# "Coffee Plant Diseases Recognition Based on Machine Learning"

Author

[1]Rohit N, [2]Prajwal P

**ABSTRACT**

*In this research paper we have taken a coffee leaf images dataset called CoLe. The main aim of this project is reducing the difficulties faced by the farmers because of the disease caused on the plant, detecting on the early stages might cause less problems for the farmers, so the aim is to build an android application which can reduce these problems. This dataset contains 1560 plus leaf images it also contains annotations which tells us about the objects about the leaves, state which tells whether the leaf is healthy or unhealthy and the severity of disease that is the leaf area with spots. These leaf images are taken from the real-world conditions from the coffee plant fields through a smart phone camera. This project mainly focuses on the approach based on image processing for detection of diseases of coffee plant leaves. For identification of plant's diseases, it basically depends on the recognition of characteristic of plant leaf. The original images from the dataset are cropped into required sizes and sequentially segmented images are proposed into the network We have used environments like Jupyter and Spyder. And the system as used a set of algorithms like image segmentation, SVM and classification problems related to plant diseases recognition are used. Classification is done by SoftMax and bounding box regressor and identified labels of segmented images are spliced together which gives us the final output. SVM is used for finding the accuracy rate of sum of aspect ratio and SVM algorithm. Before the output the images goes through a series of image processing for detected the disease.*

**Keywords:** *Image processing, Detection, Identification of plant leaf diseases, CNN, SVM, SoftMax , Plant diseases recognition, Coffee leaf rust*

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## INTRODUCTION

Coffee is originated from Ethiopia, it is one of the largest exporter of coffee. Coffee is now grown worldwide and it is the most consumed drink all over the world. One third of the world's population drinks coffee as a beverage, making it one of the most important traded commodities after petroleum. In some food processing sectors nowadays, coffee is utilized as an ingredient. For example, it is used to flavor a variety of pastries, ice creams, chocolates, and sweets. There are various types of coffee plants about 25 to 100 species like Arabica, Robusta, Liberica, Excelsa etc. Coffee trees can usually grow up to 30 feet high and it is covered with green waxy leaves which grows opposite to each other as pair and with this even coffee cherries are grown along the branches of the coffee tree, for these cherries to mature it while near take 1 year and these coffee trees can live for 100 years. There are main advantages for growing coffee plants for the farmers in the world it will increase the productive and also the economy, it even gives a living for the farmers. But there are many diseases associated with the coffee plant which might spoil the growth of the plant and the productive. Few diseases can be mild and cured by days and the plant can get back the normal stage but few diseases are very dangerous which might kill the plant and can even spread to the neighbouring plants which can spoil the whole harvest which causes loss in production and economy for the world and the farmers. There are many uneducated farmers who cannot recognise the disease caused on the plant in the early stages which might cause a problem on the later stages and also in few countries, famers don't even have the idea about calling an expert or any other facilities for their help. And even consulting the experts might be costly for the farmers and it might even take away time. In situation like these technologies might come in hands. So, we need an application which would recognise these diseases caused on the coffee plant and it also reduces the severity of the diseases when it is detected on the early stages. One of the most commonly used method of observation by the people or the farmers is detected the diseases through naked eye, this method maybe cannot be accurate enough because detection the disease is an easy job but getting to know what type of diseases and at what stage is the disease and the severity of the diseases is very hard by using this naked method for detected the diseases associated with the coffee plant. So, from the experts view they do identification and detection of plant diseases. However, identification plant diseases by the visual way are a very difficult task and also at the same time it's very hard to get accurate result and it can be done only in limited areas. Instead of this if we use automatic detection technique it reduces the efforts, less time is taken and also it gives more accurate results. Hence smarting farming is need in places like this specially in improving in the field of agriculture. A significant increase in food production must be attained, while also ensuring global availability and good nutritional quality, and safeguarding the natural ecosystems through the use of sustainable agricultural practises. It is necessary to regularly monitor, measure, and analyse many physical characteristics and phenomena in order to better understand the complex, multivariate, and unpredictable agricultural ecosystems in order to handle these difficulties. This calls for the analysis of large-scale agricultural data and the use of new information and communication technologies, both for short-term crop/farm management and for the observation of larger-scale ecosystems, enhancing the management and decision-making processes by context, situation, and location awareness. Remote sensing which uses satellites, planes, and unmanned aerial vehicles to capture wide-angle images of the agricultural surroundings, facilitates larger-scale monitoring. Being a well-known, non-destructive approach to gather information on earth features and the ability to obtain data systematically over vast geographic areas make it advantageous when used in agriculture. Images make up a sizable portion of the amount of data gathered by remote sensing. Images often provide a thorough view of the agricultural surroundings and can help with a number of problems. As a result, imaging analysis is a crucial topic for research in the agricultural field, and several agricultural applications use intelligent data analysis techniques for image identification/classification, anomaly detection, etc. In addition to providing food and energy, medicine for humans, plants have a favourable impact on preserving the ecological balance. Consequently, it's crucial to identify and safeguard plants. It is well known that plant leaves include a significant amount of species information, including noticeably different textures, hues, and morphological characteristics, which are essential for identifying different plant species. Plant leaves, as opposed to flowers or fruits, can grow in practically all seasons and undergo discernible seasonal variations. Since it is simple to derive these benefits from leaves, the classification and identification of plants based on their leaves has gained popularity in recent years. In recent years, substantial research has been done on plant leaf recognition using picture analysis and processing. Every crop that farmers grow is reportedly susceptible to one or several pomegranate diseases. Monitoring plant health and spotting diseases manually is difficult. Image processing can therefore be a useful and efficient method for identifying plant diseases. Diseases are categorised using edge information and colour characteristics. The technology provides both prophylactic measures and an infection percentage. Images captured by a mobile camera are first pre-processed, after which they are segmented, their features are retrieved, and diseases are identified. Python algorithms for sickness detection will be developed using the Open CV platform. The installation of monitoring instruments to ensure enough coffee production is necessary to ensure that plant diversity and the coffee supply are not seriously threatened by plant disease. This is an important sustainable management strategy. A widespread pandemic of a disease might significantly curtail the output of coffee, costing millions of rupees. By using machine learning techniques, the danger of crop loss brought on by disease outbreaks can be reduced. The primary symptoms of plant diseases include colour changes, the development of spots or decaying areas in the leaves, or both. The majority of diseases and pest conditions exhibit a distinct visual pattern that can be utilised to specifically identify irregularities. The majority of disease signs may start to show on a plant's leaves, which are typically the main source for identifying plant diseases. The process of photosynthesis uses the majority of a plant's leaves as a source of food, therefore when a disease damages a leaf, the photosynthesis process is hampered, which results in plant mortality. The application of technology enhances the accuracy and dependability of detection and analysis operations. For instance, people who study newly emerging diseases with the use of cutting-edge technology stand a better chance of controlling them than those who do not. With the recent coronavirus outbreak, the world relied on cutting-edge technology to create preventive measures that have slowed the spread of the illness. Crop diseases pose a serious hazard to human existence because they could trigger famines and droughts. When farming is practised with a view to making money, they can also lead to large losses. The employment of machine learning (ML) and computer vision (CV) could enhance detection. The amount and quality of the crop are decreased as a result of inconsistent and delayed plant disease detection. Twenty to forty percent of the world's annual productivity is lost because of plant diseases or other pests. Studies have been conducted to determine the estimated loss brought on by various diseases. Yield loss is another factor in the direction of rising consumer prices and declining agricultural producer profits precise and prompt identification preventing plant diseases is essential for providing the highest production and is advantageous for farms in distant places. Machine vision developments have made it possible to conduct visual recognition tasks, including these. Plant diseases can be successfully identified using visual recognition techniques. Few diseases caused on the coffee plant are Coffee leaf rust, Brown eye spot, Algal (red) leaf spot, Black rot etc. Coffee rust is currently thought to be the world's most devastating disease of coffee. It is financially devastating for coffee growers. In 1861, coffee rust was first discovered in Africa. But later, in 1867, it was discovered that the illness had infected cultivated (as opposed to wild) coffee in Sri Lanka. Within ten years, the production of coffee was destroyed here. Since then, reports of this devastating disease have come from all of the major nations that produce coffee. Leaf loss can occur as a result of minor diseases. Twigs may begin to die back from the tips in cases of severe infestations. Trees can eventually perish as a whole. The disease's long-term effects frequently cause a significant decline in yield. Each year, this causes losses worth billions of dollars in the US. Symptoms of coffee rust disease are spots which are irregular are found mostly on the upper surface of the coffee leaf and an orangish powder is found on the lower surface of the leaf. On lower surface of the coffee leaf which is infected few spores can be spotted which are the cells of the disease which can continuously reproduce rapidly which with kill the leaf faster. Hemileia vastatrix, a rust fungus, is the source of the devastating illness known as coffee rust. Production of coffee may be reduced by 30% to 50%. The degree of an infestation varies based on a number of variables. These include a disease-friendly climate, the management strategies used, and the plant's degree of resistance. High humidity fosters the disease's growth. The disease is primarily spread by rain. The infection can, however, return if the fungus is spread to new leaves by wind, animals, or people. The disease spreads more readily in warmer and wetter regions. The disease is less likely to spread in drier, colder settings. During the time of harvest, coffee rust is frequently spread. As individuals travel around the plantation gathering coffee beans, it can be transported from one plant to the next within particular plots. The harvester can also shift it from one farm to another.

Figure1

Coffee rust disease-orangish powder spores on the lower surface of the leaf

Coffee brown-eye spot is caused on the leaves, by tiny brown specks that are more noticeable on the upper surface. Within the leaf, the spots typically appear between the veins and also near the margins. The spots, which can reach a diameter of 15 mm, have light brown or occasionally light grey centres, a broad dark brown ring around them, and a yellow edge. Occasionally, the dots develop into sizable blotches, and a leaf blight takes place. This typically occurs in moist, colder regions over 600 metres. High humidity, rain, warm temperatures, and drought stress after flowering are all favourable weather factors for this disease. The fungus's spore masses can be noticed on blackened mature berries and in the grey centres of leaf blotches. The spores require water to germinate and are dispersed by the wind and rain splash. When coffee plants are not growing well due to low nutrition or insufficient shade, the disease is typically an issue. In nurseries, it can result in seedlings losing their leaves and, in extreme situations, stem dieback. On established plants, it generally doesn't matter as much, but when the conditions are right, epidemics can break out on even well-kept trees.

Figure2

Coffee brown-eye spot is caused on the leaves

Black rot is caused by a bacterium called Xanthomonas campestris pv. campestris, which can infect most crucifer crops at any growth stage, is the cause of black rot. The disease is challenging for growers to control and is widely regarded as the most devastating disease of crucifer crops (Figure 1). When warm, humid circumstances follow periods of rainy weather during the early crop development, the disease can result in severe output losses. Late infections can act as a wound through which additional rot organisms can enter and seriously harm stored goods. Depending on the host, cultivar, plant age, and environmental factors, black rot symptoms can vary greatly. The bacteria can infiltrate plants through natural cracks and sores on roots and leaves that are the result of mechanical damage. Through pores on the cotyledon margin, seedborne bacteria infect the newly emerging seedlings and subsequently spread throughout the seedling's whole system. Infected seedlings that are raised in a greenhouse under cool temperatures (below 15–18°C) typically do not exhibit any disease symptoms. When infected seedlings are transplanted into the field at times of high relative humidity (80–100%) and temperatures climb to 25–35°C, they develop stunted growth with dead spots on the cotyledons and finally wilt and die. Disease signs on sick people can be seen in temperate climates (where temperatures stay cool).

Figure3

Black rot on the coffee leaves

Like this there are many diseases associated with the coffee leaves which might affect the cultivation and create problems for the farmers and the economy. The main aim of this project to reduce these problems for which an automatic detecting technique is utilised, it will be more accurate and need less efforts. In plants, some bacterial, black, general illnesses Rust, viral, and red cotton Leaf are three other species. The process of images processing is utilised for measuring the disease's afflicted area and figuring out the variation in hue of the afflicted area. Segmentation is the method of dividing or classifying an image into many components. There are plenty now, several techniques for segmenting images, varying from the straightforward thresholding approach to modern techniques for segmenting-coloured images. The method of segmentation is based on several features discovered in the photo. This could be a colour description, portions or limits of an image. In addition to the methods already stated, deep learning (DL) has lately gained popularity. DL and ANN are both components of the machine learning computational area. However, "deeper" neural networks used in deep learning (DL) provide a hierarchical representation of the input through a variety of convolutions. This enables greater learning capacities, which leads to improved performance and accuracy. The reason for doing this survey is because DL in agriculture is a relatively new, cutting-edge, and promising approach that is gaining ground, while developments and applications of DL in other fields suggest that it has significant promise. The authors were inspired to create this survey by the fact that there are already at least 40 research projects using DL to tackle various agricultural problems with excellent results. We performed an annotation data process to obtain a fully-labelled of the 1560plus coffee leaf photos using a data labelling web-tool called "Labelbox" in order to give CoLE the capabilities to assess the effectiveness of the described and other machine learning approaches. There were two different kinds of annotations: classification and object segmentation. The goal of object segmentation in the field of machine learning is to divide an image into portions that have conceptual significance. Segmentation tasks have been carried out using artificial neural networks, genetic algorithms, and clustering. Classification, on the other hand, seeks to identify a class to which an item belongs using patterns in a labelled data set. Here, classification tasks have been carried out using artificial neural networks, SVM, and decision trees. The labeller recognises and segments each object in our dataset using annotations of object segmentation (leaf). The health of each item was further noted. The leaf as be classified as being healthy, having red mites, having level 1 or level 2 rust, or having level 3 rust, rust level 4. We use the OIRSA approach to determine the severity of the rust infection. Each level of annotations is established in accordance with the percentage of impacted leaf area. For instance, the image is labelled with the highest level, or rust level 4, when the number of spots is greater than half the leaf. The fully labelled picture dataset can be used in replicable studies that apply machine learning techniques to classification and segmentation issues. CoLe offers object annotations to segment the leaves for segmentation issues. In this case, an object can be recognised by a mask or an orange limited-area designating the area of the image where a leaf can be found. Additionally, it specifies the sort of object, such as an unhealthy leaf. The dataset CoLe is separated into six types using a classification problem: healthy, presence of red spider mites, level 1 rust, level 2 rust, level 3, and level 4 rust. Below are the images from the dataset which are classified into 6 different label classes.

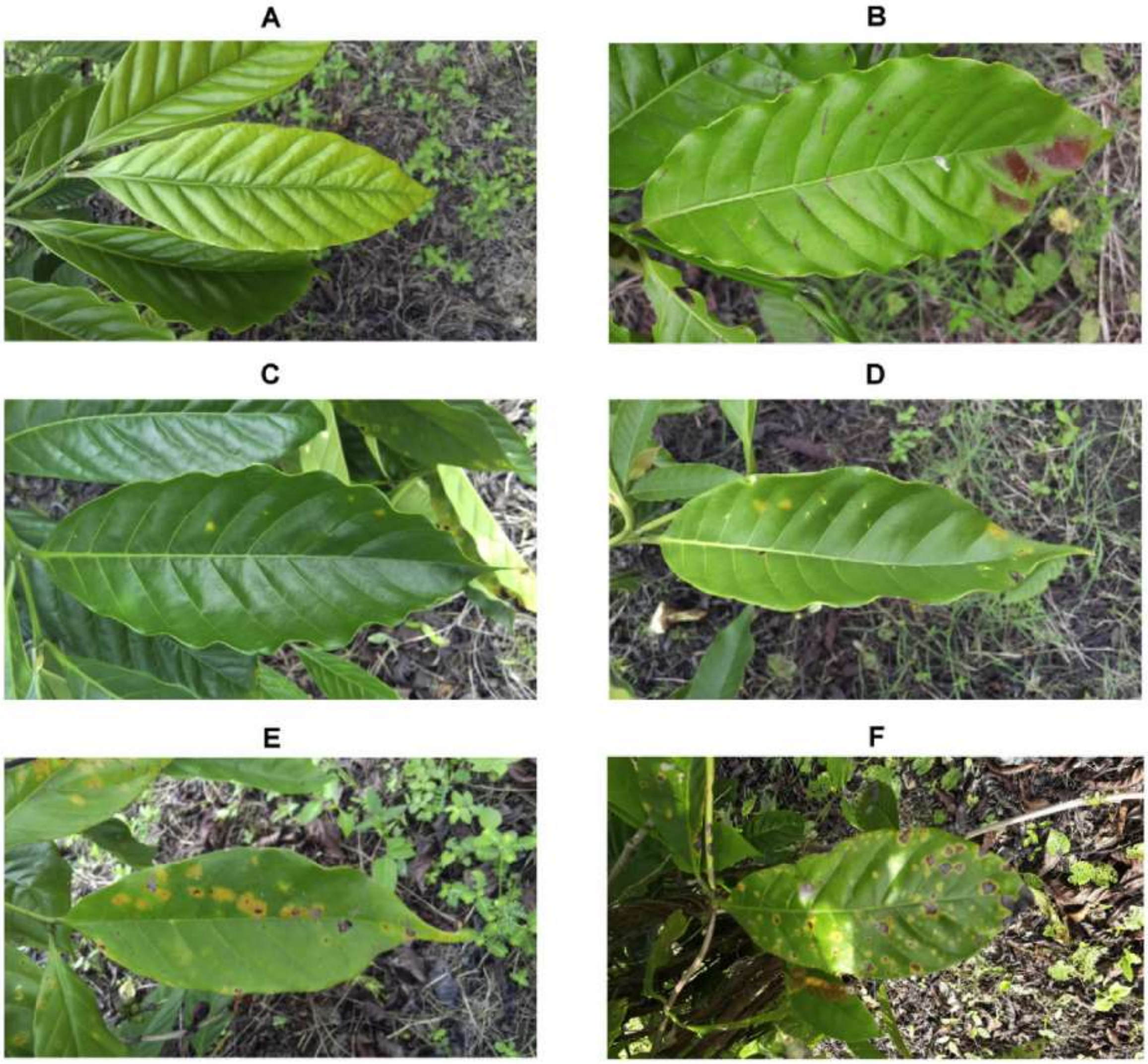



Figure4

(A) - healthy, (B)-Red spider mite, (C)- Level 1 rust; (D)- Level 2 rust, (E)- Level 3 rust, (F)- Level 4 rust

**Table 1**
Severity scale of rust in coffee leaf.

| Level | Affected leaf area (spots) |
|---|---|
| 1 | 1–5% |
| 2 | 6–20% |
| 3 | 21–50% |
| 4 | >50% |

Figure5

In this paper, a better deep convolutional neural network based on Faster RCNN and Inception V2 module is proposed in order to increase the recognition ability in the wild and decrease the computational cost. The original photos are divided into a large number of smaller sub-images, which are then successively loaded into the suggested network. Convolutional neural layers are also replaced by the inception module, which gives the subsequent network rich picture features. To forecast region proposals, the region proposal network (RPN) with shared convolutional network is used in place of category-independent approaches. The region of interest (RoI) pooling is used to extract proposal feature maps from the generated feature maps and region proposals. Then, by including a full-connected softmax classifier and bounding box regression, these feature maps may be precisely classified. In the final phase, the created findings (sub-images) are re-joined to the final recognition images. The goal of this research is to offer small farm owners in isolated locations lacking access to specialised knowledge a solution. The proposed study outlines a method for creating a system for diagnosing diseases. The proposed work can be turned into a smartphone app that can carry out the duty of diagnosing diseases using visual classification. The primary cause of crop yield loss is insect or disease assault, hence reducing the risk of crop loss can be accomplished by offering a solution for disease diagnosis in farms. The major goals of the work are to determine if a leaf is healthy or diseased and to categorise the type of the disease to an image of a diseased leaf. In situations where the leaf disease is visually identifiable, the objective can be achieved based on visual classification. This app can be used by the famers and agriculture experts to get to know the what type of disease and how much part of the leaf is affected.

## REVIEW OF LITERATURE

Paper [1]: The dataset coLe containing the images of the leaves can be used for training and to valid the performance of the machine learning algorithm which can be used in both binary and multiclass classification and it also used for segmentation tasks for recognition of plants or leaves which associated the disease.

Paper [2]: The diagnosis of plant diseases using leaf images is one of the methods that are now being used to quantify and identify plant diseases. It may be used to identify a variety of diseases and is unquestionably the simplest technique to automatically detect plant disease. The texture and colour of a leaf vary specifically when a plant disease occurs, so leaf imaging can be utilised to extract colour and texture-based characteristics to train a classifier. There are two methods for identifying plant diseases using leaf images: (i) Deep learning-based systems, which automatically learn features using sophisticated architectures. (ii) feature-based learning, in which a traditional machine learning algorithm is trained using hand-crafted data like colour and texture information. Higher accuracy has been achieved using deep learning-based techniques, but because they require more computation, they are not appropriate for mobile or handheld devices because they have a limited amount of memory and processing power. While other approaches focus on several plant diseases, some of the created systems target many illnesses of a single type of plant.

Paper [3]: one significant statistical attribute extraction method is based on the Gray Level Co-Occurrence Matrix (GLCM). The GLCM matrix counts the number of adjacent pixels with a specific grey level that occur when taking into account a reference pixel with its own grey level. The grey level values that were detected in the reference pixel and its neighbouring pixel in the original image serve as the basis for each GLCM element. Additionally, each GLCM is calculated taking into account a certain direction produced by these two pixels. shows an original image with a few pairs of grey level values taken from the reference and neighbouring pixels while taking the horizontal, left to right, direction into consideration. The comparable GLCM uses the identical pair of values for the reference neighbour pixels to count the number of pixel pairs. As a result, the numbers 2 and 3 represent the quantity of each matching pair of grey level values in the original image.

Paper [4]: Numerous techniques for automating the identification of plant diseases have been investigated in depth. Different components of the plant, such as the roots, stem, fruit, or leaves, may show symptoms of the illness. As previously mentioned, this work is mostly focused on leaves. a method for identifying plant diseases that affect the stem and leaves. The segmented images are categorised by a neural network in the proposed study after being segmented using the K-Means technique. They created an algorithm for image processing in order to create a way for identifying the visual symptoms of plant illnesses. By contrasting the manually segmented and automatically segmented photos, the algorithm's accuracy was evaluated.

Paper [3-5]: described different methods for dividing the sick area of the plant. The approaches for feature extraction and classification, as well as the classification of plant diseases, were also covered in this study. SVMs, self-organizing feature maps, back propagation algorithms, and other effective ANN techniques can be used to classify plant diseases. Utilizing image processing tools, we may precisely identify and categorise numerous plant diseases using these methods.

Paper [6]: For automated plant disease classification based on leaf image processing, a method based on image processing is utilised. The study focuses on utilising an SVM classifier to distinguish between unhealthy and healthy coffee leaves. They tested the system using a dataset of 120 photos that were directly collected from several farms using various mobile cameras. The SIFT algorithm makes it possible to accurately identify the plant species based on the shape of the leaves. The SVM classifier can assist in differentiating between healthy and unhealthy coffee leaves with an average accuracy of up to 93.79%. The primary goal of the proposed effort is to supply inputs to an autonomous DSS that would give farmers the appropriate assistance over mobile as and when needed. With little effort, this system will assist the farmer. The farmer merely needs to use a smartphone camera to take a picture of the plant leaf and email it to the DSS no other information is required.

In Paper [7]: The technique uses colour imaging to extract and categorise groundnut leaf disease. In this work, we classified only four distinct diseases with 97 Al% effectiveness using the colour imaginary transform, colour co-occurrence matrix, and feature extraction. Back propagation provides efficient groundnut leaf detection with a complex background. But as time went on, the strategy was used to spread more diseases.

Paper [8]: Includes research on the detection of plant diseases and the identification of contaminated plant parts. Prior to beginning image processing, input images are first captured. The initial phase involves segmenting both background and black pixels. The image's saturation portion is then divided as well. And finally, following the methods we suggested, the disease's name, affected portion, and infected area % are acquired. The primary goal of this work is to bring improvements and advancements in calculating classifiers using a neural network approach. The calculation of the percentage of a plant's affected area makes this study special.

In Paper [9]: gave any idea how to use deep learning the better way and also gave some basic information about convolutional neural networks. Convolutional neural networks (CNNs) offer strong performance on extracting properties, including sparse connections, multilayer perceptron, and weight sharing, which can significantly save the time required for training and classification. In contrast to two-dimensional locality preserving discriminant analysis and uncorrelated locality sensitive discriminant analysis, CNN is able to autonomously learn more critical features of samples from the dataset through operations between neurons in both convolutional layers and sub sampling layers. CNN still has some flaws, though. For instance, during training, the input distribution in each layer changes, making it possible to use only a minimal learning rate. Additionally, the CNN architecture requires input photos to be a fixed size by cropping and wrapping, which causes images in CNN to lose information. The aforementioned flaws prevent CNN from learning from a large number of training samples with sufficient recognition speed and accuracy.

Paper [10]: gave an idea from the technical side that is 17 publications, or 42% of the research studies, used well-known CNN architectures as AlexNet, VGG16, and Inception-ResNet. The remaining papers were divided into 14 papers that created their own CNN models, 2 papers that used first-order Differential Recurrent Neural Networks (DRNN) models, 5 papers that favoured using LSTM models, 1 paper using deep belief networks (DBN), and 1 paper using a hybrid of PCA and auto-encoders. Several CNN methods, including logistic regression, Scalable Vector Machines (SVM), linear regression Large Margin Classifiers, and macroscopic cellular automata, paired their model with a classifier at the output layer. All studies that utilised a well-known CNN architecture also utilised a deep learning (DL) framework, with Caffe being the most popular, followed by Tensor Flow and deep learning. While some authors choose to build their own models on top of Caffe (5 papers), Keras Theano, Keras TensorFlow, MatConvNet, and Deep Learning Matlab Toolbox, ten research works developed their own software. Caffe's widespread use may be attributable to the fact that it integrates a variety of CNN frameworks and datasets that may be employed by its user quickly and automatically. Most research used an 80/20 or 90/10 ratio to divide their dataset into training and testing/verification data. Using pre-trained CNN, or CNN models that have already been trained on some relevant dataset with potentially differing numbers of classes, is a common transfer learning technique. Then, these models are modified for the specific problem and dataset.

Paper [11]: The paper used SVM with three separate features to predict how peanut number would be classified. According to experimental findings, the accuracy of the aspect ratio and SVM combination is significantly higher than that of the HOG + SVM and Hu invariant moment +SVM combinations. The length-to-width ratio is more appropriate for the classification of peanuts since it has the highest classification accuracy. If a huge number of peanut photos can be gathered, the more popular deep learning is more appropriate to handle this issue in order to further increase classification accuracy. It is also a useful way to utilise migrating learning if it is unable to get a large number of photos, but for the volume of data this article is insufficient. hoping that this problem will eventually be fully rectified.

In Paper [12]: They examined and discussed the application of visualisation to disease detection techniques in this work. Instead of treating disease detection systems as black boxes, they showed how visualisation could be used to show how well a model detects diseases. Furthermore, a guided technique was used to attain a classification accuracy of 98%. Three visualisation techniques were used in their study: Score-CAM, Grad-CAM++, and Grad-CAM. A visual comparison of all visualisation techniques for categorising coffee diseases was also carried out. This study believed visualisation to be a crucial element in order to understand how to develop a better model for identifying plant diseases. They intend to create a method for locating and detecting coffee diseases in their further study. It is expensive to annotate photographs using object bounding boxes, especially in underdeveloped nations where knowledge and resources are limited. They've already demonstrated a useful technique for locating coffee diseases without training participants to annotate photographs with object bounding boxes. As a result, a poorly supervised coffee disease detection system was the subject of future research.

Paper [13]: in this paper they covered how ML in general and DL in particular have aided in the identification of plant diseases in this research. If infections are not properly diagnosed, crop productivity will be affected, which will lead to long-term problems like global warming and even famine. The proposed work compiles a number of works on automating and identifying plant diseases using various ML techniques. A vast area of research needs to be investigated in the near future because the proposed publication also demonstrates the widespread acceptability of a variety of CV approaches in this domain. The points that are presented here may help to advance and improve the existing state of the art and provide researchers with some prospective ideas for future research in the field. Detection of the disease's stage. One of the key topics for research in plant disease diagnosis is disease stage identification. Every disease has several stages. The majority of researches simply concentrated on identifying the type of disease in their work; no effort specifically sought to identify a particular disease stage. Additionally, these systems must be able to recommend specific treatment options based on the stage of the disease. Farmers will be able to limit damage percentage by taking appropriate measures and precautions with the use of disease predicting identification. Applications for mobile and online: numerous approaches to applications of disease identification have been published in the literature. However, only a small number of the portals and mobile apps are openly accessible online. Some of these programmes, such as Leaf Doctor and Assess Software, are accessible to the general public. These programmes, however, only function with photos that have a flat, all-black background. As a result, these online programmes and systems are crucial for identifying plant diseases. These software programmes' accessibility will aid farmers in spotting a certain ailment. Such software can be used to generate analysis reports that can be provided to a disease expert for advice.

Paper [14]: in this paper they gave a thorough overview of recent research on utilising deep learning to recognise plant leaf diseases and taught the fundamentals of deep learning. Deep learning algorithms are capable of identifying plant leaf diseases with high accuracy if there is enough data available for training. It has been discussed how to improve classification accuracy through the collection of large datasets with high variability, data augmentation, transfer learning, visualisation of CNN activation maps, and detection of plant diseases early on using small samples of plant leaves and hyper-spectral imaging. The Plant Village dataset was typically utilised in studies to gauge how well the DL models performed. Despite the large number of photographs in this dataset of various plant species with their diseases, the images were all captured in a lab. Therefore, it is anticipated that a sizable dataset of plant diseases in actual environments would be established. Although some research use hyperspectral pictures of damaged leaves and various DL frameworks are employed for the early diagnosis of plant leaf diseases, issues still exist that prevent the broad application of HSI in the early detection of plant diseases. That example, for early plant disease detection, it is challenging to gather the labelled datasets, and even seasoned specialists cannot indicate where the invisible sickness signs are, and define fully invisible disease pixels, which are crucial for HSI's ability to identify plant diseases.

Paper [15]: in this paper the input coffee image is reduced in size to 244x244 during the pre-processing stage, and noise is removed using GF, MF, and GF-MF filtering algorithms. Therefore, GF-MF filtering outperforms GF and MF filtering methods. To outline the damaged areas of the coffee leaves during the segmentation process, they utilised the K-Means clustering segmentation algorithm. Feature extraction is the third phase of the suggested model architecture. From the segmented coffee photos, they extracted high-level features using CNN feature extraction, and then they saved these features as a feature set in the database. Following feature extraction, the SVM and softmax classifiers are used to build the classification phase. They suggest that future study can build on this body of work by adding new feature extraction and classification machine learning algorithms as well as additional classes (roots, stems).

## METHODOLOGY USED

A. Deep Learning Method: For this project we can use deep learning methods like:

- Image Acquisition
- Image Pre-processing
- Image segmentation
- Feature extraction

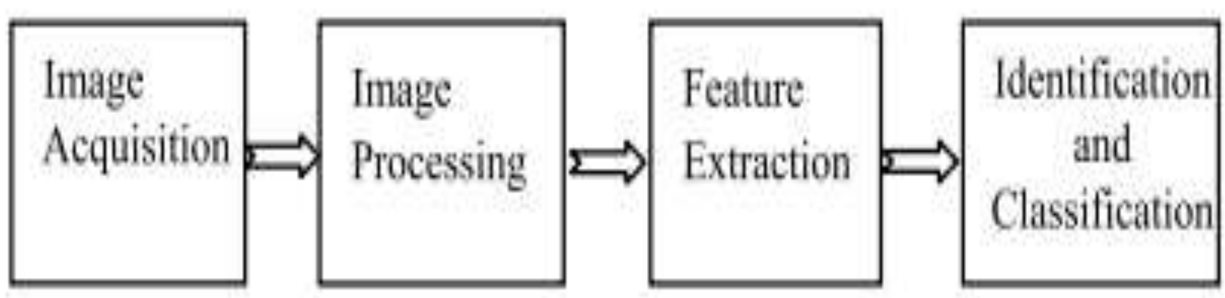



Figure 6

**Image Acquisition:** in this step the images from dataset are taken which are captured from the camera. This images in the RBG format. This RGB is used for colour transformation of the structure on the leaf image. After this an independent device colour space transformation is applied on the colour space transformation structure. The process of collecting an image from a source typically hardware such as cameras, sensors, etc is known as image acquisition.

Since the system cannot perform any meaningful processing without an image, it is both the first and most crucial stage in the workflow sequence. Typically, the technology captures an entirely unprocessed image. The process of acquiring a picture involves converting incoming light energy from an object into an electrical signal using a collection of sensors that are sensitive to that specific sort of energy. To give your machine vision algorithm the most accurate representation of the object, these tiny subsystems cooperate. While users have complete control over illumination, the sensor system and cameras largely depend on the technology available.

**Image Pre-processing:** Various pre-processing procedures are taken into consideration to eliminate noise from the image or other item removals. The weighted approach or luminosity method of the RGB to Gray Converter. Is the issue with the conventional approach. That issue can be resolved using the weighted approach. Green is the colour that has a wavelength that is shorter than red's but also has a more calming effect on the eyes due to the fact that red has the greatest wavelength of the three colours.

Large input dimensions increase the cost of computation resources and increase the likelihood of overfitting. The image is resized into a standard format, either 400* 400 for greater quality, after being converted from RGB to grey. A Gaussian blur, often referred to as a Gaussian smoothing in image processing, is the end result of blurring an image using a Gaussian function, which was created by mathematician and scientist Carl Friedrich Gauss. It is a frequent feature in graphics software and is typically used to reduce visual noise and detail. The bag-of-features technique is used to categorise leaf images as healthy or unhealthy. Images are used to extract Speeded Up Robust Features a local feature detector and descriptor.. In addition, 70% of the most powerful characteristics from each class (healthy or ill) are employed. An SVM model with a linear kernel and two classes is trained using the bag-of-features to classify the photos as unhealthy or healthy.

**Image segmentation:** Image segmentation entails breaking a picture up into groups of pixel regions that can be represented by masks or labelled images. You can process only the crucial portions of an image by segmenting it, as opposed to processing the complete image. The diseased region's Segmentation can be used to obtain discriminating traits. As the most discriminating aspect of the plant disease, the affected region is extracted for texture feature calculation in this study. As a result, it is necessary to excise the diseased segments, which is discussed further. The limited choices for the region containing the disease. Otsu's algorithm is used for unhealthy region segmentation since it is computationally cheap and an overall, reasonable selection. The Otsu algorithm is a more direct and efficient method of segmenting the sick area of the leaf. The grey-level histograms threshold is calculated in order for it to operate. The assumption is that the mean and variance values of the pixels in the foreground and background come from two separate Gaussian distributions. By maximising the variance between the two classes, it locates the ridge between two peaks, and then segments the image using the last point in the grayscale histogram as a threshold. Even while the segmentation of the diseased region is not very accurate, it is acceptable. Often based on the properties of the picture's pixels, image segmentation is a widely used method in digital image processing and analysis to divide an image into various parts or areas.

**Feature extraction:** The process of feature extraction is crucial, and the feature set has a significant impact on how well a classification system performs. Dimensionality reduction, also known as feature extraction, is a technique used to effectively portray the fascinating regions of a diseased region in a condensed manner. Different leaf-based classification factors are based on shape, colour, and texture. Although the segmented diseased region has various inter- and intra-class variabilities and would be less useful for disease diagnosis, the shape features can be used to identify healthy or diseased leaves. The colour of the diseased and healthy regions differs from one another and remain consistent within classes while changing between classes in samples. Similar to this, the texture of the affected area strongly depends on the type of disease and serves as a key indicator. Colour histograms and colour moments are the two basic categories of colour features. In the current situation, colour has less significance as a disease category predictor. The larger feature set that colour histograms offer is not particularly necessary in this situation. Colour moments, which serve as a condensed method of representing colour information, are used to characterise colour information.

The literature uses a variety of feature scaling techniques, and the needs determine which technique is chosen. Typically, feature scaling is used to limit the range of a feature, such as [0, 255] in the case of pictures or [0, 1] or [-1, 1] in the case of features with actual values. The most popular technique is called max-min normalisation, in which features are scaled to a range, or [0, 1], by scaling their maximum and minimum values to these points. Standardization, which scales the features so they have a zero mean and unit variance, is chosen in this study. This popular scaling technique for SVM, ANN, and linear regression is utilised for feature normalisation:

$$x' = \frac{x - \bar{x}}{\sigma}$$

The selection of an appropriate classification method is the last step in the process of classifying leaf diseases according to the category to which they belong. To evaluate their suitability for categorization, we have selected five significant classification methods. To create the final model, the hyper-parameters of the algorithm with the best performance are optimised. Multi-SVM, KNN, Naive Bayes, Random Forest, and artificial neural networks have all been used in this study. SVM is a supervised learning algorithm that is used for classification, regression, clustering, and outlier detection method, each class's unique classifier is matched with each other, one by one, to solve the imbalance issue. KNN: This non-parametric algorithm is used for classifying data, predicting future data, and identifying outliers. It is a lazy learning algorithm that merely saves the training instances of the data rather than attempting to build a model. The k-nearest neighbours cast their votes, and a simple majority is used to classify the objects. Because it is simpler to build, this approach is preferred for training with noisy or large training sets. The choice of K's value is a challenge for K-NN. Overfitting arises from smaller K values, while bigger K values produce smoother decision boundaries with worse classification accuracy due to increased bias. Using the naive Bayes algorithm, which is based on the Bayes theory and assumes that each feature is independent of the others, data is classified using a probabilistic approach. Each feature is assumed to be independent of the existence of every other feature in the feature set, which is Naive Bayes, however performs well in practical settings, needs little training data, and computes quickly. Nave Bayes isn't just one algorithm it's a group of classification algorithms built on the widely held belief that each characteristic operates independently of the others. Random Forest: The decision tree's inherent overfitting issue is resolved by employing various bagging or bragging techniques. Random forest, which fits a number of decision trees on various sub-samples of the training dataset and uses an average for improvement of the forecast accuracy, addresses the issue of overfitting. Except when samples are drawn using replacements, the sub-sample size is always the same as the original sample size. In most situations, random forests are more accurate than ordinary decision trees.

## A. Convolutional Neural Networks

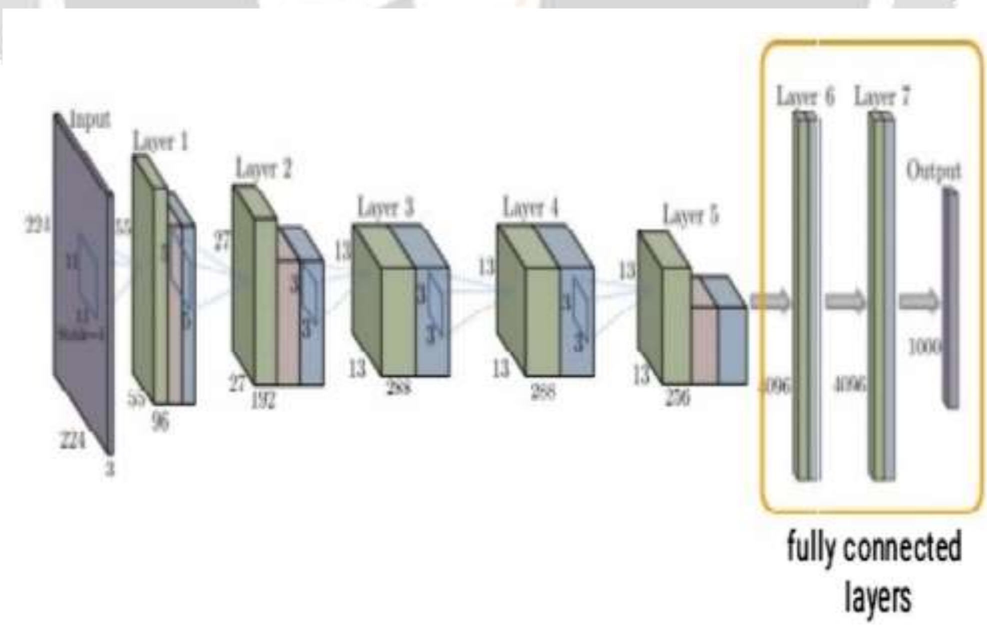



**Figure 7**

Convolutional layers spatially contextually encode numerous lower-level features into higher discriminative characteristics. They can be thought of as banks of filters that change the input image into a different one while accentuating particular patterns. The fully connected layers serve as classifiers by utilising the high-level features learnt to categorise incoming images into predetermined classes or to create numerical predictions. These layers are frequently positioned close to the model's output. They create another vector as their output after taking one as their input. It was necessary to extract the feature once the image had been cleaned of noise. For the classification of document picture, we suggest using a CNN. To recognise complicated document layouts, the primary concept is to build a hierarchy of feature detectors and train a nonlinear classifier. We downscale and normalise the pixel values of a document image before feeding the normalised image to CNN to get the class label.

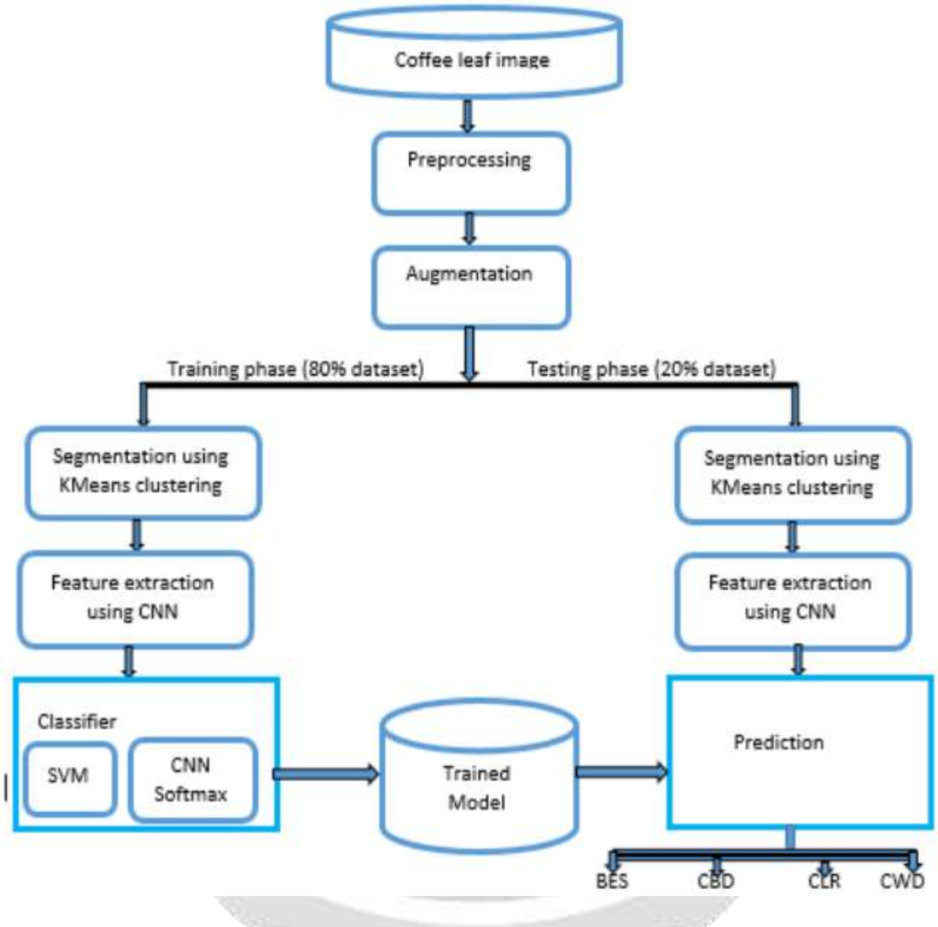



**Figure 8**

A CNN's convolution and pooling layers assist in extracting relevant features from an input image, and the fully connected layers employ the features that were extracted as input from all earlier neurons to map them into the output layer. To improve CNN performance, batch normalisation and dropout are added on top of the basic CNN layers. Three convolution layers, three pooling layers, and two fully linked layers were all used in this work. The class labels are the final layer that is entirely connected. We utilised Dropout layer below each Maxpooling layer and also used on the first fully connected layer to address the issue of overfitting in our CNN model. The foundational CNN layer that performs convolution operations is the convolution layer. It takes a source image and extracts useful elements from it. Another layer of CNN that carries out down sampling processes is the pooling layer. In order to decrease the in-plane dimensionality of the feature maps (input images), the number of parameters, and the computational complexity of the model, this layer subsamples the convolutional output as an input. By arbitrarily excluding some units or connections from the training dataset, dropout is a strategy for preventing or minimising overfitting. With a dropping probability of 0.25 for the first two dropout levels and 0.3 for the remaining layers, we employed dropout layers after each Maxpooling layer as well as after the flatten layers.

Grad-CAM: Based on the gradient of the parameter of the final convolutional layer, Grad-CAM determines the impact of each area of the image on the output and determines the degree of influence, represented by a heatmap. Grad-CAM was utilised to just highlight the faulty area. Additionally, by calculating the sigmoid heatmap prior to including the input image, we offered a Grad-CAM that was amplified.

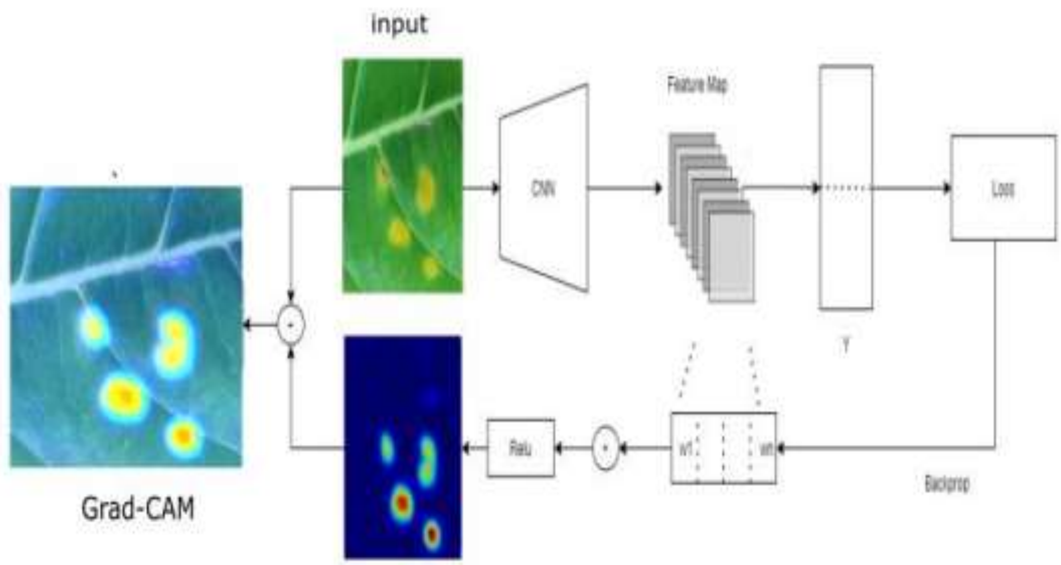



**Figure 9**

To show how the classification of coffee illness distinguishes between healthy and diseased leaves, we give a depiction of the condition in this section. In order to categorise and locate the faulty regions, we developed deep learning models. Additionally, visualisation can be a helpful tool for identifying problems with learning and even offering advice on how to fix them. As visualisation tools, Grad-CAM, Grad-CAM++, and Score-CAM were employed in this investigation. The extracted patches and full-size photos were subjected to visualisation techniques for comparison. Surprisingly, we discovered that all visualisation methods successfully located the problematic location on the image patches.

## RESULT

In this project about 80% of the dataset was used for training and 20% for testing. This network was trained using original images from the dataset. The model's accuracy in the training dataset was 99%. But in terms of test accuracy, it does very poor and less. This model does not successfully generalise from our training data to new data. Overfitting is the term for this. Overfitting typically happens when a model fits a small dataset too closely.

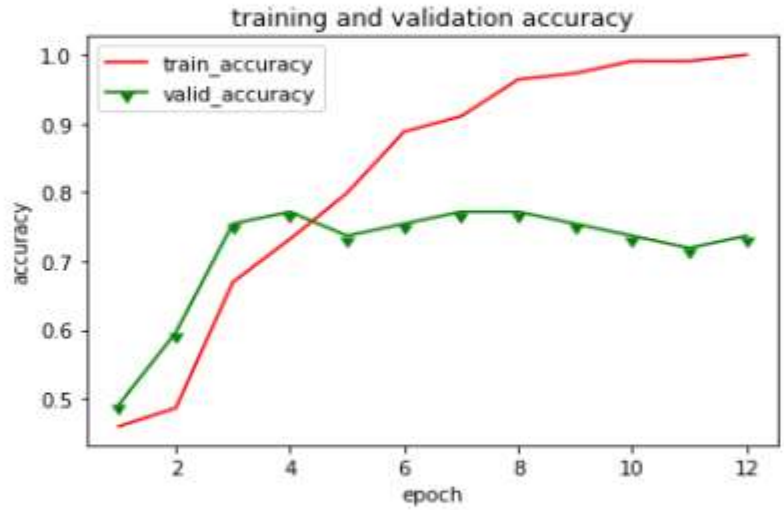



**Figure 10**

Visualising method can help to solve this problem. Visualising helps in improving classifier in different ways. Shows the visualisation outcomes of unhealthy leaves as an example. The most crucial areas for classifying objects are highlighted. Although the rusty area of the leaf was properly detected by the classifier, the background was thought to be more illuminating. The rusty area of the leaf was accurately detected by the classifier, however the backdrop was thought to be more informative than that area. Because of this, our model categorises the data by looking at off-topic areas of the image. According to the visualisation plot, our classifier is likely to link unhealthy photos with backgrounds made of dirt in its current state. This may reveal the causes of the model's divergence. The model is appropriate; the issue is how the data were provided to it, which resulted in poor test accuracy. This issue inspired us to suggest a planned strategy.

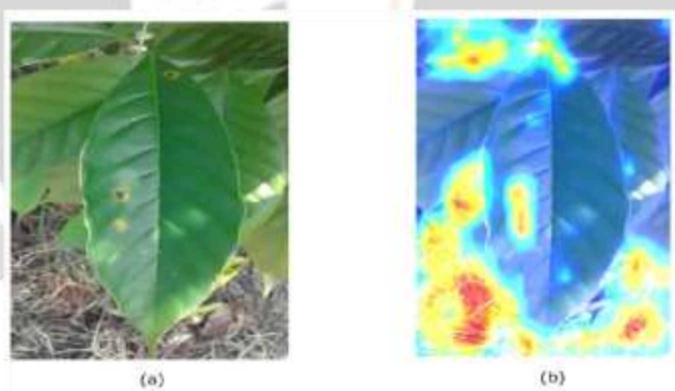



**Figure 11**

- **a)** Input image.
- **b)** the image after visualising.

Output:

```
# compiling the model
model.compile(
    optimizer=tf.keras.optimizers.SGD(learning_rate=0.001,momentum=0.9),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

```
In [9]:
# training the model
history=model.fit(
    train_datagen,
    epochs=12,
    steps_per_epoch=train_datagen.samples//train_datagen.batch_size,
    validation_data=validation_datagen)
```

```
Train for 64 steps, validate for 335 steps
Epoch 1/12
64/64 [==============================] - 38s 566ms/step - loss: 0.6175 - accuracy: 0.7762 - val_loss: 2.9752 - val_accuracy: 0.3582
Epoch 2/12
64/64 [==============================] - 21s 323ms/step - loss: 0.4059 - accuracy: 0.9512 - val_loss: 0.9999 - val_accuracy: 0.7701
Epoch 3/12
64/64 [==============================] - 20s 320ms/step - loss: 0.2888 - accuracy: 0.9861 - val_loss: 0.5173 - val_accuracy: 0.9224
Epoch 4/12
64/64 [==============================] - 20s 319ms/step - loss: 0.2456 - accuracy: 0.9974 - val_loss: 0.5181 - val_accuracy: 0.9403
Epoch 5/12
64/64 [==============================] - 24s 378ms/step - loss: 0.2371 - accuracy: 1.0000 - val_loss: 0.4082 - val_accuracy: 0.9552
Epoch 6/12
64/64 [==============================] - 20s 319ms/step - loss: 0.2362 - accuracy: 0.9993 - val_loss: 0.3901 - val_accuracy: 0.9642
Epoch 7/12
64/64 [==============================] - 20s 319ms/step - loss: 0.2357 - accuracy: 1.0000 - val_loss: 0.3941 - val_accuracy: 0.9642
Epoch 8/12
64/64 [==============================] - 21s 324ms/step - loss: 0.2348 - accuracy: 1.0000 - val_loss: 0.3973 - val_accuracy: 0.9642
Epoch 9/12
64/64 [==============================] - 20s 319ms/step - loss: 0.2344 - accuracy: 1.0000 - val_loss: 0.3998 - val_accuracy: 0.9672
Epoch 10/12
64/64 [==============================] - 20s 320ms/step - loss: 0.2342 - accuracy: 1.0000 - val_loss: 0.4017 - val_accuracy: 0.9701
Epoch 11/12
64/64 [==============================] - 21s 322ms/step - loss: 0.2341 - accuracy: 1.0000 - val_loss: 0.4028 - val_accuracy: 0.9701
Epoch 12/12
64/64 [==============================] - 20s 320ms/step - loss: 0.2339 - accuracy: 1.0000 - val_loss: 0.4035 - val_accuracy: 0.9701
```

```
In [10]:
# evaluate the model
loss, accuracy = model.evaluate(validation_datagen)
# train accuracy
train_loss, train_accuracy = model.evaluate(train_datagen)
```

```
335/335 [==============================] - 7s 21ms/step - loss: 0.4035 - accuracy: 0.9701
65/65 [==============================] - 5s 74ms/step - loss: 0.2347 - accuracy: 0.9994
```

```
In [11]:
"Trained Model for {} epochs, train accuracy: {:5.2f}%, test accuracy: {:5.2f}%".format(2, 100*train_accuracy, 100*accuracy)
```

```
Out[11]:
'Trained Model for 2 epochs, train accuracy: 99.94%, test accuracy: 97.01%'
```

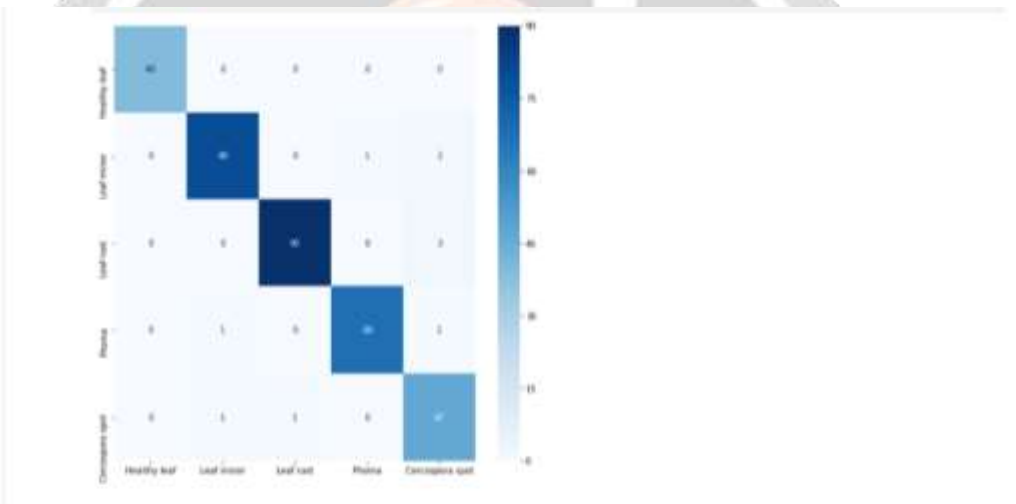
```
from sklearn.metrics import confusion_matrix
import numpy as np
Y_pred = model.predict(validation_datagen)
y_pred = np.argmax(Y_pred, axis=1)
print('Confusion Matrix')
matrix=confusion_matrix(validation_datagen.classes, y_pred)
print(matrix)
```

```
Confusion Matrix
[[40  0  0  0  0]
 [ 0 80  0  1  2]
 [ 0  0 90  0  3]
 [ 0  1  0 68  1]
 [ 0  1  1  0 47]]
```

```
14]:
from sklearn.metrics import confusion_matrix
import numpy as np
Y_pred = model.predict(validation_datagen)
y_pred = np.argmax(Y_pred, axis=1)
print('Confusion Matrix')
matrix=confusion_matrix(validation_datagen.classes, y_pred)
print(matrix)
```

```
Confusion Matrix
[[48  0  0  0  0]
 [ 0 88  0  1  2]
 [ 0  0 98  0  3]
 [ 0  1  0 68  1]
 [ 0  1  1  0 47]]
```

```
15]:
import matplotlib.pyplot as plt
labels=['Healthy leaf','Leaf minor','Leaf rust','Phoma','Cercospora spot']
import seaborn as sns
figure = plt.figure(figsize=(8, 8))
sns.heatmap(matrix,annot=True,cmap=plt.cm.Blues,xticklabels=labels,yticklabels=labels)
plt.tight_layout()
plt.show()
```



Grad-CAM and Score-CAM these two can catch the region which is infected on the surface of the leaf and other parts of the leaf are not considered. So basically, the work of Score-CAM is to localise the healthy region of the leaf and it to resembles the diseased area of the leaf. We can independently highlight the target object which has a high confidence score which is predicted by the model. Through linear combination all the evidence obtained by the target object can be assembled and taken for response. And Score-CAM can only focus on the small region of the leaf, so only the required structure is highlighted.

## CONCLUSION

This project's main aim is building an application which would identify the disease associated with the coffee leave s by using image processing. This paper provides information about deep learning and about CNN. For the future re sult on this data set we can improve the quality of the dataset, a range of images should be gathered for those leaves with a small number of training samples in subsequent studies. Additionally, the existing design should incorporate the more sophisticated and accurate convolutional neural network because it is impossible to recognise and classify small things like leaves in a complex environment with results that are as accurate as those in a simple background. We may conclude from the results of the comparisons that the suggested approach performs leaf recognition general ly significantly better than the conventional which faster compared to RCNN. Additionally, among the test samples, leaves with a distinctive form or a different colour can yield a greater identification rate. From the dataset after traini ng the model for 2 epochs, train accuracy is 99.94%, test accuracy is 97.01%

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