relying upon the application or need.

II. CONVOLUTIONAL NEURAL NETWORK

CONVOLUTIONAL NEURAL NETWORK (CNN) A CONVOLUTIONAL NEURAL NETWORK, OFTEN KNOWN AS CONVNETS, HAS THREE LAYERS:

i) Convolutional layer (CONV)

They are responsible for performing convolution operations and are the core part of CNN. The element that does the convolution operation in this layer is the Kernel/Filter (matrix). The kernel executes horizontal and vertical shifts based on the stride rate until the entire image has been scanned. They are responsible for performing convolutional operations and are the core part of CNN. The element that does the convolution operation in this layer is the Kernel/Filter (matrix). The kernel executes horizontal and vertical shifts based on the stride rate until the entire image has been scanned.

ii) Pooling layer (POOL)

This layer does the dimensionality reduction. The amount of computing required to process the data is reduced as a result. The two different types of pooling are average pooling and maximum pooling. Max pooling returns the highest value from the picture's covered region by the

kernel. The result of average pooling is the average of all the values in the region of the picture that the kernel is covering.

iii) Fully Connected (FC) Layer

Each input is connected to each neuron in a fully connected (FC) layer, which operates on a flattened input. The FC layers (if present) are usually located near the end of the CNN architecture.

III. DATA SET

This data set contains three catalog classes: Red Rot, Red Rust, and Healthy. I visited and collected sugar cane mold and collection methods through Google lectures on kaggle.com. The red Rot has 74 images, the red rust has 74 images, and finally the healthy one has 76 images. You can then finally split it into two sets: training and testing. 112 images are tested and 112 images are also trained. Then, finally, this image can be used to identify sugar cane diseases.

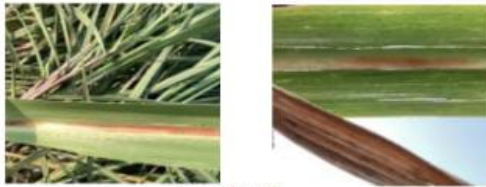


Fig 1 : Red Rot



Fig 2 : Red Rust



Fig 3 : Healthy

IV. EXISTING SYSTEM

Plants are helpless against several issues and attacks brought on by diseases. There are a few factors that can be categorized as having an effect on plants, including ecological variables such as temperature, stickiness, nutrient quantity or lack, light, and the most well-known. authors' attention The role of color transformation structure in the use of texture for the detection of sugarcane disease Since HSV is a suitable way to describe colors, RGB is

transformed into space. Segmentation and specified threshold levels are used to mask and remove green pixels

We can use the matlab software tool to analyze the result of a pre-trained network. Using the kaggle.com website for collecting data sets. The data set consists of three categories: Red Rot, Red Rust, Healthy. All the three categories are used in pre-trained networks.

PRE-TRAINED WORKS

Alexnet, Resnet101, Densenet201, Shufflenet, Mobilenetv2, Resnet18, Darknet19, Xception.

DISADVANTAGE

Although theoretically feasible, these are rarely used because of the lengthy calculating process and the complexity of the interpretation. The values of all the characteristics rise proportionally with the size of the image from which the texture features are retrieved.

PRE-TRAINED NETWORK	ACCURACY
Alexnet	71.43
Resnet101	79.47
Densenet201	73.21
Shufflenet	78.57
Mobilenetv2	75.89
Resnet18	75
Darknet19	77.68
Xception	75

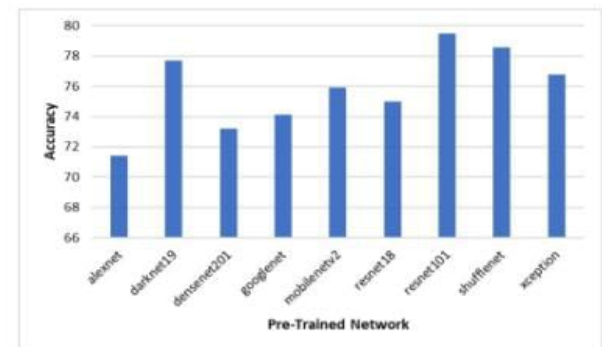


Fig 4: to show the specificity level of pre-trained networks.

The highest level of accuracy is resnet101. The number of layers is 101 layers deep. You can load a pre-trained version of network trained on more than a million images from the imagenet database. fig 4: to show the specificity level of pre-trained networks. fig 5 is represented as on specificity level and accuracy in Resnet 101. fig 6 is represented as on specificity level and accuracy in shufflenet. fig 7 is represented as on specificity level and accuracy in darknet19.

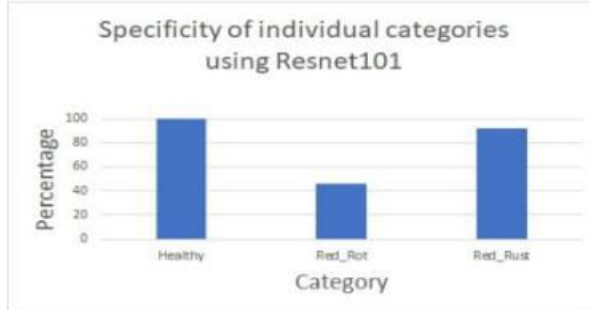


Fig:5 is the specificity level of resnet101.

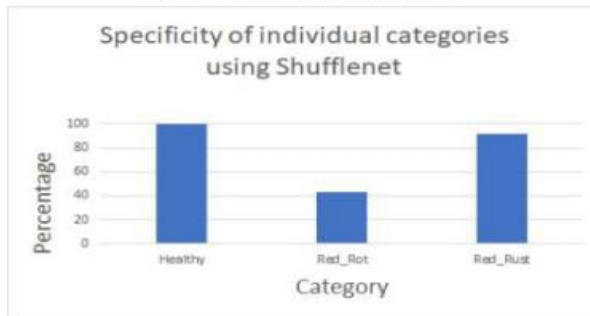


Fig:6 Specificity level of shufflenet.

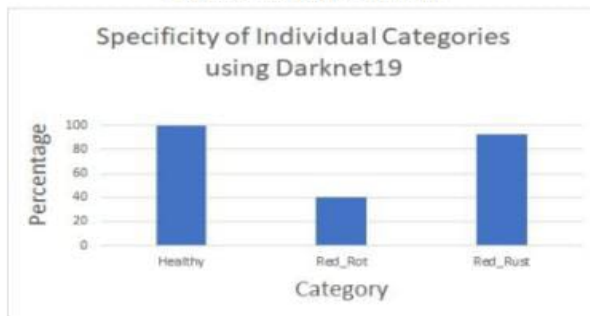


Fig:7 Specificity level of darknet19.

V. PROPOSED SYSTEM

The traditional neural networks that serve as the basis for many computer vision applications are called ResNets, short for Residual Networks. This model won the 2015 ImageNet competition. ResNet's major innovation allows us to successfully train very deep neural networks with over 150 layers. A convolutional neural network with layers of 101 are called ResNet-101. The ImageNet database contains pretrained versions of networks trained on over a million images [1].

Thus, the network acquired rich feature representations for various images. The neural network accepts images with a resolution of 224 x 224. For other pre-trained neural networks in MATLAB®, see Pre Trained Deep Neural Networks.

New photos can be classified using the ResNet-101 model. Classify the image using GoogLeNet instructions, but replace GoogLeNet with ResNet-101.

Finally, there are 32 sets in Resnet101 with 347 layers and 379 connections. Then you can add another set: 3 convolutions, 3 batch normalization, 3 leakRel layers, 1 extra layer. con1 filter size is 1.1, filter number is 512, con2 filter size is 3.3, filter number is 512, con3 filter size is 1.1. The filter number is 2048. Fixed in Resnet 101. Forms a modified resnet101, so the result is 81.25.

NETWORKS	ACCURACY
Resnet101	79.47
Modified_Resnet101	81.25

VI. RESULT AND ANALYSIS

Then the highest validation accuracy is 79.47 obtained over 6 epochs of training section using resnet101. Then the shufflelet model achieves the rate of 77.68 and dark19 achieves the rate of 77.68. So we can modify the highest accuracy rate in Resnet 101. Fig.8 to show the specificity level of modified Resnet 101.

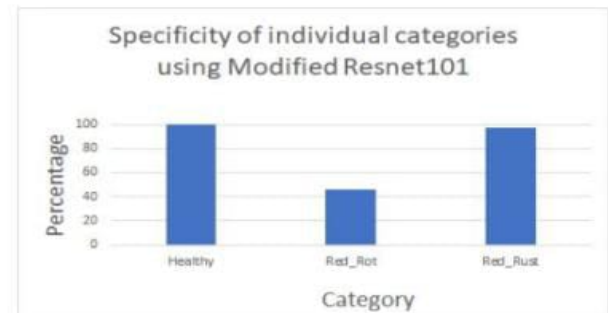


Fig:8 modified resnet101

Then the results show the models perform well on the classification of sugarcane leaf disease. Then finally we can modify the highest accuracy rate in Resnet101. Fig.9 show the comparison between actual resnet101 and modified resnet101.

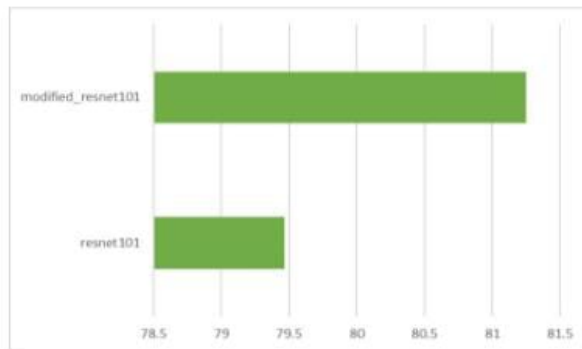


Fig:9 comparison b/w Resnet101 and modified Resnet101.

VII.CONCLUSION

In order to identify and categorize leaves according to the diseases they carry, we used an approach in this paper that relies on image processing combined with deep learning (Convolutional Neural Networks). According to our test, the Resnet101 model has the highest rate accuracy for detecting sugarcane leaf disease. The lowest rate is achieved by Resnet 18 however. The modified resnet101 is 81.25, while the actual resnet101 is 79.46. For the upcoming work, we can expand the datasets to be used to verify, speed up learning, and optimize the models indicated above. This decision-making tool is intended to help farmers identify and recognise the sugarcane diseases that were discovered during the course of our project's research.

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