PLANT LEAF DISEASE DETECTION USING MACHINE LEARNING ALGORITHMS

A Project Report submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

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ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES

(UGC AUTONOMOUS)

(*Permanently Affiliated to AU, Approved by AICTE and Accredited by NBA & NAAC)*

Sangivalasa, Bheemili mandal, Visakhapatnam dist.(A.P)

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CERTIFICATE

This is to certify that the project report entitled **"PLANT LEAF DISEASE DETECTION USING MACHINE LEARNING ALGORITHMS"** submitted by **T.Lalithya Rama(319126512058), V.Praveen(319126512061), G.Jayanth(319126512019), S.Jaya Prakash(319126512051)** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** *in* **Electronics & Communication Engineering** of Anil Neerukonda Institute of Technology and Sciences(A), Visakhapatnam is a record of bonafide work carried out under my guidance and supervision.

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ABSTRACT

Plants are very essential in our life as they provide source of energy and overcome the issue of global warming. Plants now a days are affected by diseases like bacterial spot, late blight, Septoria leaf spot. These diseases effect the efficiency of crop yield. So ,the early detection of diseases is important in agriculture. Detection of diseases as soon as they appear is vital step for effective disease management.

Aim of the project is to detect plant leaf disease by Machine Learning using image and videos. For Image, the proposed algorithm is Random forest classifier-Machine learning Algorithm used for classification and for video the proposed technique is Resnet50- Deep Learning Algorithm. These techniques will obtain prediction results using various metrics like accuracy, precision and efficiency. This project can be implemented in agriculture, nursery, college gardens etc.

KEYWORDS: Random forest classifier,Resnet-50.

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TN	True Negative	28
FP	False Positive	28
FN	False Negative	28

CHAPTER 1
INTRODUCTION

1.1 Project Objective:

The primary objective of plant disease detection is to identify and diagnose plant diseases accurately and quickly. This is important to prevent the spread of the disease and to minimize crop loss. Early detection of plant diseases is crucial to prevent the spread of the disease and to minimize crop damage. Disease detection using Machine Learning Algorithms should be reliable and produce consistent results.

1.2 Plant Leaf Disease:

A disturbance in the stock situation of a herb that destroys or alters crucial. All types of herbs, both unbroken and educated, are susceptible to illness. Each family is prone to specific diseases, but each of these is relatively rare. The incidence and prevalence of plant illness vary from prime to prime, pivoting on the company of pathogens, territory conditions, and the supply and cultivars grown. Some plant varieties are particularly susceptible to disease epidemics, while others are more resilient. See also list of herb illness.

- **Definitions of plant disease**

Generally, when plants are consistently disturbed, they might catch illness. pathogens that result in abnormal physiological processes that disrupt the normal structure, growth, function, or other activities of the plant. The essential physiological or biochemical processes of the plant are disrupted, which results in the typical diseased states or symptoms. Depending on whether the primary cause of the disease is infectious or non-infectious, plant diseases may be broadly categorised. Infectious plant diseases are caused by pathogens such as fungi, bacteria, mycoplasma, viruses, viroids, nematodes, or parasitic flowering plants. Within or on a host, infectious organisms can grow and spread from one vulnerable host to another. Unfavorable growth circumstances, including as excessive temperatures, unfavorable moisture-oxygen ratios, soil and air pollutants, and an abundance or shortage of vital minerals, are the root causes of non-infectious plant illnesses.

- **Temperature**

All pathogens have an optimum growth temperature. In addition, the optimal temperature may differ slightly due to different stages of fungal growth, such as the production of spores (reproductive units), their germination, and the growth of the mycelium (the filamentous body of the fungus). Warehouse conditions for certain berry, greens, and nest produce are manipulated to control fungi and bacteria that cause storage spoilage, so long as the febricity does not alter the quality of the produce. Aside from limited dip protection, there is little you can do to control the temperature in your field, but you can adjust the temperature in your greenhouse to reduce disease outbreaks. Combined with high humidity conditions, it allows the development of diseases such as vine downy mildew (Pseudoperonospora cubensis), lima bean (Phytophthora phaseoli) and late blight on potatoes. These include precision tomato (Phytophthora infestans), sugar beet leaf spot . However, temperature effects can mask the symptoms of certain aggressive and mycoplasmal diseases, making them more onerus to detect.

- **Relative humidity**

Relative moisture is exact important for the germination of fungal spores and the evolution of warehouse rot. Rhizopus stolonifer of sweet potatoes is an example of a storage illness that does not evolution when the relative moisture of the black skin of potatoes is maintained between 85-90%, even though the storage temperature is optimal for the growth of the pathogen. Under these conditions, sweet potato roots produce a slippery (corky) tissue that protects the Rhizopus fungus. You are more likely to get sick. Humidity is generally required for spore germination, bacterial growth and invasion, and allusion of infection. mustiness germinate best at 90-95% relative humidity. disease of Greenhouse crops such as Botrytis species rotting herbs, leaves, stems and seedlings of herbs plants are controlled by reducing humidity levels or not spraying the plants with water.

- **Soil pH**

As a gauge of bite, soil pH has a significant impact on conditions like: B. Cruciferous plant gall root and potato scab (Plasmodiophora cruciferous). pH 5.2 or lower inhibits the growth of potato scab (pH 7 is neutral; values below 7 indicate acidity, values over 7 indicate alkalinity). If the pH of the natural soil is about 5.2, scabs are typically okay. To keep the pH of their potato soil at 5.0, some growers use sulphur. On the other hand, by thoroughly incorporating lime into the soil until the pH is 7.2 or higher, it is typically possible to control the root knot of cruciferous vegetables.

Requirements for disease development

If any one of the following three fundamental requirements is absent, infectious illness cannot occur:(1) the right conditions, with the most crucial conditions being the quantity and frequency of rain or heavy dews, the relative humidity, and the temperatures of the air and soil, (2) the presence of a virulent pathogen, and (3) a vulnerable host. Breaking this triangle between environment, pathogen, and host is the goal of efficient disease prevention strategies. For instance, if the host can be made more resistant or immune by methods like plant breeding or genetic engineering, the loss brought on by the disease is lessened. In addition, the environment might be changed to promote the growth of the host plant more than the invasion of the pathogen. Finally, the infection can be eliminated or stopped from spreading.

Classification of plant diseases by causal agent

The physiological effects or symptoms of plant diseases are frequently used to categorise them. However, many diseases have essentially same symptoms and signs but are brought on by totally different bacteria or substances, necessitating the employment of entirely different control strategies. The classification of diseases based on their symptoms is also insufficient because a causal agent may generate a variety of symptoms, even on the same plant organ, several of which frequently coexist. The classification may take the afflicted plant species into account. Host indexes, or listings of diseases known to affect particular hosts in particular areas, nations, or continents, are useful in the diagnosing process. When an apparently novel disease is discovered on a well-known host, looking up the host's entry in the index frequently identifies the responsible agent. Diseases can also be categorized.

Noninfectious disease-causing agents

Unfavorable soil moisture-oxygen relations, extremes in soil acidity or alkalinity, high or low temperatures, pesticide injury, other poisonous chemicals in the air or soil, changes in soil grade, girdling of roots, mechanical and electrical agents, and soil compaction are all factors that contribute to the development of non-infectious diseases, which can sometimes occur very suddenly. Losses are frequently caused by unsuitable preharvest and storage conditions for fruits, vegetables, and nursery stock.

Numerous plant species that are present in a certain area or environment might be affected by non-infectious diseases. Noninfectious diseases and injuries frequently result in severe losses yet are challenging to prevent or treat because they frequently reflect ecological conditions that are out of human control. Several weeks or months after an environmental disturbance, symptoms may start to manifest. Accidental, poisonous, or severe environmental injuries frequently leave a plant with weak tissues that allow bacteria, fungus, or viruses to penetrate and cause even more harm. A clear reason, like hail or lightning, may be present, although this is not always the case. It is frequently difficult to determine the causal component solely from symptoms. a detailed analysis of current weather patterns, the health of nearby plants, and cultural.

- **Infectious disease-causing agents**

Thousands of species from incredibly varied families of creatures can infect plants. Few are macroscopic, while the majority are tiny. The infectious agents, also known as pathogens, include bacteria, fungi, nematodes, generally known as mycoplasma-like organisms (MLOs), and parasitic seed herbs.

Diseases caused by viruses and viroids

- **General characteristics**

Of all the infectious agents, viruses and viroids are the tiniest. A virion is an infectious particle that has reached structural maturity. The sizes and forms of virions range from about 20 nanometers (0.0000008 inch) to 250-400 nanometers. In contrast to viruses, viroids lack structural proteins, such as those that make up the protein coat (capsid) of viruses. Both viruses and viroids are obligatory parasites, meaning they can only replicate or multiply inside a specific host's live cell. A single plant species could be vulnerable to a variety of viruses or viroids. Viral infection causes serious disease in essential **.**

- **Diseases caused by fungi**

An estimated two thirds of infectious plant illnesses are caused by fungi. All commercially significant plants appear to be under the attack of one or more fungi, and in many cases, many fungi from different species can affect a single plant species.

- **General characteristics**

The fungus are a very varied and expansive class of eukaryotic microorganisms. The cells lack chlorophyll and have hard cell walls. They also have a membrane-bound nucleus. Many fungi have a vegetative body that resembles a plant made of microscopic branching filaments of different lengths, known as hyphae (plural hypha), some of which extend into the air and others of which pierce the substrate on which they develop. The network of hyphae is known as the mycelium. The "cottony" or "fuzzy" appearance of fungal growth is caused by the mycelium's bulk. Fungi can reproduce in a number of ways, including asexual and sexual ones. They generate enormous amounts of spores of various types. For instance, A piece of mouldy bread gets its colour from.

- **Diseases caused by nematodes**

Roundworms with no segments that are active and parasitic on plants are called nematodes. (also called nemas or eelworms). Due to their size and transparency, the vast majority cannot be seen with the unassisted eye. Practically all adult forms have a length between 0.25 and 2 mm. Plant disease is caused by about 1,200 species. At least one species of nematode feeds on practically every type of plant life. Although they mostly dwell dirt and prey on tiny roots, several species also live in and feed on bulbs, buds, stems, leaves, and flowers. Nematodes that live on plants as parasites feed by suckling their juices. A hollow, needle-like mouthpart known as a spear or stylet is used for feeding. When the stylet is pushed into plant cells, the nematode injects a liquid containing enzymes that break down the contents of the cells. The stylet is then used to draw the liquid contents back into the nematode's digestive system. Nematode feeding decreases natural resistance, weakens plant vigour and yield, and provides a simple entry point for nematodes that cause root rot or wilt. Plants with nematode infestations are fragile and frequently exhibit symptoms of disease, excessive soil moisture, sunburn, frost, a mineral shortage or imbalance, and insect damage to the roots or stems. Stunting and a loss of green colour are typical signs of nematode injury. When tissues react, cells frequently either grow or degenerate; occasionally both. Numerous native nematodes prey on cultivated plants when their natural hosts are eliminated. Others have been spread by seedling plants, bulbs, tubers, and in particular in the soil that has gathered around the roots of infected nursery stock. Nematodes may spend some of their time unencumbered in the soil near roots or in fields and fallow gardens. They can enter a plant by wounds, natural holes, or by entering roots. They can also tunnel inside plant tissues (endoparasites) or feed externally from the surface (ectoparasites). For reproduction, all nematodes that parasitize plants need living plant tissues. Nematodes are drawn to host roots by the perception of either the heat that roots emit or the substances that roots release. Most species go through four stages of development, from egg to adult and back to egg, in a generation that takes 20 to 60 days to complete. Even while some nematodes only have one generation each year, they still generate several hundred young. The duration of the growing season, temperature, the amount of water and nutrients available, as well as the type, texture, and structure of the soil, all have an impact on soil populations and nematode development rates. Populations of viruses, protozoans, mites, flatworms, or other pests, as well as other nematodes and nematode-parasitic bacteria are also significant. Crop rotations and previous cropping practices, toxic substances applied to the soil or released by plant roots, species, variety, age, and nutrition.

1.3 Importance of Plant Disease Detection:

It is Important for Correct Plant Disease Identification? Disease control initiatives may result in a waste of time and resources without accurate identification. Additional plant losses could result from the application of disease control strategies that are inadequate to handle the disease-causing agent. Infectious parasites including nematodes, fungi, oomycetes, viruses, and bacteria are the root cause of plant illnesses. Because a large range of organisms can cause a variety of symptoms (Figure 1), accurate pathogen identification is essential to creating a management plan. Injury vs. Illness It's critical to comprehend the distinctions between a plant injury and a disease. A sudden injury results from an outside force over a brief period of time.

1.4 Techniques For Disease Detection:

1.4.1 Machine Learning Methods

K-Nearest Neighbour (KNN) Algorithm for Machine Learning

- One of the simplest Machine Learning algorithms, K-Nearest Neighbor is based on the Supervised Learning approach.
- The K-NN algorithm makes the assumption that the new case and the data are comparable to the cases that already exist, and it places the new instance in the category that is most similar to those cases.
- The K-NN algorithm saves all the information that is accessible and categorises additional data points based on similarity. This means that utilising the K-NN method, fresh data can be quickly and accurately sorted into a suitable category.
- Although the K-NN approach can be used for both classification and regression

problems, classification challenges are where it is most frequently applied.

- Since K-NN is a non-parametric technique, it makes no assumptions about the underlying data.
- It is also known as a lazy learner algorithm since it saves the training dataset rather than learning from it immediately. Instead, it uses the dataset to perform an action when classifying data.
- KNN algorithm simply stores the dataset during the training phase and subsequently classifies new data into a category that is quite close to the new data.
- **Example:** When training, the KNN algorithm simply stores the dataset; when it receives new data, it then classifies that data into a category that is quite similar to the new data.

Support Vector Machine Algorithm

One of the most popular supervised learning algorithms is called the Support Vector Machine (SVM), and it is employed to solve Classification and Regression problems. However, it is mostly used in Machine Learning Classification issues. The objective of the SVM method is to find the best decision boundary or line that can classify the n-dimensional space, allowing us to classify additional data points with ease in the future. A hyperplane is the name for this optimal boundary. To assist in creating the hyperplane, SVM selects the extreme vectors and points. Support vectors, which are used to represent these extreme scenarios, are the basis of the SVM methodology. View the graphic below to see how a choice classifies two separate groups.

Types of SVM

There are two types of svm**:**

- **Linear SVM:** The phrase "linearly separable data" describes information that can be split into two categories using just one straight line. This type of data is classified using Linear SVM, and the classifier that is utilised is called the Linear SVM classifier.
- **Non-linear SVM:** A dataset is considered to be non-linear if it cannot be classified using a straight line, in which case the classification technique used is called a non-linear SVM classifier.

- **Hyperplane and Support Vectors in the SVM algorithm**:

Hyperplane: In n-dimensional space, the classes can be divided into a variety of lines or decision borders; nevertheless, it is necessary to choose the best decision boundary for categorising the data points. This ideal boundary is known as the SVM hyperplane.
Given that the dataset's features define the hyperplane's dimensions, a straight line will be the hyperplane if there are just two features (as in the example image). In addition, if there are three features, hyperplane will be a two-dimensional plane.

Support Vectors: The closest data points or vectors near the hyperplane and those that have the most bearing on the hyperplane's position are called support vectors. Because they support the hyperplane, these vectors are referred to as support vectors.

- **Random Forest Algorithm**

Preferred machine learning algorithm Random Forest is a part of the supervised learning strategy. It might be applied to ML issues that call for both regression and classification. It is built on the idea of ensemble learning, which is a method for integrating many classifiers to solve complex issues and enhance model performance.

Random Forest, as the name indicates, is a classifier that increases the projected accuracy of the dataset by averaging numerous decision trees applied to different subsets of the provided data. Instead of depending just on one decision tree, the random forest gathers forecasts from each decision tree and predicts the result based on the votes of the majority of projections.

- **Logistic Regression in Machine Learning**

➢ Logistic regression is one of the most well-known Machine Learning algorithms that falls under the umbrella of Supervised Learning. It is used to forecast the categorical dependent variable using a specified set of independent variables.

➢ Logistic regression may be used to forecast the outcomes of a categorical dependent variable. The outcome must thus be a discrete or categorical value. It offers the probabilistic values that lie between 0 and 1 rather than the precise values between 0 and 1. It can be either True or False, 0 or 1, or Yes or No.

- The use of logistic regression and linear regression differs significantly. In contrast to linear regression, which is used to address classification issues, logistic regression addresses regression issues.
- Instead of fitting a regression line, we use a logistic function with a "S" shape that predicts two maximum values (0 or 1) in logistic regression.
- The logistic function's curve displays the probability of a number of events, including whether or not the cells are cancerous, a mouse.

- **Logistic Function (Sigmoid Function):**

- A mathematical function called the sigmoid function is employed to convert anticipated values into probabilities.
- It transforms any real value between 0 and 1 into another value.
- Since the logistic regression's value must lie within the range of 0 and 1, it can never go above or below this limit, resulting in a "S"-shaped curve. The sigmoid function or logistic function is another name for the S-form curve.
- We apply the threshold value idea in logistic regression, which establishes the likelihood of either 0 or 1. Examples include values that incline to 1 over the threshold value and to 0 below it.

- **Assumptions for Logistic Regression:**

- A categorical variable must be the dependent one.
- Multicollinearity should not exist in the independent variable.

- **Type of Logistic Regression:**

Logistic regression may be divided into three types according to the categories:

- Binomial: A dependent variable in a binomial logistic regression may only be one of two potential kinds, such as 0 or 1, Pass or Fail, etc.
- Multinomial: The dependent variable in multinomial logistic regression may be one of three or more potential unordered kinds, such as "cat," "dogs," or "sheep."
- Ordinal: In an ordinal logistic regression, the dependent variables may be categorised as "low," "Medium," or "High."

CHAPTER 2
LITERATURE SURVEY

1. Unsupervised image translation using adversarial networks for improvedplant disease recognition.

Reference: Nazki et al.

Dataset: 2789 tomato plant disease images

Technique used: Generative Adversarial Network And Deep CNN

Output: Accuracy= 86.1%

Advantages:

Better demonstrating of information appropriation (pictures more honed and more cleared).GANs can prepare any sort of generator organization.

Disadvantages:

Difficult to prepare, unstable training process. Require many guidelines to obtain satisfyingresults. Mode Collapse issue.

2. Cucumber leaf disease identification with global pooling dilated convolutional neural network.

Reference: Zhang et al.

Dataset: Acquisition of 600 cucumber sick leaves of 6 regular cucumber leaf infected

Technique used: GPDCNN

Output: Accuracy = 94.65%

Advantages:

GPDCNN is more robust than different strategies.

Disadvantages:

Completely associated layer has such a large number of parameters which decreases the speedof preparing (training) and effectively bring about over-fitting.

3.Multilayered Convolution neural network for the Classification of mangoleaves infected by Anthracnose Disease.

Reference: SINGH CHOUHA N et al.

Dataset: Captured images at SMVDU, Katra

Technique used: Multilayer convolutional neural network (MCNN)

Output: Accuracy = 97.13%

Advantages:

The essential advantage of MCNN diverged from its paradigms is that it therefore perceivesthe critical features with no human administration.

Disadvantages:

MCNN has a few layers then the training process takes a ton of time if the PC doesn't compriseof a good CPU.

4.Sunflower leaf diseases detection using Image Segmentation based onParticle swarm optimization.

Reference: Vijai Singh

Dataset: Capture Sunflowers leaves.

Technique used: Particle Swarm Optimization Algorithm.

Output: Accuracy = 98%

Advantages:

The upsides of PSO are that PSO is easy to implement and there are scarcely any boundariesto change.

PSO perform in a way that is better than the GA as for computational efficiency.

Disadvantages:

PSO is one of the well known techniques, however its application for the issue isn't confoundedbecause of the simple characteristics.

5.Deep Convolutional neural network based detection system for real timecorn plant disease recognition.

Reference: Mishra et al.

Dataset: Plant Village dataset.

Technique used: Deep Convolution Neural Network

Output: Accuracy = 88.46%

Advantages:

With little dependence on pre-processing, this algorithm requires less human effort. It isactually a self-learner, which makes the preprocessing phase, easier.

Disadvantages:

It requires an enormous dataset to process and train the neural organization.

6.Performance analysis of deep learning CNN models for disease detectionin plants using image segmentation

Reference: Sharma et al.

Dataset: Tomato healthy and infected leaves images

Technique used: Convolution Neural Network

Output: Accuracy = 98.6%

Advantages:

Perhaps the greatest favorable position of CNN is the programmed extraction of highlights byhandling straightforwardly the crude pictures.

Disadvantages:

CNNs don't have arranged outlines which are a fundamental component of human vision.

7.Tomato Leaf Disease Detection using Convolution Neural Network.

Reference: Agarwal et al.

Dataset: Images taken from Plant Village dataset.

Technique used: Images taken from Plant Village dataset.

Output: Classification Accuracy= 76% to 100%, Average Accuracy for disease=91.2 %

Advantages:

The Storage space needed by proposed model was of order of 1.5MB where as pre prepared models had additional room need of around 100MB appropriately demonstrated the upside ofthe proposed model over pre-trained models.

Disadvantages:

A CNN is essentially more slow because of an activity, for example, pooling.

8. Seasonal Crops Disease Prediction and classification Using Deep Convolutional Encoder Network

Reference: Khamparia et al.

Dataset: Plant Village Dataset

Technique used: Deep Convolution Encoder Network

Output: Accuracy = 97.50%

Advantages:

Softmax classifier is used at output layer. It returnsthe probabilities of each class if there should arise an occurrence of a multiorder model, and the target class should have high probability.

Disadvantages:

This method lack a mechanism to map deep layer feature maps to input dimensions.

9. Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification

Reference: Sladojevic et al.

Dataset: Capture images by agricultural experts. **Technique used:** Deep Convolution Neural Network**Output:** Accuracy= 96.3%

Advantages:

DCNNs included image and object classification, face detection, and image segmentation.DCNN have more hidden layers especially more than 5, which increases the accuracy.

Disadvantages:

CNN don't encode the position and direction of an object.

Absence of ability to be spatially invariant to the input information.

10. A Review of Machine Learning Approaches in Plant Leaf Disease Detection and Classification

Reference: MAJJI V APPLALANAIDU, G. KUMARAVELAN.

Dataset: plant village dataset

Technique used: Color Co-occurrence Matrix(CCM), Gray Level Co-occurrence Matrix(GLCM),Minimum Enclosing Rectangle(MER), Color Co-occurrence Matrix(CCM), CCM,GLCM, Discrete Wavelet Transform(DWT) Scale Invariant Feature Transform(SIFT)

Objective: This review provides a comparative analysis of various stateof-the-art ML and DLalgorithms to identify and categorize plant leaf diseases.

11. Research on machine learning framework based on random forest algorithm

Reference: Qiong Ren , Hui Cheng and Hai Han.

Technique used: Random forest algorithm

Objective:

This article examines and analyses the machine learning framework based on the random forest algorithm with the goal of enhancing the random forest algorithm's current restrictions. It also creates and implements a number of machine learning frameworks.

12. Random Forest with Adaptive Local Template for Pedestrian Detection

Reference: Tao Xiang, Tao Li, Mao Ye, and Zijian Liu.**Dataset:** TUD Pedestrians, INRIA pedestrians **Technique used:** Random forest

Output: Accuracy= 90.8%

Objective: Detection of pedestrians in cluttered environments. The main concept of our approach is to combine several weak classifiers that are specified by adaptive local templates and to do it using Random Forest. Iteratively and layer-by-layer, the forest is constructed. The splitting functions in the forest are learned using the adaptive local templates, and when they are all of the same depth, they produce a weak classifier. By minimising a global loss and adding each new weak classifier, sample weights are updated. The suggested technique achieves the state-of-the-art or competitive performance, according on the final experimental findings on two difficult pedestrian datasets.

13. Improving the Random Forest Algorithm by Randomly Varying the Size of the Bootstrap Samples

Reference: Md Nasim Adnan.

Technique used: Random Forest

Objective: By using the Random Subspace technique on bootstrap samples for large dimensional datasets, the Random Forest algorithm provides quite a variety of decision trees as the basic classifiers. By introducing more variation among the decision trees, we may improve the ensemble accuracy. Every time a decision tree is generated as the basis classifier in Random Forest, the size of the bootstrap files stays the same. To improve the accuracy of the forest, we suggest changing the size of the bootstrap samples at random within a predetermined range. We do a thorough experiment using a variety of datasets from the UCI Machine Learning Repository. The outcomes given in this research demonstrate the enormous potential of our method.

14. An Ensemble Random Forest Algorithm for Insurance Big Data Analysis

Reference: Ziming Wu, Weiwei Lin, Zilong Zhang and Angzhan Wen.

Technique used: Random Forest

Objective: This paper analyses the imbalance distribution of insurance business data, concludes the preprocessing algorithms of the imbalance dataset, and proposes an ensemble random forest algorithm based on Apache Spark which can be used in the large scaled imbalanced classification of insurance business data. The experiment results showed that the ensemble random forest algorithm is more suitable in the insurance product recommendation or potential customer analysis than the traditional tra Preprocessing for unbalanced classification algorithms might make use of the suggested bootstrap undersampling approach in conjunction with KNN. Together with bootstrap sample preprocessing, ensemble learning techniques may be able to speed up learning even further. They also provide a useful comparison to other unbalanced data mining strategies.

15. leaf and skin disease detection using image processing

Reference: Manjunath Badiger ,Varuna kumara ,Sachin CN shetty,Sudhir poojary

Technique used: K-means algorithm and SVM classifier

Output: Accuracy = 96.3%

Advantages:

Easy to understand and implement. Can handle large datasets well. Disadvantages of K-MeansSensitive to number of clusters/centroids chosen.

Disadvantages:

It requires to specify the number of clusters (k) in advance.It can not handle noisy data andoutliers.It is not suitable to identify clusters with non-convex shapes.

16.plant disease detection using machine learning

Reference: Niveditha M, pooja R, prasad Bhat N, shashank N

Technique used: HOG, Random forest

Output: Accuracy = 70%

Advantages:

Work well for small resoultions.Typically does detection via classification,i.e uses a binaryclassifier.

Disadvantages:

More time consuming to construct than a frequency polygon.

17. plant disease detection using CNN

Reference: Nishant Shelar ,Suraj shinde ,Shubham sawant ,Shreyas dhumal

Technique used: CNN **Output:** Accuracy = 96%**Advantages:**

local spatial coherence in the input (often images), which allow them to have fewer weights assome parameters are shared. This process, taking the form of convolution makes them especially well suited to extract relevant information at a low computational cost.

Disadvantages:

Classificationof Images with different Positions, Adversarial examples, CoordinateFrame, Other minor disadvantages like performance.

18. Pest detection in crop using video and Image processing

Reference: Madhuri Devi Chodey ,Dr.Noorilla Shariff c ,Gauravi Shetty

Technique used: K-means algorithm and SVM classifier

Output: Accuracy = 96.3%

Advantages:

SVM works relatively well when there is a clear margin of separation between classes. SVM ismore effective in high dimensional spaces.

Disadvantages:

SVM algorithm is not suitable for large data sets.SVM does not perform very well when thedata set has more noise i.e. target classes are overlapping.

19. Image Classification Using Resnet-50 Deep Learning Model

Reference: Aryan Garg **Dataset:** STL-10 **Technique used:** Resnet-50

Output: Accuracy= 76.229%

Advantages:

Networks with large number (even thousands) of layers can be trained easily without increasingthe training error percentage.

Disadvantages:

High computational complexity - Residual neural networks can often require significantprocessing power and may not be suitable for certain tasks.

20. Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer

Reference: Devvi Sarwinda , Radifa Hilya Paradisa , Alhadi Bustamam ,Pinkie Anggia

Dataset: Warwick-QU

Technique used: Deep Residual Network (ResNet)

Output: Accuracy= 73% -88%

Advantages:

ResNets help in tackling the vanishing gradient problem using identity mapping.

Disadvantages:

High memory requirements - Residual networks require large amounts of memory in order to store the necessary parameters and weigh

CHAPTER 3
IMAGE PROCESSING

3.1 Introduction to Image Processing:

It is a technique for translating a physical image to digital form so that it can be manipulated, added to, or extracted information from. In the field of image science, image processing denotes to any category of indication treating where the contribution is an image, such as a picture or video frame, and the yield can either be another copy or a set of parameters or characteristics that relate to the image. Although optical and analogue image processing are also feasible, digital image processing is the most common type. Imaging is the process of acquiring images, which initially produces the input image.

Image processing is used to improve an existing image or to extract useful data commencing it. This is significant in various Deep Learning-based Computer Visualization applications, because such preprocessing can significantly improve model performance. Another application, particularly in the entertainment business, is picture manipulation, such as adding or deleting items from photos.

The bulk of image processing algorithms treat the image as a two-dimensional signal, which is subsequently processed using standard signal processing techniques. Sub-images in a photograph might be thought of as ROIS plain counties. This concept considers the fact that images typically comprise clusters of elements, each of which might serve as the foundation for an entire province. Because the damaged portion will be the focus of attention, image processing has been employed to detect surface imperfections. It is currently one of the most rapidly emerging technology, with applications popular a wide range of industries. Image processing is a key study topic in the manufacturing.

Image processing fundamentally includes the succeeding three steps:

- Uploading the image by a digital camera or an optical scanner.
- Data compression, picture augmentation, and the detection of patterns that are invisible to the human eye are all examples of image analysis and manipulation.
- The output step is the final one when a portrait or report based on image examination might be adjusted.

3.1.1 Purpose of Image Processing:

Image processing is classified into five categories. They are as follows:

1.Visualization - Pay consideration to the articles that exist not apparent.

2.Image polishing and re-establishment - Towards improve the quality of an image.

3.Measurement of pattern - Regulates the size of discrete things in an image.

4. Image acknowledgement - Categorize things in an image.

3.1.2 Types of Images:

The image's intensity or Gray level at any pair of coordinates (x, y) is the amplitude off at that location. An image is a two-dimensional function with the coordinates x and y being spatial (plane). The image is referred to as a digital image .The use of a digital computer to process digital images is referred to as digital image processing.

The amplitude off at that location is the strength or Gray level of the image at any pair of coordinates (x, y). An image is a two-dimensional function with the coordinates x and y being spatial . The field of digital image processing refers towards the use of a digital computer to process digital pictures. In most cases, each pixel in an image has a value that is made up of one or more values (samples) that are linked to that pixel's "position" in some 2-D region. Python can deal with two types of images.

- Binary images
- Grey scale images

3.1.2.1 Binary Image:

This type of images are stored in a logical array. It are also referred to as bi-level or two-level images. (This idea is known as black and white, or B&W). Certain i/o equipment, for instance laser printers and computer displays, can only be utilised with bi-level images.

Fig.3.1 Binary Image

A binary image will be shown in the figure 3. In this, each pixel undertakes one of only two isolated principles: 1 or 0.

3.1.2.2 Gray Scale Images:

This type of image is frequently collected of ranging from dark at the lowest concentration to white at the highest. This is because the value of each pixel represents a particular trial. Grayscale images are frequently produced when measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum. (For example, infrared, visible light, ultraviolet, and so on). Grey scale images are frequently created by gauging the strength of images at towards each pixel. It is for visual displays are commonly saved with 8 bit per sample pixel in order to record 256 intensities, or shades of grey. A grayscale copy is displayed in the figure 3.2.

Fig.3.2 Gray scale Image

3.1.3 Kinds of Image Processing:

The two types of image processing used are:

- Analog
- Digital

3.1.3.1 Analog Image Processing:

Analogue image processing is a term used in and computer science to describe any work done on two-dimensional analogue signals using analogue methods. (instead of using digital picture processing). Image processing techniques for tangible copies like prints and photos might be analogue or visual. Image analysts use various interpretive fundamentals when utilising these visual approaches. The image processing is constrained by analyst skill as well as the area that needs research. Reminder is a critical module of image processing that uses visual techniques. Analysts thus integrate their own knowledge with minor data when analysing pictures.

3.1.3.2 Digital Image Processing:

Computer-based numerical picture variation is made possible with the use of digital processing techniques. Defects can be found in the raw data from satellite imaging sensors. Information must go through a number of processing stages in order to overcome these defects and get originality. When employing digital technique, all forms of data must go through three general phases: pre-processing, enhancement and display, and information extraction. Digital computers are utilised in this instance to process the image. A digital scanner-digitizer will be used to turn the image into digital form, which will then be processed. It is described as the process of performing a sequence of operations on a numerical representation of an item to produce the desired outcome. Starting with a single image, it creates a altered form of the original. Consequently, a picture which transforms one image into a new.

3.2 METHODOLOGY FOR IMAGE PROCESSING:

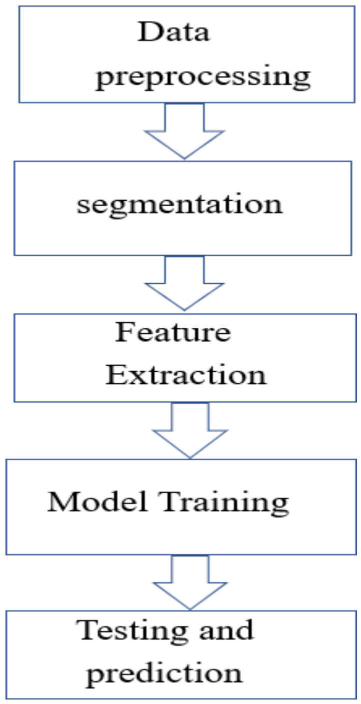

Fig.3.3 Flow Chart

Steps involved:

1. Data Pre-processing:

The initial stage is preprocessing the data. Data pre-processing involves numerous processes, including: 800 photos of leaves from the classes Diseased and Healthy are loaded into the machine as it trains. A Python image processing library called Open CV does RGB to BGR picture conversion. Images must be converted to the original format, BGR format, since it only accepts images in RGB colouring format. Luma, or picture intensity, is separated from chroma, or colour information, when an image is converted from BGR to HSV.

2. Image segmentation:

A digital image is distributed into numerous image sectors, also known as image districts or image objects, by the process of image segmentation (sets of pixels). Image separation, in more exact terms, is the process of giving each pixel in an image a label so that pixels with the same label have detailed assets. Picture segmentation is necessary to separate the leaf image from the backdrop and perform colour extraction.

3. Feature Mining:

The process of turning raw data into mathematical features that may be managed while keeping the info in the innovative data set is referred to as feature abstraction. Related to using machine knowledge on the raw data directly, it yields improved effects. To extract the image's overall features, three feature descriptors are employed, including:

a) For Color: Color Histogram

b) For Shape: Hu Moments

c) For Texture: Haralick Texture

Once the features are extracted, they are stacked together.

4. Model Training:

For a better understanding of the device, the labels are numerically encoded depending on the photographs in the folder. Two sections of the dataset have been separated. They are divided 80/20 as the training set and the testing set. Data pre-processing should include feature scaling so that it can manage extremely variable magnitudes. Extraction of Features: The features are taken from the photos and saved in an HDF5 file. Modeling: The following five machine learning models are used to train the model:

a) Random Forest
b) Logistic Regression
c) KNN
d) Naive Bayes
e) SVM

Once model is trained , The 10 k fold cross validation technique is now being recycled to authorize the model.

5. Prediction and Testing:

The prediction is to be done whether the leaf is Diseased or Healthy. Prediction is done using confusion matrix which determines accuracy,precision,f1 score and recall for the applied algorithms.

3.2.1 Confusion Matrix

A matrix is active to evaluate how well a given set of test data performs the categorization models. Only after the true values of the test data are known can it be resolute. It is also referred to as an error matrix since it displays the errors in the model performance as a medium. The subsequent list of Confusion matrix features includes:

Real values are the real values for the in case data, whereas projected values are the values that the model expects.

• True Negative: The typical projected no, and the actual or else real value also indicated no.

• True Positive: The model correctly predicted yes, and the outcome matched that prediction.

• False Negative: This error is now and then referred to as a Type-II error and occurs when the model forecast no but the actual value was yes.

• False Positive: Even though the model predictable Yes, the actual result was No. Another name for it is a Type-I error.

Table 3.1 Confusion Matrix

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

3.2.2 Evaluation Parameters

Accuracy:

The proportion of correctly confidential data occasions over all data instances is known as accuracy.

$$\text{Accuracy} = \frac{TN+TP}{TN+FP+TP+FN}$$

Precision:

A good precision should rather be 1 . Only when the numerator and denominator are equal, or when TP = TP + FP, does precision become 1, which also implies that FP is zero.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall:

Recall should ideally be 1 for a good classifier. Recall becomes 1 only when the numerator and denominator are equal i.e TP = TP +FN, this also means FN is zero.As FN increases the value of denominator becomes superior than the numerator and recall value decreases.

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1-Score:

$$\text{F1-Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1 Score becomes 1 only when precision and recall are both 1. F1 score converts high only when both precision and recall are high. F1-score is the harmonic mean of precision and recall and is a better measure than accuracy.

3.2.3 Introduction to Machine Learning:

Machine learning is a subset of artificial intelligence (AI). Machine learning's primary goal is to recognise data's structure and incorporate it into models that are easy for users to understand and utilise. Machine learning is distinct from traditional computational systems while being a subfield of computer science. In traditional computing, procedures are sets of expressly created instructions that computers utilise to calculate or solve issues. On the other hand, machine learning approaches enable computers to train on data inputs and use statistical analysis to create results that fall within a specific range.

Tasks in machine learning are typically categorised into broad groups. These classifications are based on how information is absorbed or how feedback on learning is provided to the system that produced them. The following are the three main groups into which machine learning implementations fall: -

a) Supervised Learning
b) Unsupervised Learning
c) Reinforcement Learning

a) Supervised Learning:

A mathematical model of a set of data that embraces the intended inputs and outputs is created by this techniques. The information is a collection of training examples and is referred to as training data. Each training example is represented in the mathematical model by an array or vector, sometimes referred to as a feature vector, while the training statistics is signified by a matrix. Administered learning procedures develop a function that can be used to antedate the output connected to additional inputs through repeated optimisation of an objective function. The system will be able to determine the output with an optimal function about inputs that weren't included. An prime task will tolerate the system to appropriately decide the output.

for inputs that remained not a amount of the training data. An procedure that improves the accuracy ofits outputs or estimates over time is said to have learned to accomplish that task.

b) Unsupervised Learning:

These algorithms take a set of data that only contains inputs and find arrangement in the data, such as data point assemblage or clustering. As a result, the algorithms learn from test data that has not been labelled, classified, or categorised. It rather than responding to feedback, identify harmonies in data and react based on the presence or absence of such cohesions in each new portion of data. Unsupervised learning is widely used in the arena of compactness estimation in figures, for instance determining the probability mass function. Although unsubstantiated learning incorporates other fields concerning data summarization and explanation.

Classification is division of usual of annotations into subcategories (called bands) so that annotations within the same collection are related based on one or more predetermined criteria, whereas annotations drawn from different clusters are dissimilar. Different clustering performances make changed norms about the structure of the data, which is often defined by some similarity metric and evaluated, for example, by external compactness, or the similarity between band members, and separation, or the variance amongst clusters. Other approaches rely on estimated density and display connectivity.

c) Reinforcement Learning:

It is of machine learning with how software proxies should behave in a given environment in order to maximise some concept of aggregate reward. The environment is classically represented as a Markov decision process in machine learning (MDP). Many bolstering learning algorithms employ dynamic programming techniques. Reinforcement learning algorithms are used when exact mathematical models of the MDP are infeasible and do not assume knowledge of an exact mathematical model of the MDP. Reinforcement learning algorithms are used in self-driving cars or when learning to play a game against rival**.**

3.2.4 Algorithms used:

3.2.4.1 Random forest classifier:

RF is a eminent machine learning process from the directed learning technique. It can be applied to both sorting and deterioration problems in machine learning. It indeed is created on the perception of cooperative learning, which is a process that involves combining multiple classifiers to solve a compound problematic and expand the typical act.

"RF is a classifier that comprises a total of decision trees on amenities for low of the given and takes the mean to improve the analytical skill of that dataset," as the name indicates. Instead of relying on a particular decision tree, the rf takes the predictions from each tree and envisages the ultimate output constructed on the mainstream division of forecasts.

Random Forest is effective. RF mechanism in two-phase major is to create by merging N decisiontree, and second is to make calculations for each tree shaped in the first segment.

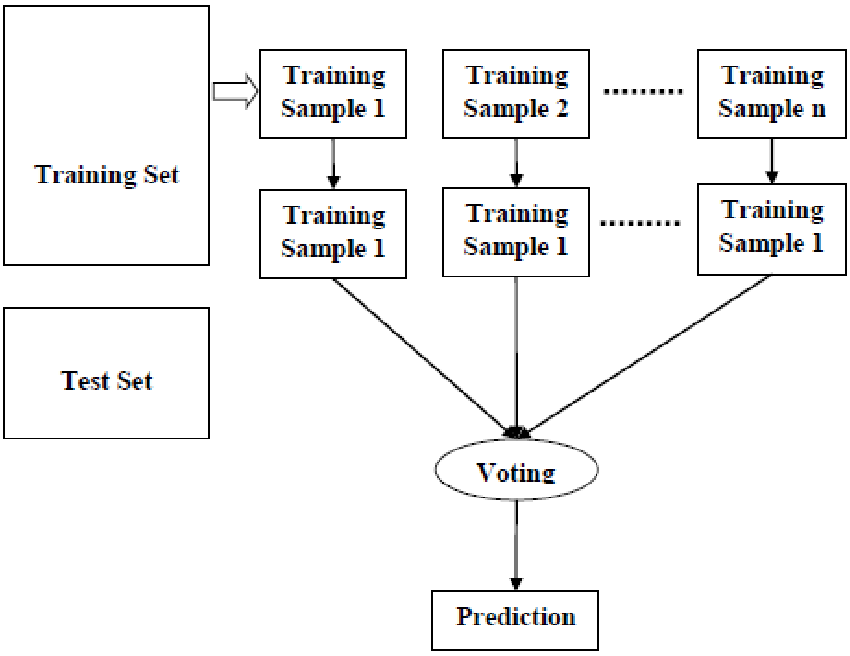

Fig.3.4 Working of Random Forest Algorithm

The method can be illuminated in the below stages and figure:

Step 1: Pick K data points at arbitrary from the preparation set.

Step 2: Build decision trees for the chosen data points .

Step 3: Determine the size N for the numeral of decision trees you want to construct.

Step 4: Reverse steps 1 and 2.

Step 5: Find the conventions of every decision tree for new records arguments and allot the new data points to the segment that obtains the peak divisions.

3.2.4.2 Logistic Regression:

- It is a prevalent Machine Learning system that falls under the Machine learning Learning method. It is used to estimate the definite reliant on variable from a set of self-determining variables.
- The output of a category independent variable is prophesied by logistic regression. As a result, the outcome must be categorical or discrete. It can be 0 or 1, true or False, and so on, but instead of giving the exact values , it gives the probabilistic values that drop between 0 and 1.

- In the field of logistics, In Logistic regression, as a substitute of appropriate a regression line, we fit an "S" shaped logistic function, which foresees two extreme values (0 or 1).

3.2.4.3 Support vector machine(SVM):

- Support Vector Machine (SVM) is a prominent Supervised Learning algorithm that is used for Classification and Regression problems. However, it is chiefly used in Machine Learning for Classification problems.
- The SVM algorithm's goal is to find the top line or decision boundary for categorising n-dimensional space so that we can easily place new data facts in the accurate class in the future. A hyperplane is the best decision frontier.

3.2.4.4 K-Nearest Neighbour:

- It is a modest Machine Learning procedure that uses the Supervised Learning system.
- It adopts correlation between the fresh case/data and existing cases and places the new case in the classification that is most similar to the existing categories.
- It supplies all accessible data and uses similarity to catalog new data points. This means when new data is generated, it can be rapidly secret into a well-suited category using this algorithm.
- This technique can be located used for both deterioration and classification, but it is most frequently recycled for organization difficulties**.**

3.2.4.5 Naive Bayes:

- This approach is a managed knowledge system that practices the Bayes theorem to solve arrangement problems.
- It is mainly used in text labeling with a large training dataset.
- This is a simple and useful Classification algorithm that aids in the expansion of firm machine learning prototypes adept of making quick predictions.
- It is a classification algorithm, which funds it expects created on an object's probability.

3.2.5 TECHNOLGIES USED

3.2.5.1 Python:

Python is an advanced, universal-persistence software design language that is interpreted. Python's core idea emphasises encryption readability, as evidenced by its extensive use of indentation. Its language structures and object-oriented approach are planned to support systems analyst in writing clear, rational

It is dynamically typed. It is compatible with a selection of computing paradigms, counting structured (primarily procedural), object-oriented, and functional programming. Python is frequently mentioned to as a "strategies included" language due to its general typical library. Guido van Rossum began developing Python as a beneficiary to the ABC programming language and it was first released in 1991 as Python 0.9.0. Python 2.0 was released in 2000, and it included innovative topographies like list comprehensions and a trash collection system that used orientation totaling. Python 3.0, released in 2008, was a significant revision of the language that is not completely completely well-suited, and much Version 2 code does not run basic on Python 3. Python 2 was phased out with version 2.7.18 in 2020.
Python is a language for programming that supports multiple paradigms. Various of its features sustenance functional programming and aspect-oriented programming (including metaprogramming and metaobjects (magic methods)). Object-oriented programming and structured programming are fully braced. Many other frameworks, such as design by contract and logic programming, are maintained by delays.

3.2.5.2 Libraries

Python's large ordinary collection, which is widely viewed as one of its greatest assets, provides tools suitable for a inclusive series of responsibilities. Many regular formats and protocols, such as HTTP, are stayed for Internet-facing applications. It has modules for developing user interfaces with graphics, connecting to interactive databases, generating pseudorandom numbers, arithmetic with arbitrarily chosen decimals, attempting to manipulate regular expressions, and unit analysis.

Some parts of the source file are covered by specifications (for example, the Web Application Gateway Interface (WSGI) integration follows PEP), but most modules are not. Their code, interior documentation, and test suites define them. However, because the majority of the codebase is merge Python code, only very little segments require modification or revising for alternative.

3.2.5.3Pandas

It is a computer software library printed for the Python programming language for data handling and examination. In individual, it offers data gatherings and acts for handling geometric tables and time series. It is permitted software unrestricted under the three clause BSD license. The title is consequent from the term "board files", an econometrics tenure for data sets that include remarks over numerous epochs for the same individuals. Its name is a playon the phrase "Python data analysis" itself. Wes McKinney started construction what would turn out to be pandas at AQR Capital while he was a investigator from 2007 to 2010.

Features:

- Data Frame object for data handling with united indexing.
- Apparatuses for understanding and characters data between in-memory data edifices and different fileformats.
- Data alignment and integrated handling of missing data.
- Reforming and twisting of data sets.
- Statistics organization column insertion and deletion.
- Assemblage by appliance allowing split-apply-association operations on data sets.

3.2.5.4 Scikit-learn

Scikit-learn is a free software machine learning reference library forthe Python programming language.

It features various classification, regression and gathering algorithms, including support vectormachines, random forests, k-means and DBSCAN, and is intended to interoperate with the Python geometric and scientific libraries NumPy and SciPy.

Scikit-learn is written mainly in Python and uses NumPy comprehensively for high-performance linear algebra and arrangement operations. Furthermore, some essential algorithms are written in python to advance performance.

3.2.5.5 NumPy

NumPy is a Python library that augments backing for large, multidimensional arrays and matrices, as well as a huge gathering of high-level mathematical operations to operate on these arrays. Jim Hugunin created NumPy, Numeric, with help from various other developers. Scientist by providing features of the able to compete Num array into Numeric with major improvements. NumPy is offers a bunch with numerous contributors.

Features:

- NumPy is aimed at the Python C Python mention implementation, which is a non-enhancing bytecode interpreter.
- Algorithms written for this description of Python are frequently much slower than compiled equivalents.
- NumPy addresses the slowness issue in part by so long as multidimensional arrays as well as functions and hands that operate proficiently on arrays without the need for rewriting.

3.2.5.6 Seaborn

It is a data visualisation library. It offers a high-level interface for forming visually pleasing and informative quantitative graphics.
Seaborn aids in data investigation and command. Its plotting functions operate on data structures and arrays containing entire datasets, performing the necessary concept mapping and statistical aggregation internally to generate informative plots.

Its dataset-oriented, declarative API allows you to focus on what the individual aspects of the plots mean rather than the details of how to draw them.There is no single best method for visualising data. Different plots are better suited to answering different questions. Seaborn's consistent. When statistical values are estimated, seaborn uses bootstrapping to compute confidence intervals and draw error bars representing the estimate's uncertainty.

Statistical analyses require knowledge about the distribution of variables in your dataset. The seaborn function displot() supports several approaches to visualizing distributions.

3.3 RESULTS

3.3.1 Confusion matrix Result

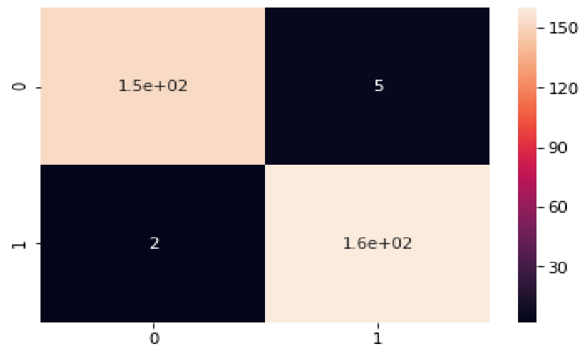

Fig.3.5 Plot of Confusion Matrix

In the above confusion matrix, 5 images are predicted as false negative and 2 images arepredicted as false positive.

3.3.2 Comparison Table for Different Machine Learning Algorithms

.

Parameters	**Random forest**	**Logistic Regression**	**KNN**	**Naive Bayes**	**SVM**
Precision	0.98	0.88	0.96	0.88	0.94
Recall	0.98	0.86	0.96	0.86	0.94
f1-score	0.98	0.86	0.96	0.86	0.94
Accuracy	0.9812	0.9265	0.9562	0.8578	0.94

Table 3.2 Comparison Table For Different Machine Learning Algorithms comparison table for different algorithms such as RF, LR, SVM, Naive Bayes, KNN with parameters like Precision, Recall, F1-score, Accuracy.

Random Forest Algorithm results better accuracy of all algorithms with 98%.

3.3.3 Boxplot Comparison for Different Algorithms

Models are trained on different plant leaves. The machine is given 1600 images of leaves for each class Diseased and Healthy in order to train different models.

A Boxplot comparison is plotted for different machine learning techniques. The figure shownbelow depicts the accuracy vs different machine learning algorithms.

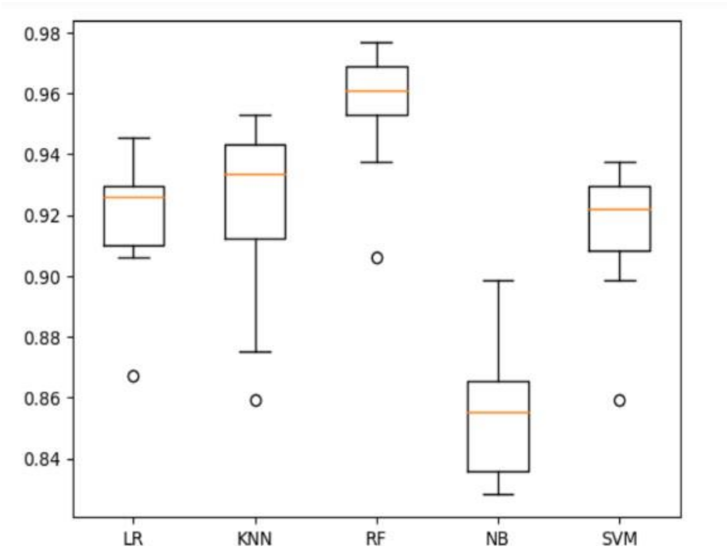

Fig.3.6 Boxplot Comparison

3.3.4 Results of Plant Leaf Images:

Loading Original Image- For training, the machine is given a total of 1600 images of leaves, This 1600 images are divided into two classes namely Healthy and Diseased. The image is changed from RGB format to BGR.

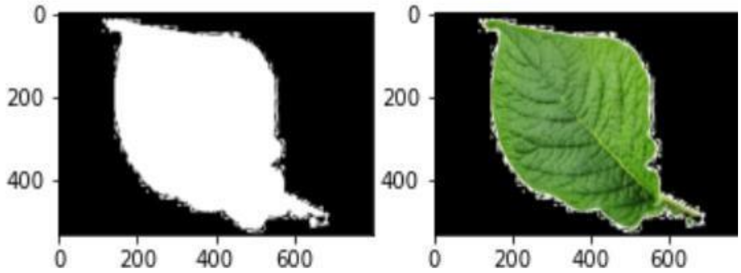

Fig.3.7 Healthy Leaf

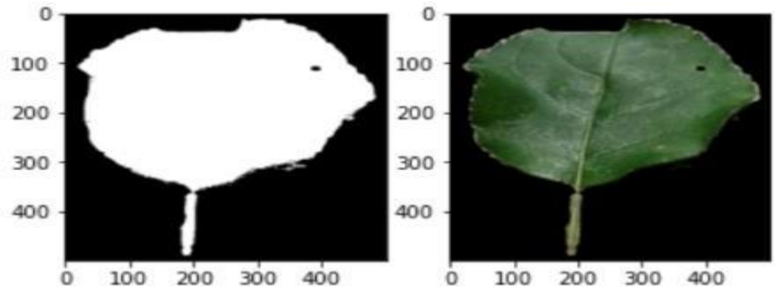

Fig.3.8 Diseased(Low)

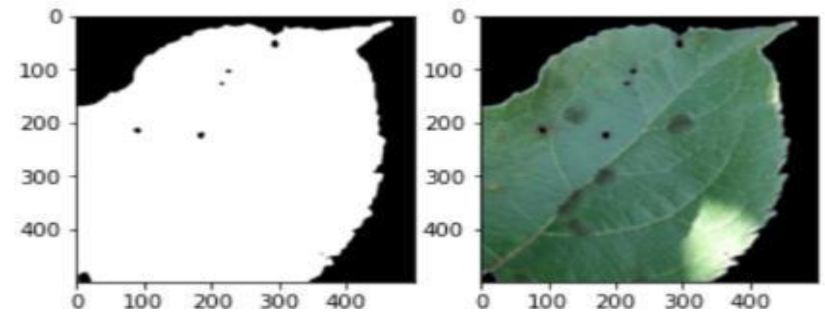

Fig.3.9 Diseased(Medium)

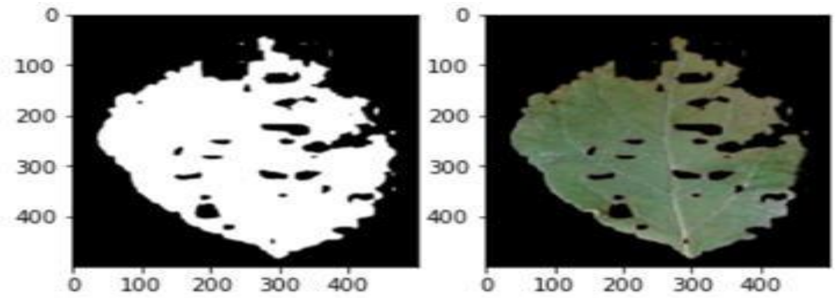

Fig.3.10 Diseased(High)

CHAPTER 4
VIDEO PROCESSING

4.1 Introduction:

There are 570 million farms worldwide. Over 90% of people have a connection to farming. Of the 80% of food, farmers produce a significant portion. Crop diseases are a main reason of productivity and quality loss for producers of broadacre crops.They can be due to bacteria, virus, nematodes, etc. and these damages the parts of the plant which are top and bottom of ground. Numerous causes, including pollinator decline and climate change, pose a threat to food quality. These can disturb the food quantity also and have terrible effects on farmers. Farmers lose money and other resources trying to stop plant diseases. We must recognise these disorders in light of the current environmental changes.By knowing the diseases name and how to control them are ongoing challenges in agriculture. Some diseases are challenging to diagnose based just on their outwardly apparent symptoms. For disease prevention and long-term agricultural sector viability, crop disease detection is essential. By utilising automation, information, and communication technologies in the processes of cultivation and commercialization, agriculture needs technological innovation to better its production processes and organisational structures. To detect these diseases in this situation, we need to apply technology. Otherwise, people would have to rely on imported food, which would be more expensive and could threaten people's health. Fungicide, disease-specific chemicals, and pesticide application are a few examples of applications. If we had early warning of plant illnesses, we could have been able to carry out these applications. These programmes help us manage illnesses and increase our productivity.

Smartphone-assisted disease detection has indeed become a reality in recent years, thanks to the widespread adoption of smartphones across the globe and the development of advanced machine learning techniques. Machine learning and deep learning algorithms have been increasingly applied to improve the accuracy and recognition rate of plant disease identification and diagnosis. There have been numerous studies conducted in this field, using a variety of techniques and approaches. There are several traditional machine learning techniques that have been used in various applications, including those related to image processing and plant disease identification.

4.1.1 Support Vector Machine:

This model services classification to locate hyperplane in N-dimensional space. In essence,It is useful for sorting data into multiple types. Two distinct classes are divided by a line in a two-dimensional space. For instance: Let's say that two different vegetable types' data are provided for a plot. The Support Vector Machine takes into account the data and aids in line-by-line data separation. This line is produced by taking into account the separation between the points of various classes. Kernel, regularization, gamma, and margin values are a few variables that impact the type of the line.

4.1.2 K-Nearest Neighbours:

The most fundamental supervised learning technique used in machine learning to address various regression and classification issues is K-nearest neighbours. The KNN algorithm predicts a real number as the output in regression issues. In contrast, the KNN method produces a discrete number and can also be used to classify data. The KNN (k-nearest neighbors) operates on the assumption that similar or related data points tend to be located close to each other in space. The KNN algorithm employs brute force methods to calculate the Euclidean distance between each point on the map and the input test point. As a result, it can forecast where the test point will fall. The classification of the data requires more time and is a sluggish method.

4.1.3 Naive Bayes:

In this, The "naive" conditional independence assumption over the training set is combined with the Bayes Theorem to create the effective supervised learning algorithm. The machine learning algorithms utilized in various applications share a common principle of assuming that each feature provided to the algorithm is not dependent on the others.

4.1.4 K Means Clustering:

In essence, It is a form of unsupervised model of learning that groups items based on their similarities and differences. It can be summed up as the process of finding data subgroups where data points are substantially similar with the similar subgroup (cluster) but dissimilar within other remaining clusters.It is an continuous clustering method which divides data sets into specified K number of groups, each of which comprises just single group to which each data point relates to.Here the data objects are categorised by this algorithm into related K-groups

This model makes use of Euclidean distance. The data is grouped using its mean after being iteratively spread across the points' Euclidean distances.

4.1.5 Random Forest:

It mostly employs classification but also regression. There are many wide count of trees in a forest, which make up forest, provides precise information. Similar to this, decision trees are built using a random forest method on datasets, and after receiving predictions from each decision tree, the best option is ultimately chosen by voting. Because it gives the result as an average, it reduces over fitting and is therefore superior to a single decision tree. currently,It is the most truthful algorithm.It operates precisely on large databases. It offers greater stability and accuracy in comparison to a single decision tree, while also eliminating the need for data scalability. The model maintains its accuracy highly even with the addition of new data.

4.1.6 Convolutional Neural Networks:

Image classification classifies the photos as a dataset of unprocessed pixels and defines the images as objects. The CNN model of neural networks makes us to derive image with more accurate representations. Contrary to this,image recognition techniques,we specify the picture characteristics ourselves, CNN begins with the image's pixel data which is raw data, trains the model is trained , and then extracts many number of features automatically for improved categorization.

4.1.7 Transfer learning:

It uses a model which was trained for single job as the foundation for a model on another. When the other task is identical to the previous task or when there was a dearth of data for the second task, this can be helpful. The model can learn more quickly and efficiently on the second challenge by starting with the learnt features from the first task. Because the model will have already picked up broad features that are likely to be helpful in the second task, this can also aid in preventing overfitting. It can sometimes be unavailable or impractical to train a network from starting because it needs a lot of data information , power, and time.It is a method for applying to the neural networks which are trained previously (such Alexnet, Inception net, and VGG16) to new tasks by altering the final classification layer. As we move deeper in the network, layers lean towards learn different patterns more specialised to the work which they were they were trained. The earliest levels learn relatively general features. The models which were trained before are on a vast Compared to a neural network created from scratch, images can learn these abstract properties more effectively.

Block Diagram of Transfer Learning:

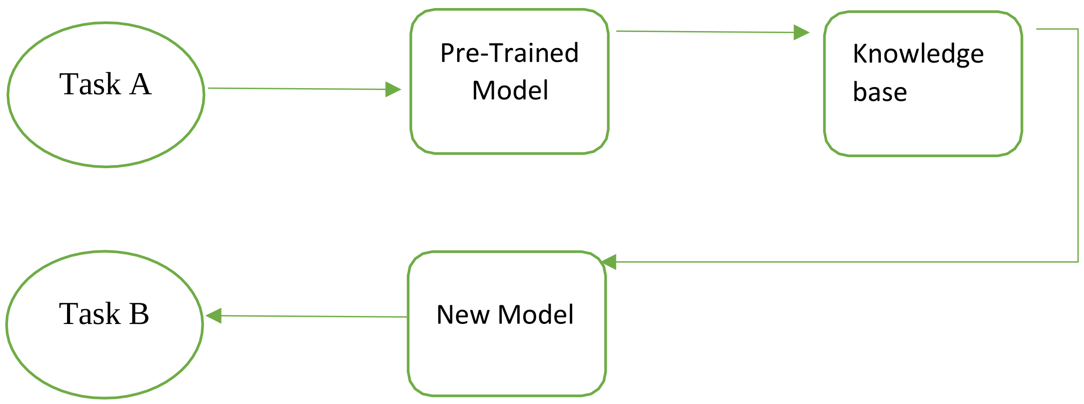

Fig.4.1 Transfer Learning

4.1.7.1 Need of Transfer learning:

Transfer learning is required in machine learning when a pre-trained model is used to solve a new problem that is different but related to the original problem for which the model was trained. This technique is particularly useful when dealing with complex, hard-to-solve problems that require a significant amount of training data and computational resources. By leveraging the knowledge and expertise gained from pre-training on a large dataset, transfer learning can significantly reduce the amount of data and time required to train a new model for the target.

4.1.7.2 Advantages of transfer learning:

• Quicken the learning process: By employing a model that has already been trained, the model may learns the another task more accurately,fastly and efficiently since it is already familiar with the characteristics and patterns in the data.

• Improved performance: Because the model can use the first task's information to its advantage, transfer learning can result in improved performance on the second task.

• Handling a tiny dataset: Since the model has already learnt general features that are likely to be helpful in the second task, transfer learning can assist prevent overfitting when there is a dearth of data for the second task.

4.1.8 Resnet50:

Residual Network, often known as ResNet, is a network that supports ongoing learning. Resnet50 stands for Residual Network with 50 layers. This network's pretrained version was trained on greater than 10 lakh photos from the database and is used as the foundation for a variety of tasks. It was the victor of the 2015 challenge on imagenet.In comparison to models like CNN, InceptionV3, MobileNetV2, GoogLeNet, and others, ResNet50 has a higher accuracy. The best model for identifying plant diseases is Resnet50, which has been demonstrated in numerous journals and studies. This Resnet50 model is also one of the Top 4 Pre-trained Models for picture classification. The ResNet50 model is a transfer learning model, which implies that it doesn't require intensive computing because it takes into account these three factors.

The main modernization with ResNet was that it empowered us to train very deep neural systems with more than one hundred fifty films. A main downside of convolutional networks is the problem of "Vanishing Gradient ".This pointedly diminishes throughout the technique called backpropagation, consequently masses will alteration slightly. Therefore this working to grow round that. It contains SKIP CONNECTION method.

Connection(skip): Connecting the convolutional block's output to the initial input. A direct link known as a skip connection neglects the some layers of the prototypical. The outcome is not the equivalent because of this connection. Without this connection, input X is multiplied with the weights of the layer trailed by adding a term called bias.This technique made the network to evade certain layers and reuse features from former stages of the network, which helps avoid the issue of vanishing gradients and allows for deeper and more accurate training of the model. Essentially, skip connections help confirm that important features are conserved and passed through the network, even as the data travels through multiple layers of the model.

4.1.8.1 Residual block:

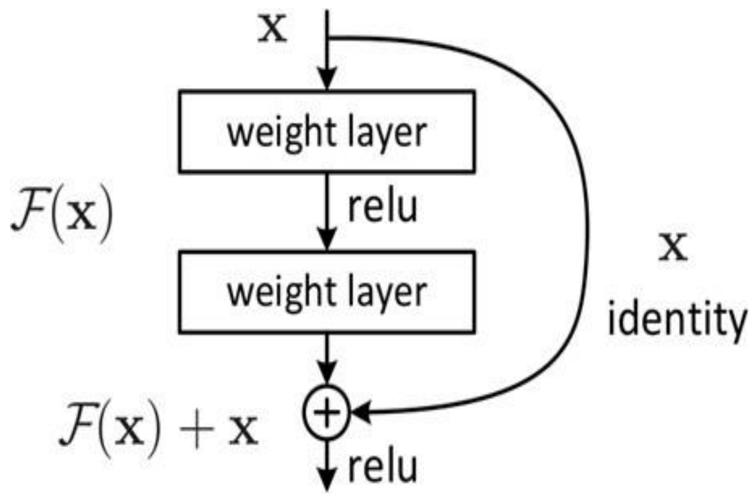

Fig.4.2 Residual block

The skip connection is the most vital idea in play here, as can be seen in Fig 4. 1. In essence, a skip connection is an uniqueness mapping in which the outcome of one film is added to the previous layer input. A straightforward residual function can be summarised like this using the preceding figure:

When x- is applied input and Here f(x) -the layer's outcome, the block's output can be articulated as like this:

$$\mathbf{y} = \mathbf{f}(\mathbf{x}) + \mathbf{x}$$

This is the furthermost straightforward characterization of a block.Now, there can be approximately circumstances where the outcome from the film and the input which is identical have diverse proportions. For kindly, if we took a CNN where we distinguish that subsequently intricacy operation, the size of the input is condensed(proportionally), then adding effort to it is a problematic. So, what here can be finished is that in the connection(skip), we improve some procedure or meaning (in this case intricacy operation) such that the input is reformed or constituted to the obligatory magnitudes.

So, the description can be modernized as follows:

$$\mathbf{y} = \mathbf{f}(\mathbf{x}, \{\mathbf{wi}\}) + \mathbf{ws}^* \mathbf{x}$$

At this point, Wi is the constraints specified to the layers,ws tenure can be done with convinced intricacy conformation to make input and output magnitudes identical.

4.1.8.2 Block diagram of Resnet50:

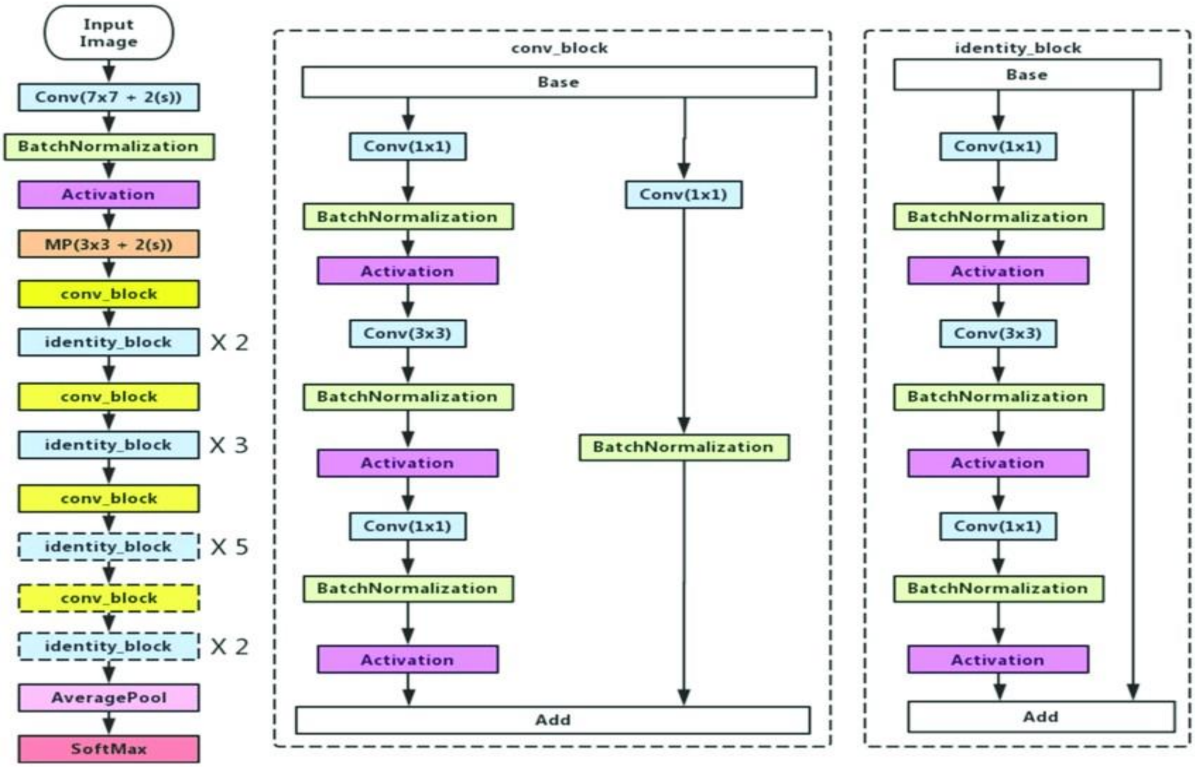

Fig.4.3 Resnet50 Architecture

The 50-layer ResNet construction embraces the ensuing elements, as shown in the below:

- A seven*seven kernel intricacy together with sixty four additional kernels with a two-stride.
- A maximum pool layer with a two stride.
- Nine additional layers-three*three, sixty four kernel intricacy, additional with one*one, sixty four kernels, and a third with one*one, two hundred fifty six kernels. These three layers are recurrent three epochs.
- Twelve additional layers with one*one, one hundred kernels, three*three , one hundred twenty eight kernels, and one*one, five hundred twelve kernels, recapitulated four many times.
- Eighteen extra films with one*one, two hundred fifty six cores, and two cores three*three, two hundred fifty six and one*one, one thousand twenty four, recapitulated six times.

- Nine additional films with one*one, five hundred twelve cores, three*three , five hundred twelve cores, and one*one, two thousand forty eighty cores recapitulated three times.

There are 2 core categories of lumps are castoff in a Res Net, reliant chiefly on if the in/outcome magnitudes are the equivalent and diverse.

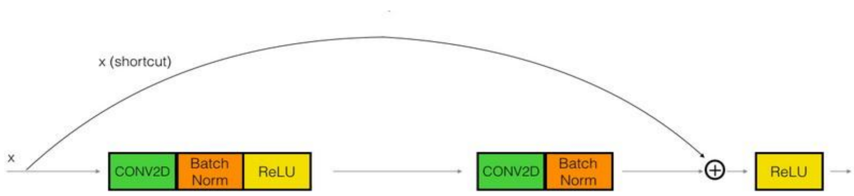

Fig.4.4 Identity Block

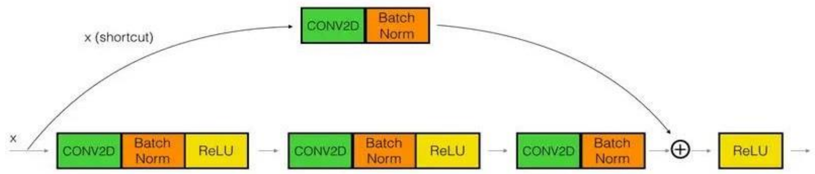

Fig.4.5 Convolution Block

.

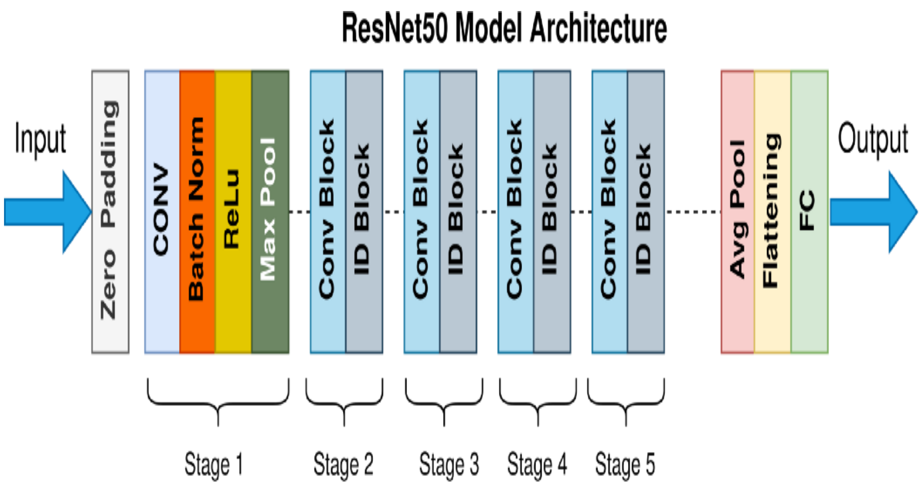

Fig.4.6 Resnet50 Architecture

1. Identity Block: This lump is typical lump used in Residual Nets and resembles to the case wherever the input stimulation has the identical measurement as the productivity stimulation.

2. Convolutional Block: We can use this kind of lump when the input,output magnitudes do not be similar. The transformation with the similar block is that nearby a CONVOLUTION layer which is two dimensional in the shortest and easiest pathway.

The ResNet-50 prototypical comprises of five steps individually with a intricacy and Identity block. Each intricacy lump has three intricacy layers and individually identical lump likewise has three intricacy layers. It contains 25 million trainable criterion.

4.1.8.3 Special characteristics of ResNet-50:

The construction of ResNet-50 is based on the perception shown, with one significant exemption. The holdup element is castoff in the fifty layer Res Net. A holdup enduring lump, likewise referred to as a "holdup", uses eleven intricacies to expurgated on the count of strictures and matrix developments. It styles individual layers training suggestively quicker. As a substitute by means of a load of 2 steps, it services 3 number of layers.Kkip connection that is added to the ResNet design greatly improved the presentation of the network with various layers. ResNets are fundamentally just other networks with a few minor amendments. The construction follows the same purposeful steps as CNN or other systems, but an spare step is encompassed to address apprehensions like the problem like vanishing gradient, among others.

4.1.8.4 Compensations of ResNet:

- Systems with bulky quantity (even 1000s) of layers can be trained effortlessly deprived of cumulative the training error proportion.
- It helps in embark upon the vanishing gradient delinquent using identity mapping.

4.2 Methodology:

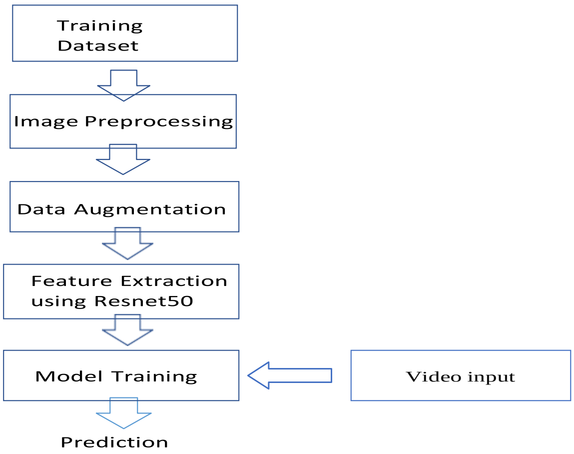

Fig.4.7 Methodology

4.2.1 Dataset:

4.2.1.1 Training Dataset:

It is castoff to train and suitable the ML prototypical, is the principal subcategory of the unique dataset. The ML procedures learns how to do prophecies for the specified action,data is first abounding into them for training purpose. Whether we are consuming supervised learning or unsupervised, the training data varies.

In unsupervised learning, inputs do not tagged with the apposite outputs, henceforth the training data contains not labeled data points. In order to yield prophecies, models must citation patterns from the afforded datasets which are training. In otherside, labels are encompassed in the training data for administered learning in command to help the model be trained and prophecies made.

The type of training data that we offer to the model is exceedingly accountable for the model's accuracy and prophecy ability. It means that the recovering the superiority of the training data, the improved will be the presentation of the model. Training data is roughly in excess of or equal to 50% of the whole data for an ML development or deep learning project.

4.2.1.2 Testing Dataset:

As soon as the prototypical has been accomplished using the dataset(training), it is stint to assessment it consuming the test dataset. This dataset evaluates the prototypical's recital and assurances that it can oversimplify efficaciously to newfangled or unmapped dataset. The assessment dataset is a unalike subcategory of the original data from the training set of data. When the model working out is finished, it exploits it as a standard because it has some comparable geographies and a alike class distribution of probability. A glowing-systematized dataset called test data affords evidence for each type of setting the prototypical strength happenstance in the authentic creation. Characteristically, the set of data which is test varieties up 25–30% of the inclusive innovative dataset.

At this time, we may also scrutinize and disparity the challenging accuracy with the training accuracy, or, more unambiguously, the exactness of our model when pragmatic to the test dataset in assessment to the learning set of data. The model is well-thought-out to have overfitted if its accurateness on training data is sophisticated its accurateness on testing data. In a point to make exact assumptions, the testing data must moreover abundantly or moderately resemble to the innovative dataset.

4.2.1.3 Requirement of Splitting Dataset:

One of kind decisive phases in data pre-processing is distributing the set of data into learn and examine sets. By making use of this, we may augment the recital of our prototypical and hence deliver improved obviousness. We can contemplate of it as if we accomplished our model with a learning set of data and then established it with a test dataset that is utterly dissimilar from the training dataset, at which point our model would be impotent to diagnose the associations amongst the topographies. As a consequence, the model's concert will agonize if it is trained and tested on two dissimilar datasets. Thus, it is decisive to rift a dataset into a train and a test set.

In this way, we can straightforwardly appraise the presentation of our prototypical. Such as, if it accomplishes glowing with the learning data, but does not accomplish glowing with the test set of data, then it is appraised that the prototypical may be overfitted. For excruciating the dataset, we can use the traintestsplit purpose.

4.2.1.4 Difference between Training Data and Testing Data:

- The main discrepancy between working out data and challenging data is that working out data is the subdivision of innovative data that is used to train the prototypical, whereas testingdata is used to check the accurateness of the prototypical.
- The training dataset is normally grander in proportions associated to the testing dataset. The universal fractions of piercing train and test are 80 and 20, 70 and 30, or 90 and 10.

- Training data is glowing acknowledged to the prototypical as it is castoff to train the prototypical, however testingdata is like nor seen data /new-fangled data to the model.

4.3 Image Pre-Processing:

Pictures need to be treated before they can be used for prototypical learning and disturbance. This include, but is not inadequate to, variations in shade, magnitude, and direction. Pre-processing is ended to progress the picture's quality so we can analyze it more efficaciously. Through pre-processing, we are able to get rid of undesired falsifications and increase certain attributes that are crucial for the request we are evolving. Those potentials could amend based on the application. For software to effort correctly and deliver the required results, an image might be preprocessed.

4.3.1 Importance of Image Pre-Processing:

To formulate portrait statistics for prototypical input, preprocessing is obligatory. For illustration, convolutionalneural networks' copiously associated layers necessitated that altogether the metaphors be in arrangements of the equivalent size.

If the input descriptions are very large, dwindling the proportions of these metaphors will greatly diminution the expanse of time looked-for to train the model without suggestively distressing model performance.

Even nevertheless geometric renovations of images (like alternation, clambering, and transformation) are regarded as as pre-processing procedures, the goalmouth of pre-processing is an upgrading of thetwin data that overwhelms inadvertent falsifications or augments some image geographies decisive for succeeding processing.

4.3.2 Criterion of Image PreProcessing:

- For accomplishing recovering consequences from the practical prototypical in machine learning developments the presentation of the statistics has to be in a appropriate style. Some quantified model needs statistics in a quantified presentation, for specimen, Random Forest procedure does not provision insignificant morals, consequently to accomplish random forest procedure valueless morals have to be accomplished from the inventive underdone set of data.
- Additional characteristic is that the set of data might be configured in this type of way that more than singular ML and Deep Learning procedure are accomplished in single set of data, and bestoutput of among is selected.
- Since metaphors occur in diverse presentations, i.e., ordinary, duplicate etc., we required to take to contemplation and homogenize before alimentation them into a system.

4.3.3 Image pre-processing techniques:

There are different image preprocessing techniques are present.They are:

1. Grayscale alteration
2. Standardization
3. Data Expansion
4. Image tuning

1. Grayscale alteration: It is purely adapting metaphors from tinted to B&W. It was customarily castoff to diminish totaling complication in ML procedures. Meanwhile furthermost depictions no requirement of color to be familiar, it is prudent to use scale i.e gray, which condenses the numeral of pixels in a twin, consequently, tumbling the calculations obligatory.

2. Standardization: Also mentioned to as statistics rescaling, it was the development of jutting picture datapixels to a defined previous range.It is frequently used on diverse set of data, and you hunger to standardize all to put on the equivalent procedures overthem . Standardization is usually pragmatic to alter an pictures values ideals to a distinctive or high accustomed intellect.

It’s assistances embrace:

- Impartiality transversely on all images – so mounting all pictures to an identical assortment of [zero, one]consents all descriptions to subsidize correspondingly to the full damage somewhat than when otherimages have more and less pixels assortments stretch durable and scrawny waste, individually.
- Delivers a typical lr- Subsequently more pixel metaphors necessitate a low lr and less pixel pictures high lr, scaling again benefits deliver a ordinary erudition rate.

3. Data expansion:It is the progression of making negligeable adjustments to prevailing information to surge the situation assortment without assembling newfangled data.It is a procedure used for enlarging a dataset. Ordinary data expansion procedures includes parallel & erect spinning,harvesting, shearing, etc. Performing data augmentation helps in avoiding a neural network from learning extraneous features. This outcomes in better model presentation. Standard data expansion techniques include parallel & erect flipping, rotation, harvesting etc. There are 2 forms of expansion:

    1. Off_line expansion - Castoff for insignificant datas. It is functional in the statistics pre-processing stage.
    2. On-line expansion- Used for bulky datasets. It is customarily functional in instantaneous.

4. Standardizing images: Standardization is a technique used to ensure that images have similar sizes by rescaling them. It involves adjusting the data so that it has a average of zero. This process enhances the quality and consistency of the data..

4.3.4 Steps for loading custom dataset for Deep Learning Models:

1. Sweeping the image file:The arrangement of the dossier can be JPEG, BMP, etc.
2. Resizing the twin to contest the input size.
3. Renovate the metaphor pixels to datatype which is float.
4. Standardize the metaphor to have picture element values scrambled down between zero and one from zero to two hundred fifty five.
5. Metaphor data should be either a numpy array or a tensor object.

4.4 Data augmentation:

It is a procedure cast-off in ML and deep learning to surge the amount and variety of information available for training models. This technique involves creating new data from existing data by applying transformations such as flipping, rotating, scaling, or cropping. The goal of data augmentation is to advance the performance and oversimplification of representations by divulging them to a broader choice of training information.

By generating new data with different variations, data augmentation can help models learn to recognize objects from different perspectives and in different lighting conditions. This technique can also reduce overfitting by providing more diverse examples for the model to learn from.

Some common types of data expansion practices include random cropping, parallel flipping, upright flipping,zooming, and color shifting. These techniques can be applied towards several categories of information including pictures, text, and audio. In summary, data expansion is a powerful technique for improving the quality and robustness of machine learning models by creating additional training data with different variations and reducing overfitting.

4.4.1 Data(Image) Augmentation steps:

There is no ordinary set of expansion steps that are instantaneously going to progress the recital of the model on which you are employed. In fact, approximately expansions may have a negative impact on your model presentation.

1) Grayscale: Color fluctuations are an specimen of duplicate alterations that may be functional to all pictures (learn and examine) or arbitrarily rehabilitated in learning solitary as expansions. Normally, gray scaling is a color variation added to all metaphors. Although we may contemplate “high indication is constantly good; we should demonstrate the prototypical color,”we might perceive more appropriate prototypical recital when pictures are scaled.In addition, color is sometimes not as pertinent to a model. If you use greyscale, you don't need to apprehension about gathering images for every color of an object; your model will learn more wide-ranging features about an object that do not depend on color.Color pictures are deposited as different color values, whereas grayscale images are only deposited as a range. This means for CNNs, our model only requirements to labor with single matrix per single picture, not 3.

2) Random Flips: Flipping an image about its x- or y-axis pushes our model to recognise that an object does not necessarily have to be read from left to right or up to down; flipping may be irrational in order-dependent circumstances, such as deciphering text.

3) Random Rotations: Rotating a picture is especially critical when a prototypical will be utilised in a position that is not fixed, such as in a phone applications.It can be difficult because it, causes pixels to be damage on the boundaries of our pictures and needs mathematics to apprise any jumping cases.

4) Random brightness and exposure:Image brightness is adjusted to be arbitrarily sunnier and shadier is most useful if a prototypical must operate in a diversity conditions. It is critical to evaluate the highest and tiniest light levels in the apartment.

4.4.2 Image augmentation in Keras:

The Keras ImageDataGenerator class is a speedy and relaxed way to improve your images. It provides numerous expansion methods, such as standardization, rotation,brightness alterations, and many more. The fundamental advantage of the Keras ImageDataGenerator class is that it is designed to provide real-time data expansion. That is, while your model is still being trained, it is providing augmented images in real time. The ImageDataGenerator class provides the prototypical with new copies of the images at each epoch. It does not, however, include it in the original amount of photographs; instead, it merely distributes the updated images. If that were the case, the model would have seen the original images more than three times, which would clearly be excessive for our prototypical. Another advantage of ImageDataGenerator is that it devours fewer space. This is due to the reason,we would load entirely of the photos at once if we may not utilise this class. Nevertheless, when we practice it, we freight the pictures in consignments, which hoards a lot of retention.

4.4.2.1 Techniques present in Image_Data_Generator class:

1. Random alternation: Image alternation is a popular approach that allows the prototypical to develop insensitive to entity orientation. By fleeting a number in the range argument to the Image_Data_Generator class, you can randomly spin images by any degree between zero and 360degrees.When the image isspin, some values travel separate the picture, leaving an empty space that must be filled. You can fill this in a variety of ways, such as a continuous value or nearest values. The fill_mode option specifies this,

and the defaulting rate is nearest which merely swaps the unfilled region with the closest standards.

2. Random Shiftings: It is possible that the thing is not continually in the centre of the picture. To resolve this difficulty, we can move the pixel values of the picture parallelly or steeply by adding a constant number to all pixels. The Image_Data_Generator class accepts the parameter shift height range for a vertical picture shift and breadth_shifting_range for a horizontal image shift. If the value is a floating quantity, it indicates the proportion of the image's width or height to shift. Otherwise, if it is an integer number, the breadth or elevation are simply shifted by that more pixels.

3. Random Flips: It is also an excellent improvement technique that can be given to a wide variety of things. For flipping along the vertical or horizontal axis, the ImageDataGenerator class has options horizontal_flip and vertical_flip. This method moreover, should be tailored to the object in the photograph. Vertically overturning an vehicles ,it would be absurd associated to responsibility it with a object like a football.It quantified that, I'm working to jesting my picture in both ways only to show how the expansion is working.

4. Random Brightening: It aimlessly fluctuates the intensity of the picture. It is an excellent expansion strategy so that our object will not always be in optimal lighting circumstances. As a result, we must train our model on images obtained in a variety of lighting conditions.The ImageDataGenerator class's brightness_range option can be used to control the brightness. It selects a brightness shift value from a lean of 2 floating points. Standards fewer than one make the picture darker, where it is greater than one make it brighter.

5. Random Zooming: It randomly zooming in or out of the picture. For zooming, the ImageDataGenerator class's zoom range parameter allows a float value.We should deliver a lean of 2 quantities that define the lesser and higher bounds. If we provide a floating parameter, zooming shall take place in the range [one minus zoomrange,one plus zoomrange].If the quantity is less than one, the image will zoom in. Any value larger than one causes the image to zoom out.

4.4.2.2 ImageDataGenerator methods:

There are a few methods in the ImageDataGenerator class which implement augmentation.

1. Flow_from_directory:While the neural network model is learning on the training data, the flow_from_directory() method allows you to read photos directly from the directory and enhance them. This technique wants photos from various classes to be present in different files but within the same parent folder. The following are some critical parameters of this method:

- directory: This is the pathway to the parent binder which contains the subfile for the dissimilar class images.
- Size of the target:Given the imput image size.
- Mode of the color:rgb is set for coloring pictures else scaling gray.
- Scope of batch: Size of the groups of information.
- Mode of class: The setting is for 1 dimensional labels(binary), however the unconditional setting is for two-Done parameters.
- Seeding :Result is set to reproduction

2. Flowing_from_frames of data:

The flow-from-frame data() is additional prodigious technique in the Image_Data_Generator session that consents you to unswervingly supplement images by understanding its term and board value from a data frame. This originates very conveniently when we had many pictures deposited inside the equivalent file .This method also has a few parameters.

- Frames of data:It comprehends the picture labels and board values.
- manual: The pathway to the file that encompasses all the pictures.
- xcol:Support name in the Data Frame that had twin variable terms.
- ycol:Support name in the Data Frame that has the goal values.
- classmode: Fix to binary values is for one dimensional binary parameters whereas unconditional is for two dimensional 1-hot values.
- Size of target: Input pictures size.

- Size of batch: Batches size
- seed: Set to reproduce the result.

4.5 Features extraction using Resnet50:

Feature extraction is part of the dimensionality reduction process, which splits and condenses a starting collection of raw data into smaller, easier-to-manage groupings. As a result, processing will be more straightforward. The fact that these massive data sets contain a large number of diverse variables is their most important aspect. Processing these variables necessitates a significant amount of computational resources. Feature extraction helps to extract the best feature from enormous data sets in order to efficiently reduce the amount of data by selecting and combining variables into features. These features are straightforward to utilise while correctly and uniquely describing the actual data set.

4.5.1 Need of Feature extraction:

When you have a large data set and need to reduce the number of resources without sacrificing any critical or relevant information, the feature extraction technique comes in handy. Feature extraction assists in reducing the amount of redundant data in a data source.Finally, data reduction allows the prototypical to be built with low mechanism struggle while simultaneously growing learning space and generalisation processes in the ML method.

4.5.2 Building the Resnet50 model:

We can build the Resnet50 model by using the following default code by passing the necessaryparameters based on the requirement.

```
tf.keras.applications.resnet50.ResNet50(
includetop=False,
weights='imagenet',
input_tensor=None,
input_shape=None,
pooling=None,
classes=14,
**kwargs
)
```

Here weights='imagenet',we can load the pretrained ImageNet weights. Otherwise weights=None. So initializing the model with random weights.include_top=False to not include the final pooling and fully connected layer in the original model. Different Pooling layers can be added based on the requirement and a dense output layer to the ResNet-50 model.Number of Classes parameter depends on the dataset.

4.6 Training the model:

The Python deep learning modules keras.fit() and keras.fit_generator can be used to train our machine learning and deep learning models.(). These two functions can achieve the same result.The primary difference is that.fit is employed when the entire training dataset fits into memory without the need for data augmentation.The.fit_generator is used when fitting a huge dataset into memory or when data augmentation is required. Before training, the model must be built.After training the model, we can use the keras.fit method to determine its validity.

Keras.Fit method: We developed iterators for picture enhancement. We input it to the neural network, which augments it.All we need to do is pass the iterator, together with epochs,size of the batch, and remaining essential parameters,into the fit method used to the network prototypical. A Convolutional Neural Network (CNN) prototypicalwill be used. The fit method applies the prototypical to figures generated in batches by a Python generator.The following are fit method arguments.

- The first argument is used for iterating for the training of different images that we get from the flow().
- Epoch makes the count of forward and backward authorizations of the working out information.
- Number of epochs is an imperative parameter postulates the quantity of batches of images that are in a single epoch. It is habitually engaged as the measurement of the original set of data alienated by the length of batch.
- Validationdata took the corroboration set of data or the corroboration generator outcome from the generator technique.
- Steps of Validation is comparable to number of steps in epoch, but for corroboration data. This can be castoff when we are expanding the justification set of pictures as well.
- Batchsize : it can gross any integer value or NULL and by default, it will be set to 32 generally.It postulates no. of models per gradient.

```
65/65 [==============================] - 25s 390ms/step - loss: 0.3392 - accuracy: 0.8924
Epoch 13/25
65/65 [==============================] - 25s 390ms/step - loss: 0.2861 - accuracy: 0.8992
Epoch 14/25
65/65 [==============================] - 25s 389ms/step - loss: 0.3290 - accuracy: 0.8841
Epoch 15/25
65/65 [==============================] - 26s 394ms/step - loss: 0.2654 - accuracy: 0.9127
Epoch 16/25
65/65 [==============================] - 25s 389ms/step - loss: 0.2787 - accuracy: 0.9089
Epoch 17/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1922 - accuracy: 0.9346
Epoch 18/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1748 - accuracy: 0.9438
Epoch 19/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1725 - accuracy: 0.9438
Epoch 20/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1077 - accuracy: 0.9670
Epoch 21/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1306 - accuracy: 0.9569
Epoch 22/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1323 - accuracy: 0.9564
Epoch 23/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1825 - accuracy: 0.9443
Epoch 24/25
65/65 [==============================] - 25s 390ms/step - loss: 0.1768 - accuracy: 0.9438
Epoch 25/25
65/65 [==============================] - 25s 390ms/step - loss: 0.0939 - accuracy: 0.9714
```

Fig.4.8 Training accuracy

```
[ ]  print("Evaluate on test data")
     results = model.evaluate(x_test, y_test, batch_size=32)
     print("test loss, test acc:", results)

     Evaluate on test data
     22/22 [==============================] - 5s 148ms/step - loss: 0.9971 - accuracy: 0.7602
     test loss, test acc: [0.9971484541893005, 0.7601743936538696]
```

Fig.4.9 Validation accuracy

4.7 Results:

The dataset is given as an input to perform Pre-processing and Data Augmentation. After thatfeatures are extracted using Resnet50 by pooling and model is trained for the given dataset(70%trained) and for the model, video is given as input and gives output as healthy or diseased leafas shown in Fig.4.10,Fig.4.11,Fig.4.12,Fig.4.13, Fig.4.14 and Fig.4.15.

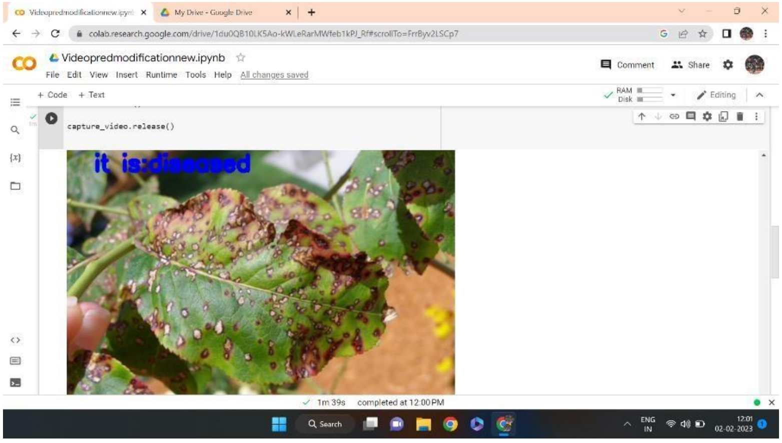

Fig.4.10 Diseased leaf

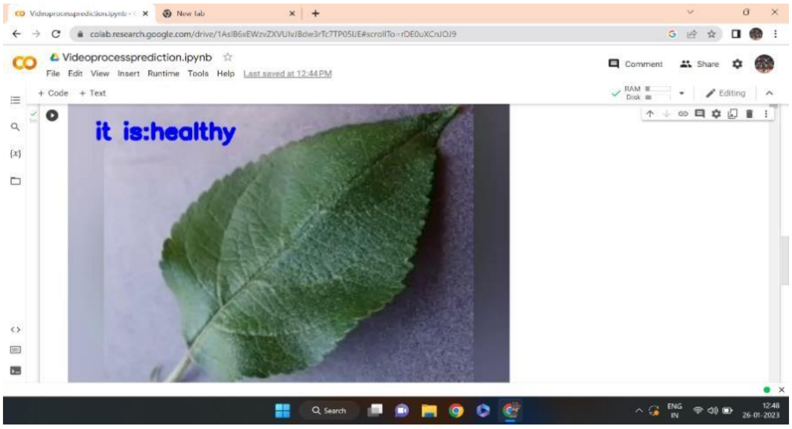

Fig.4.11 Healthy leaf

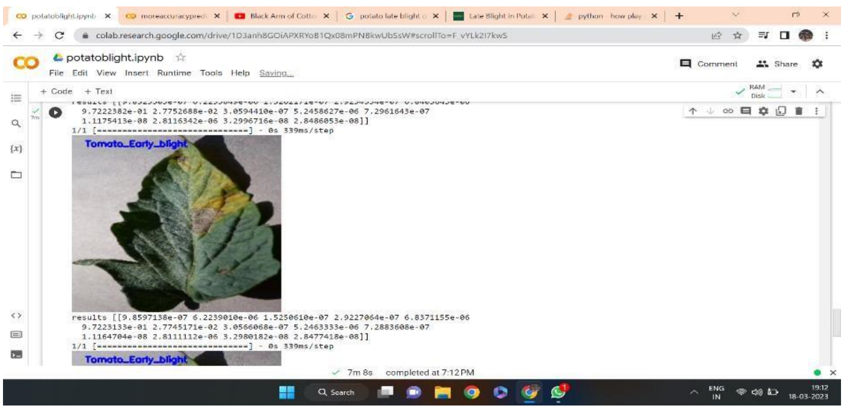

Fig.4.12 Diseased with tomato early blight

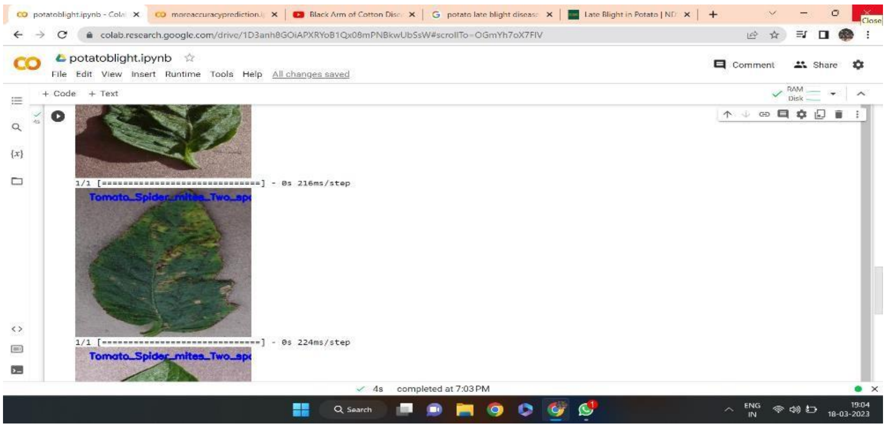

Fig.4.13 Diseased with Tomato spider mites

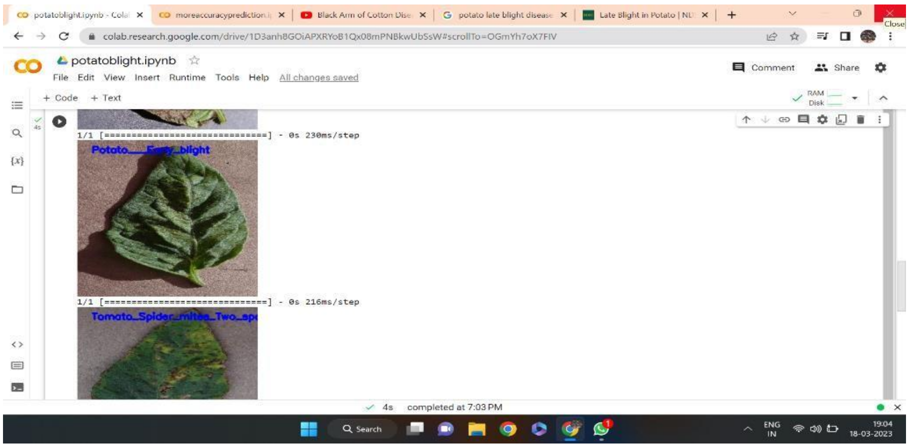

Fig.4.14 Diseased with Potato early blight

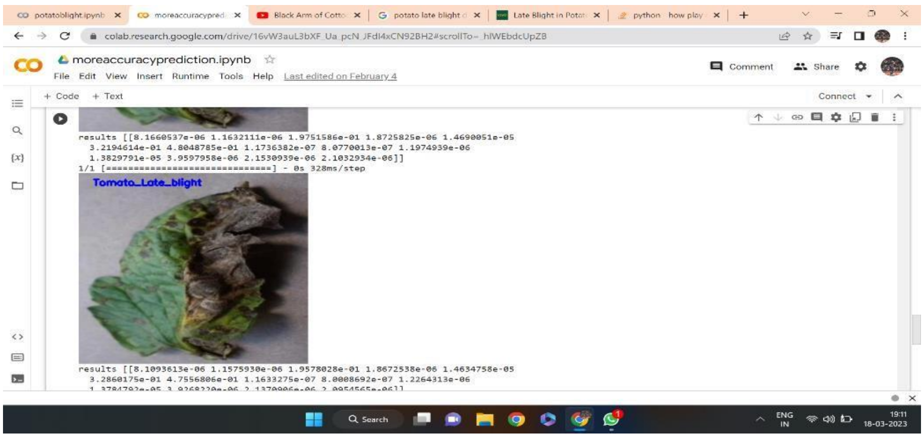

Fig.4.15 Diseased with Tomato late blight

CHAPTER 5
CONCLUSION AND FUTURE WORK

Plant leaf disease detection using machine learning algorithms has shown promising results inrecent years. Machine learning algorithms can accurately classify plant leaves into healthy and diseased categories, thus helping farmers to identify and treat plant diseases early on, and preventing crop damage and yield loss.

In this project, we have explored various machine learning algorithms such as Logistic Regression, KNN, Navie Bayes, Support Vector Machines (SVMs), and Random Forests for plant leaf disease detection. We have also examined the performance of these algorithms on different datasets and evaluated their accuracy, precision, recall, and F1 score.

we also explored the use of ResNet-50, a deep convolutional neural network, for plant leaf disease detection using machine learning algorithms for video datasets. ResNet-50 is a powerful algorithm that can extract high-level features from images, making it well-suited forplant leaf disease detection. We evaluated the performance of the algorithm on various datasetsand achieved high accuracy in detecting plant diseases.

Overall, the results of our experiments show that Random Forests Classifier outperform otheralgorithms in terms of accuracy and generalization on image datasets and Resnet-50 for video datasets. Therefore, these algorithms can be used as a reliable and efficient algorithm for plantleaf disease detection.

The use of automated monitoring and management systems are gaining increasing demand withtechnological advancement. .In the agricultural field loss of yield mainly occurs due towidespread disease. Mostly the detection and identification of the disease is noticed when the disease advances to severe stage therefore, causing the loss in terms of yield, time and money.The proposed system is capable of detecting the disease at the earlier stage as soon as it occurson the leaf, Hence saving the loss and reducing the dependency on the expert to a certain extentis possible. It can provide the help for a person having less knowledge about the disease, Depending on these goals, we have to extract the features corresponding to the diseases.

REFERENCES

1. Haseeb Nazki, Sook Yoon, Alvaro Fuentes, Dong Sun Park "Unsupervised image translation using adversarial networks for improved plant disease recognition" Published by Elsevier B.V,(2020).
2. Shanwen Zhang, Subing Zhang, Chuanlei Zhang, Xianfeng Wang, Yun Shi "Cucumber leaf disease identification with global pooling dilated convolutional neural network" Published by Elsevier B.V, (2019).
3. Uday Pratap Singh, Siddharth Singh Chouhan, Sukirty Jain, And Sanjeev Jain "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease" (2019).
4. Vijai Singh "Sunflower leaf diseases detection using image segmentation based on particle swarm optimization" 2019 Published by Elsevier,(2019).
5. Sumita Mishra, Rishabh Sachan, Diksha Rajpal "Deep Convolutional Neural Network based Detection System for Real-time Corn Plant Disease Recognition" 2020 Published by Elsevier B.V, (2019).
6. Parul Sharma, Yash Paul Singh Berwal , Wiqas Ghai "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation" open access 2019 Published by Elsevier B.V, (2019).
7. Mohit Agarwal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, Suneet Gupta "Tamato Leaf Disease Detection using Convolution Neural Network" 2019-2020 Published by Elsevier,(2019).
8. Aditya Khamparia, Gurinder Saini, Deepak Gupta, Ashish Khanna, Shrasti Tiwari, Victor Hugo C. de Albuquerque "Seasonal Crops Disease Prediction and Classification Using Deep Convolutional Encoder Network" ,(2019).
9. Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk and Darko Stefanovic "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification", Volume 2016 Hindawi Publishing Corporation,(2016).
10. Majji V Applalanaidu, G. Kumaravelan "A Review of Machine Learning Approaches in Plant Leaf Disease Detection and Classification" IEEE,(2021).
11. Qiong Ren , Hui Cheng and Hai Han "Research on machine learning framework based on random forest algorithm" : AIP Conference Proceedings,(2017).
12. Tao Xiang, Tao Li, Mao Ye, and Zijian Liu "Random Forest with Adaptive Local Template for Pedestrian Detection" Hindawi Publishing Corporation,(2015).

13. Md Nasim Adnan "Improving the Random Forest Algorithm by Randomly Varying the Size of the Bootstrap Samples"Adnan,(2014).
14. Ziming Wu, Weiwei Lin, Zilong Zhang and Angzhan Wen "An Ensemble Random Forest Algorithm for Insurance Big Data Analysis"IEEE,(2017).
15. Manjunath Badiger, Varuna kumara,Sachin CN shetty,Sudhir poojary "Leaf and skin disease detection using image processing" Global Transactions Proceedins,(2022).
16. Niveditha M, Pooja R, Prasad Bhat N, shashank N, "Plant disease detection using machine learning" IEEE (2021).
17. Nishant Shelar ,Suraj shinde ,Shubham sawant ,Shreyas dhumal "Plant disease detection using CNN " Turkish Journal of Computer and Mathematics Education, (2021).
18. Madhuri Devi Chodey, Dr.Noorilla Shariff C, Gauravi Shetty "Pest detection in crop using video and Image processing" IJRASET (2020).
19. Aryan Garg"Image Classification Using Resnet-50 Deep Learning Model"Analytics vidya,(2022).
20. Devvi Sarwinda , Radifa Hilya Paradisa , Alhadi Bustamam ,Pinkie Anggia "Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer" International Conference on Computer Science and Computational Intelligence,(2020).