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Original Article

Lemon Leaf Disease Detection using Machine Learning

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Abstract - *Agriculture income and manufacturing are decreased by leaf diseases, which results in food resource vulnerability. Thus, it results in huge economic costs. The most popular of all citrus plants, the lemon, is widely distributed around the globe and utilised for a variety of applications, particularly those related to health and nutrition. Parasites and different illnesses, however, seriously impair lemon output. Lemons are a crop that is very important to the global economy. Lemon cultivation consequently suffers from severe purity reductions and harvest issues. Upwards of 50 percent of the commodities are just not utilised in lemon harvesting annually because of several leaf illnesses as well as outside variables. Visual analysis and learning procedures have recently been widely applied in numerous industries, notably farming, and depend on the advancement of technology. This makes it possible to identify and classify plant pathogens straight on. Gardeners can benefit again from the automatic recognition of infections in order to protect their vegetation from them. Consequently, the purpose of this work is to identify and categorise both good and bad leaves using photographs. For that purpose, various photos first from the Lemon Leaf collection were pre-processed using techniques notably ROI, noise removal with the Mean filter, image improvement with the histogram equalisation, and augmentation data source offered for the research. Discrete wavelet transforms grey level co-occurrence and principal component analysis extract features in the second stage. Third, classification is done with KNN, CNN and SVM. The evaluation process is completed by creating a confusion matrix. A confusion matrix results in the creation of a contemporary design that uses CNN. The mean scores for the F1-score, precision, recall, and accuracy (%) according to the test outcomes of the developed framework were 96%, 94%, 100%, and 97%, respectively. The suggested framework essentially characterises lemon leaf as healthy or unhealthy, in keeping with the literature review. The suggested strategy is offered as a helpful website named "lemon leaf disease identification," where we may determine whether lemon leaf is healthy or sickly by submitting a picture.*

Keywords - *SVM, KNN, CNN, DWT, GLCM, PCA, ROI, Noise removal, histogram equalization, Augmentation, F1-score, Precision, Recall, Accuracy, machine learning, website called "lemon leaf disease identification".*

1. Introduction

In this, we employ ML algorithms to find lemon leaf illness. A developing technology called machine learning makes it possible for systems to train themselves autonomously through historical information. Machine learning employs multiple methods to construct computer programme frameworks and make assumptions based on previous knowledge or data.

This information was taken from the website and contributed by Chouhan, Siddharth Singh; Kaul, Ajay; Singh, Uday Pratap; and Jain, Sanjeev, in "A Database of Leaf Images: Practise Towards Plant Pathology Conservations" in order to help us teach the system by the data of Mendeley. Both photos of healthy and sick leaves belong to this resource. 159 photos of healthy leaves and 77 images of sick leaves make up this collection. A few of the photos in the collection are shown below.

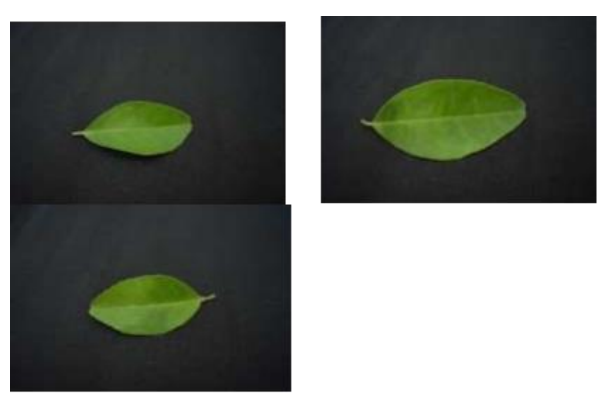

Fig. 1 Healthy leaf

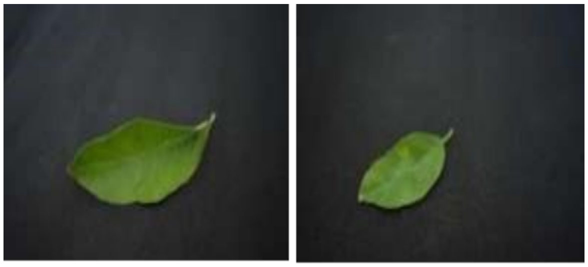

Fig. 2 Diseased leaf

Initially, we carried out a thorough pre-processing such as ROI, noise removal with the mean filter, picture improvement with the histogram equalisation, and augmentation to discover the optimal computational method to determine whether the leaves were good or bad.

[1] An area or zone inside a photo that has major relevance or significance for examination or processing is referred to as a Region of Interest (ROI) in the photograph. It may be a particular section of the picture containing an artefact or an element of interest, which might be a digital image, a band of squares, or a narrow band of the scene. In images processed by computer vision and projects where the objective is to gather or evaluate different details from a photograph, constructing a perimeter can be helpful. Handling duration and computational capacity can sometimes be reduced by focusing only on the ROI and disregarding the remainder of the image. ROIs can be created manually through the utilisation of a keyboard or touchscreen to choose a region within a photograph, or they can be discovered automatically by utilising techniques like background subtraction or object identification.

[2] The mean filter is used to fade a visual in order to lessen noise. Someone should determine the norm of the pixel intensities contained within an n-unit. Every grayscale level of the cantering portion is replaced with the optimum.
This lessens some of the motion blur and softens the picture's boundaries.

[3] Histogram A software digital image method called equalisation is used to boost visuals' vibrancy. It achieves this by efficiently extending the sensitivity range of a picture and scattering around the most common concentration levels. Since significant information is conveyed through strong contrast ratings, this strategy typically boosts the overall brightness of the photos. This makes it possible for regions with less brightness and contrast to acquire more contrast.

[4] Augmentation is a group of methods for enhancing the collection automatically by changing clones of already-existing knowledge or creating different replicas of the collection dynamically through the application of the already-existing dataset. It serves as regularisation during machine learning algorithm building and lessens generalisation errors. Following augmentation, each dataset found that the addition was converted into 250 photos of healthy leaves and 250 photos of sick leaves.

Images	Before Augmentation	After Augmentation
Healthy	159	250
Diseased	77	250

Feature extraction is happening once data pre-processing is finished. DWT (Discrete Wavelet Transform), GLCM (Grey Level Co-occurrence Matrix), and PCA are used to extract the feature (Principal Component Analysis).

[5] The Discrete Wavelet Transform (DWT) is a method for image retrieval from digital images in image processing and computer vision. The image is divided up by DWT into various frequency sub-bands with varying degrees of smoothness and detail. The image is initially broken down into a series of wavelet coefficients using the DWT in DWT-based feature extraction. Afterwards, features, including texture, edges, and forms, are extracted using these coefficients. By performing various mathematical as well as statistical operations on the wavelet coefficients, such as computing the mean, sample variance, radiation, and efficiency, the information can be produced.

In contrast to conventional techniques like the Fourier transform and GLCM, multidimensional feature extraction has a lot of benefits because it can simultaneously record combined intensity and orbiting the earth. In order to identify more significant characteristics from a photo, the image also has the capacity to divide the data into various frequency bands. In many different applications, including picture classification, object tracking, and object recognition, DWT-based image enhancement has been extensively used. The progress of computer vision as well as image processing has been greatly aided by this effective method for analysing digital images.

[6] In image processing and computer vision, the Gray Level Co-occurrence Matrix (GLCM) approach is used to extract features from digital images.

The vertical distance connecting pairs of pixel values in an image is described by a mixture. The imagery is first made grayscale, and then it is subdivided into little overlap sections, or "dark spots," to create a GLCM. The co-occurrence matrix is created per patch by noting the occurrences within each pair of grey levels inside that cover in a straight line and at a certain height. Many empirical metrics, including comparison, electricity, heterogeneity, and heterogeneity, can be retrieved from the binary image once it has been obtained. These measurements record many facets of the document's grain and spatial information, and they can be utilised as functionalities in later examination to identify objects or classify images.

Ultimately, GLCM-based extracted features are already extensively employed in a variety of domains, including diagnostic devices, environment monitoring, and predictive maintenance, and may serve as a potent instrument to obtain textures and specific arrangements in digital pictures.

[7] Principal Component Analysis (PCA) is a method for face recognition that is frequently used within pre-processing. By converting the original picture data into a space closer to zero while keeping the majority of its diversity, it's possible to use it to decrease the dimensions of a wide digital image. The picture information was only encoded as a matrix of neighbouring pixels in PCA-based feature extraction, and the PCA is then utilised on this matrix to separate the data's singular value decomposition. Those major elements are a collection of elements that are totally statistically independent and that are used to extract the most important variance from the digital image.

As a condensed collection of properties, the primary components can be utilised for picture identification, identification, and other applications. This might prove highly helpful when working with larger data sets, where the records could include a large degree of scale, making them computation-intensive or challenging to analyse and process. In general, PCA-based feature extraction may prove a strong instrument for visual processing and learning applications, assisting in the collection of the most key data from good data and streamlining assessment.

Following background subtraction using DWT, GLCM, and PCA techniques, classification is carried out using SVM, KNN, and CNN algorithms.

Classification is used to create a model for carrying out this investigation.

[8] Support vector machine, or SVM for short, is a supervised machine learning technique used in regression and classification. SVM is a strong method that can handle both linear and non-linear data by determining the best boundary or hyperplane for dividing the data into different groups. The optimum hyperplane that optimises the margin between the various classes is what SVM seeks to identify. The margin is the separation between the nearest data points from each class and the hyperplane. In order to improve generalisation and the model's performance on unobserved input, SVM identifies the hyperplane with the largest margin.

[9] KNN can be used in picture training for tasks like object detection and image categorization. The initial step in using KNN for image training is to extract features from the images. Many methods, including SIFT (Scale-Invariant Feature Transform), SURF (Speeded Up Robust Feature), HOG (Histogram of Oriented Gradients), and others, can be used to extract the features. These methods take the photos and extract attributes like texture, edges, and forms. A KNN classifier is trained using the features that have been extracted. Based on the majority class of an image's k-nearest neighbours in the feature space, the KNN classifier assigns a class to a test image. To improve accuracy, the value of the hyperparameter k must be adjusted.

[10] Convolutional neural networks, or CNNs, are a particular kind of neural network that has had great success with image processing and training. Convolutional layers, which extract and learn features from the input images, are used in CNNs to learn the features from images automatically. The input image is convolved using a collection of filters, or kernels, in the convolutional layers to create a feature map. The image's borders, corners, and textures are just a few examples of the patterns and features that the filters learn to detect. The feature maps are routed through pooling layers after the convolutional layers, which down-sample the feature maps and lower the input's spatial size. The pooling layers aid in lowering the network's computational cost and avoiding overfitting.

Following categorization, evaluation is carried out utilising accuracy, precision, recall, and F-measure. We were able to determine which model would be optimal for this project's implementation by analysing the evaluation results.

[11] One of the most often employed evaluation measures in machine learning is accuracy. It calculates the percentage of cases in the dataset that were correctly classified. It's outlined as follows:

Accuracy = accuracy is equal to the proportion of correctly classified instances (the total number of instances).

[12] Precision is a machine learning evaluation statistic that counts the fraction of real positive predictions among all the model's positive predictions as true positives. It's outlined as follows:

(false positives +true positives)/true positive = precision

In plenty of other words, precision refers to the ratio of the actual number of positive forecasts that the model generated to the actual number of positive cases that were correctly identified as positive. When we want to reduce false positives or be sure that the model's positive predictions are very likely to come true, precision is a valuable statistic.

In other words, precision is the ratio of the number of true positive predictions (i.e., the number of positive instances that were correctly classified as positive) to the total number of positive predictions made by the model. Precision is a useful metric when we want to minimize false positives, i.e., when we want to ensure that the positive predictions made by the model are highly likely to be true. [12] The F1 score is a machine learning evaluation statistic that combines recall and precision into a single metric. It is characterised as the harmonic mean of recall and precision.

*(recall *precision)*2 / (recall + precision)= F1 score*

The F1 score has a range of 0 to 1, with 1 representing flawless recall and precision. Balancing both accuracy and recall in the assessment of a classifier is a helpful metric. Only when the dataset is unbalanced or when there are not an equal number of cases in each class is the F1 score especially helpful. In these situations, accuracy might not be the best metric to use because it can be skewed in favour of the dominant class. Contrarily, the F1 score considers both accuracy and recall, which are significant measures when working with unbalanced datasets. F1 score is frequently employed in binary classification problems. However, it may also be applied to multi-class classification issues by calculating the F1 score for each class and then averaging the results using various techniques, such as macro-averaging, micro-averaging, or weighted averaging.

[14] The capacity of a model to accurately identify positive examples out of the total number of real positive instances in a dataset is measured by the metric recall, which is used in Machine Learning (ML) evaluation. It is frequently applied to issues involving binary classification, where the objective is to determine whether a given occurrence belongs to a particular class or not. The percentage of positive cases (TP) instances to all of the real positive cases in the dataset is used to calculate recall. It has the following mathematical expression: $TP/(FN+TP) = recall$, where TP denotes the quantity of true positives, and FN denotes the quantity of false negatives. In other words, recall assesses the model's capacity to recognise all occurrences of positivity, even those that it would mistakenly classify as negative.

Even though a low recall suggests that the programme is neglecting some positive cases, a high recall demonstrates that it is effective at detecting them. In ML assessment, recall is a helpful indicator, particularly when missing positive occurrences may be expensive or damaging. For instance, failing to make a favourable diagnosis in a medical diagnosis should result in an interruption in treatment, which would worsen the patient's health results. In these circumstances, even if it produces more false positives, a strategy containing essentials would be preferred.

The regression model will be constructed when the evaluation is complete to determine which model is suitable for the investigation.

[15] A table called a confusion matrix is used in algorithm (ML) assessments to assess how well a classification model is performing.

An error matrix is another name for it. The predicted and actual known values of a testing data set are shown in a tabular fashion in a confusion matrix. Four items, or cells, in the table are filled based upon this model's categorization outcomes:

- True Positives (TP) are instances that match the model's classification of positivity as positive.
- False Positive (FP) instances are those that the model incorrectly classifies as positive but are essentially negative.
- False Negatives (FN) are situations that the model classifies as negative but are clearly positive.
- True Negative (TN): Situations that the model classifies as negative but are, in fact, negative.

The confusion matrix gives a summary of the designer's success by indicating how frequently it forecasts each target class correctly or inaccurately. It is especially helpful when there is an imbalance in the courses or when certain errors are more serious than others.

Accuracy, precision, recall, and F1 score are just a few of the evaluation metrics that may be calculated using the variables in the confusion matrix. These metrics are capable of being utilised to compare two models or different versions of an identical model and serve to evaluate how well a model is doing.

2. Related Work

The domain of plant disease detection has gained substantial attention due to its implications for global agriculture and food security. The increasing impact of diseases on citrus plants, especially lemons, has led researchers to explore advanced technologies, particularly in the intersection of machine learning and image processing.

2.1. Previous Research in Plant Disease Detection

Previous studies have focused on utilizing various technologies for plant disease detection, including traditional methods and modern technological advancements. Early methods relied on visual inspection and manual diagnosis, often resulting in delayed responses and limited accuracy.

Modern approaches leverage technological advancements, with a significant shift toward machine learning and computer vision techniques. The work by Chouhan et al. [1] provided a valuable resource—a leaf image database—for training machine learning models, laying the foundation for subsequent research in this domain.

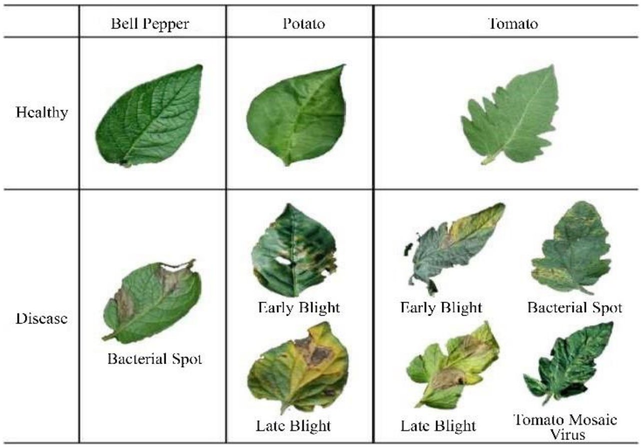

Fig. 3 healthy and diseased leaf

2.2. Machine Learning in Plant Pathology

Machine learning, with its ability to analyze large datasets and recognize intricate patterns, has emerged as a powerful tool for plant pathology. Studies such as [2] explored the application of machine learning algorithms for disease identification, showcasing the potential for automating the detection process.

Notable approaches include the use of Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN). SVM, a powerful classifier [8], seeks to find an optimal hyperplane to separate different classes. KNN, an instance-based learning method [9], relies on the similarity between instances for classification. CNN, a specialized neural network [10], has shown remarkable success in image-processing tasks.

2.3. Advances In Image Processing Techniques

Concurrently, advances in image processing techniques have enhanced the quality and accuracy of disease detection. Region of Interest (ROI) selection [1] allows the focus on critical areas within images, reducing computational load and enhancing accuracy. Techniques like noise removal with the Mean filter [1] and histogram equalization [3] contribute to refining image quality and accentuating features.

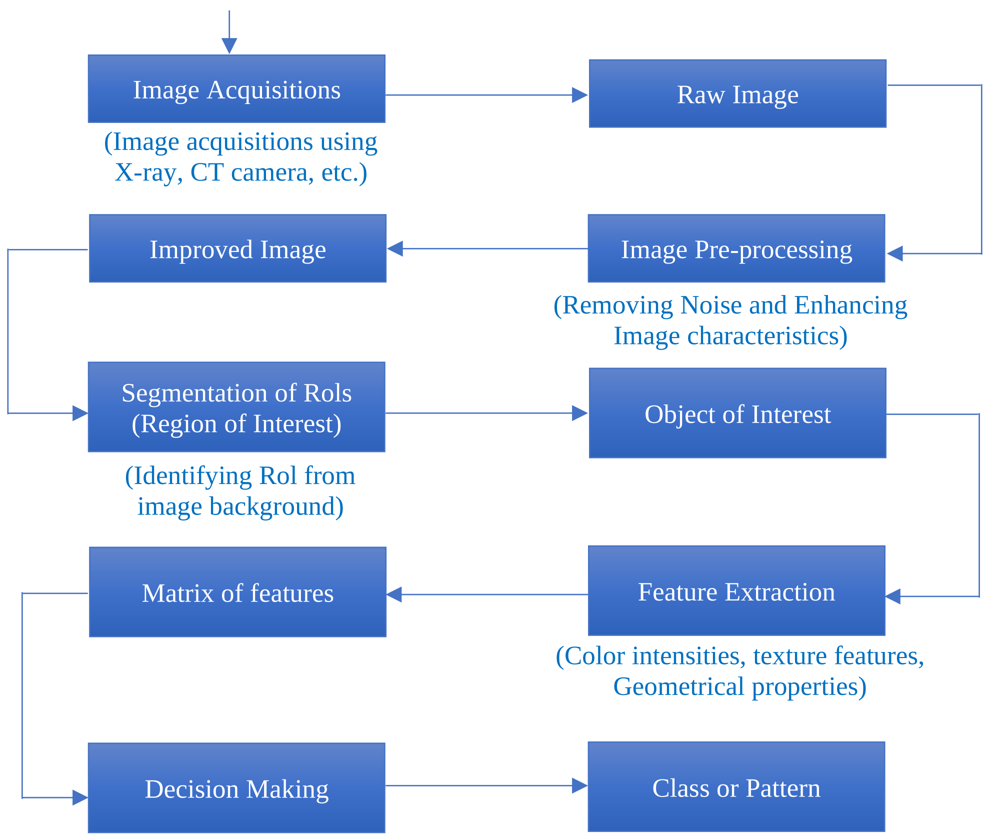

Fig. 4 Image processing techniques

2.4. Gaps in Existing Approaches

While existing literature has made significant strides in automating plant disease detection, certain gaps remain. Challenges include addressing the specificity of disease identification, scalability, and the ability to adapt to diverse environmental conditions. The proposed study aims to contribute to these areas by integrating advanced machine learning techniques with a comprehensive preprocessing pipeline.

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3. Methodology

3.1. Data Collection

The foundation of this study lies in the Lemon Leaf dataset, a comprehensive collection curated by Chouhan et al. [1]. This dataset comprises 159 images of healthy lemon leaves and 77 images of diseased leaves, forming a valuable resource for training and evaluating machine learning models.

3.2. Preprocessing Techniques

3.2.1. Region of Interest (ROI) Selection

The first step in the preprocessing pipeline involves the selection of Regions of Interest (ROI) within the leaf images. ROI selection enables the model to focus on critical areas with significant relevance to disease identification. This manual or automated process minimizes computational complexity and enhances the efficiency of subsequent processing steps [1].

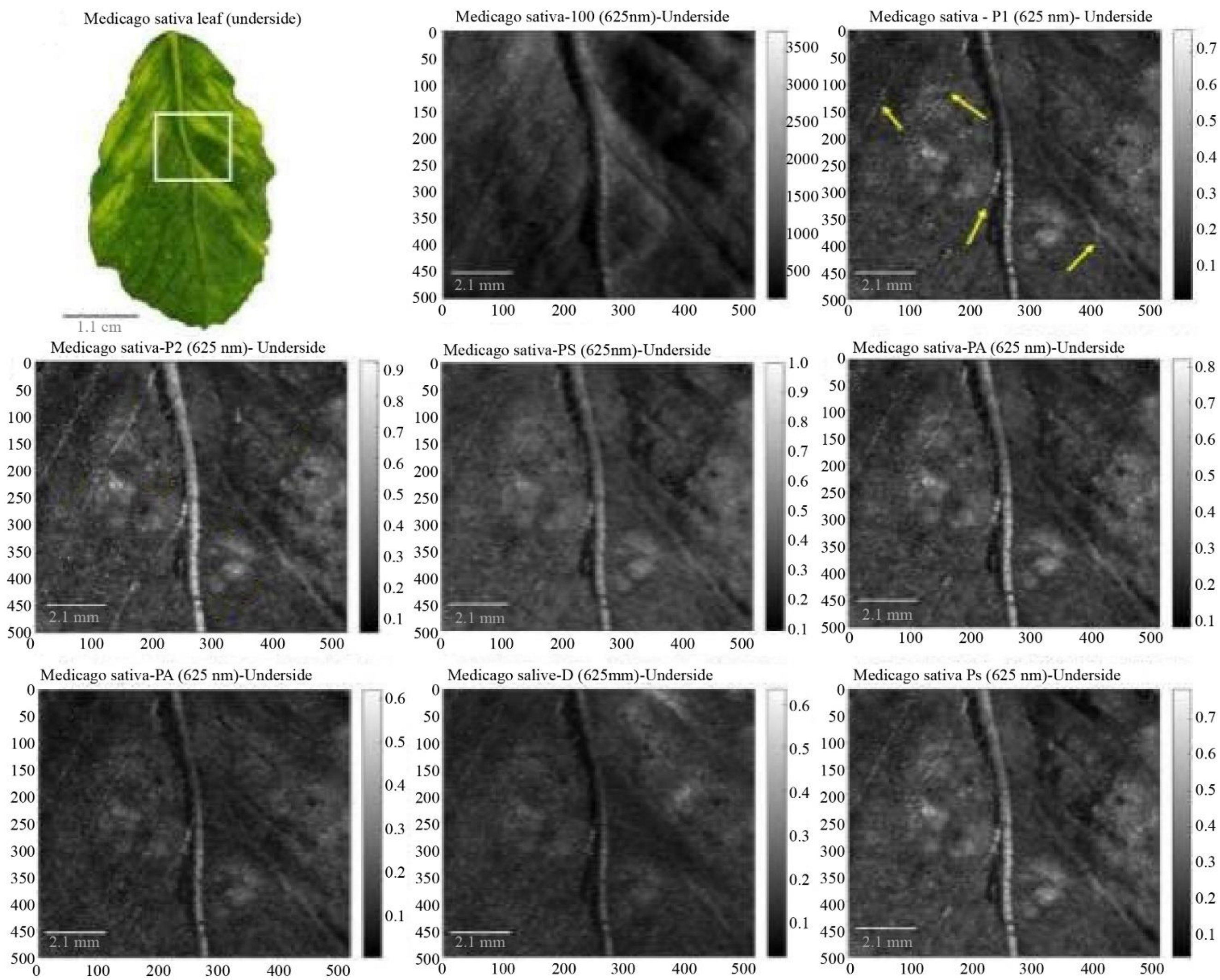

Fig. 5 ROI in leaf

3.2.2. Noise Removal with the Mean Filter

To reduce noise and enhance image clarity, a Mean filter is applied. This technique involves calculating the mean pixel intensity within an n×n neighbourhood, replacing each pixel's intensity with the computed mean. The application of the Mean filter contributes to the reduction of motion blur and the smoothing of image boundaries [1].

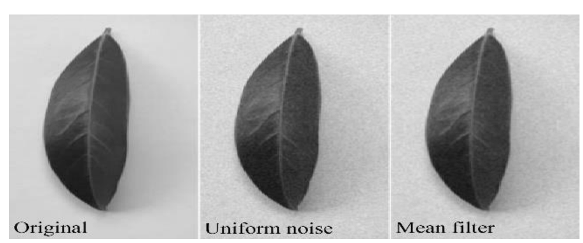

Fig. 6 Noise removal with the mean filter

3.3. Histogram Equalization

Histogram equalization is employed to improve the vibrancy of visuals. By extending the sensitivity range of an image and redistributing concentration levels, this technique enhances contrast and overall brightness. This is particularly crucial for images where significant information is conveyed through strong contrast ratings [3].

3.4. Augmentation

Augmentation serves as a regularization technique during machine learning algorithm construction and aids in reducing generalization errors. In this study, augmentation involves creating replicas of existing images, effectively expanding the dataset dynamically. Following augmentation, the dataset is increased to 250 images of healthy leaves and 250 images of diseased leaves.

[4].

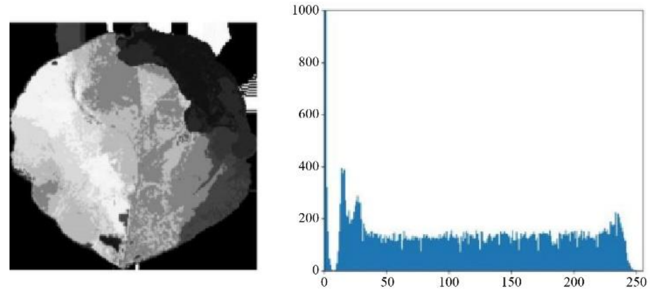

Fig. 7 Histogram Equalization

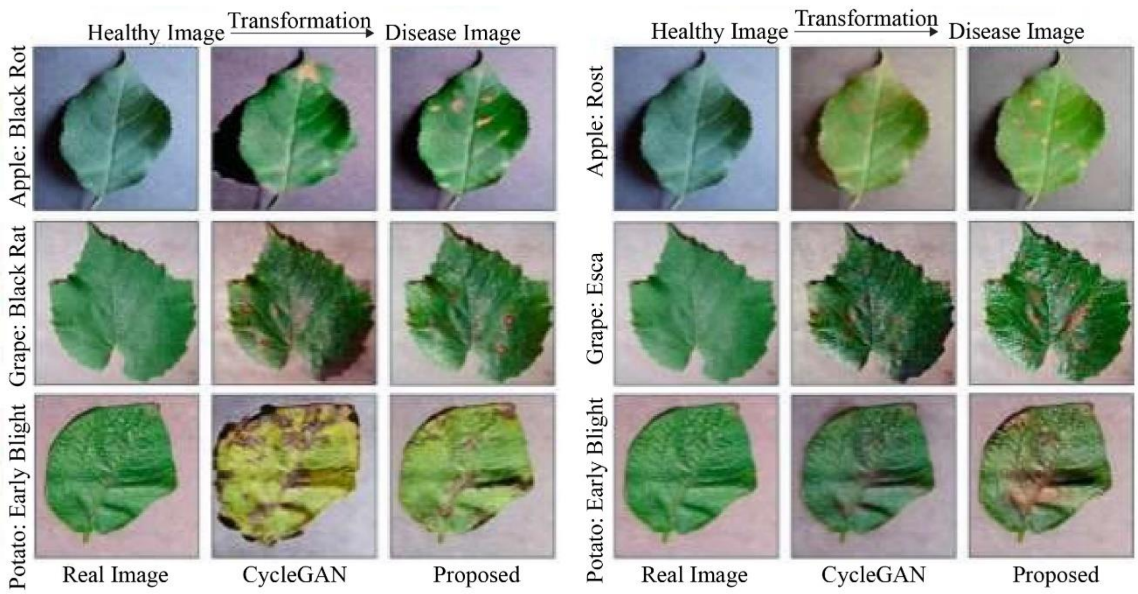

Fig. 8 Augmentation

3.5. Dataset Overview

The table below provides an overview of the dataset before and after augmentation:

	Before Augmentation	**After Augmentation**
Healthy	159	250
Diseased	77	250

3.6. Feature Extraction

3.6.1. Discrete Wavelet Transform (DWT)

DWT is employed for image retrieval from digital images. It divides the image into various frequency sub-bands with varying degrees of smoothness and detail. The wavelet coefficients obtained through DWT are used to extract features related to texture, edges, and shapes. This multiresolution analysis contributes to a more comprehensive representation of image characteristics [5].

3.7. Grey Level Co-Occurrence Matrix (GLCM)

GLCM is utilized for feature extraction, describing the vertical distance connecting pairs of pixel values in an image. By creating a co-occurrence matrix per patch, GLCM captures spatial information and texture details. Various empirical metrics, including contrast, energy, and homogeneity, are extracted from the binary image obtained through GLCM [6].

3.8. Principal Component Analysis (PCA):

PCA is employed for face recognition and dimensionality reduction. It transforms the original image data into a space closer to zero while retaining the majority of its diversity. By encoding image information as a matrix of neighbouring pixels, PCA separates the data through singular value decomposition. The principal components obtained serve as a condensed set of features for image identification and classification [7].

4. Result

After completion of data pre-processing, feature extraction, classification, and evaluation, a confusion matrix will be built using machine learning models.

For training, the model 400 leaf images are used, and for testing, the model 100 leaf images are used.

4.1. Confusion Matrix

MODEL	TP	TN	FP	FN
SVM	48	47	4	1
KNN	46	45	3	6
CNN	48	49	3	0

MODEL	ACCURACY	RECALL	PRECISION	F-Measure
SVM	95.00	97.96	92.31	95.05
KNN	91.00	88.46	93.88	91.09
CNN	97.00	100.00	94.12	96.97

From analysing the confusion matrix, we found that CNN is suitable for designing a model.

Below is an illustration of the graphs for ML model comparison on lemon leaf disease identification by using the above confusion matrix.

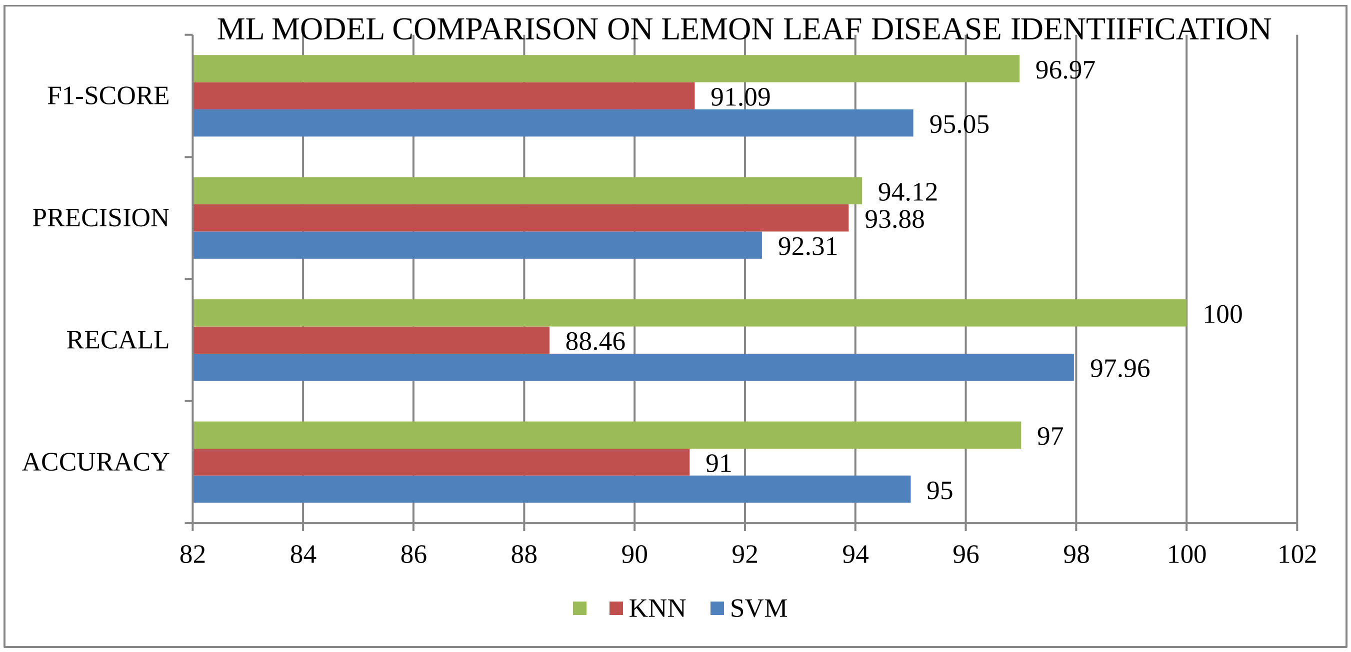

Fig. 9 Machine learning model comparison

After analysing the best model for this study, a website called "Lemon Leaf Disease Identification" was created to implement this study.

On that website called "lemon leaf disease identification," there are two options: upload an image and predict an image. By clicking the "upload image option, we could be able to upload the image of the lemon leaf. After the uploading of the image is complete, if we click the predict image option, it will show the result, whether the leaf is healthy or diseased.

If we didn’t upload any images but we clicked the prediction image option, it would show the error message "no image found.
"Please upload the image".

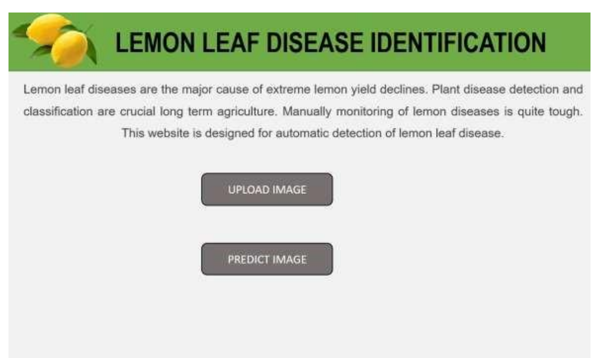

Fig. 10 lemon leaf disease identification website homepage

The above image is the homepage of the website called “Lemon Leaf Disease Identification.”

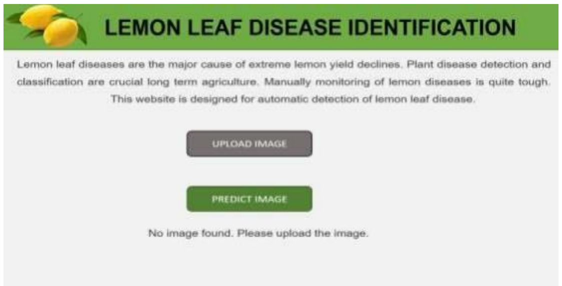

Fig. 11 Error message that no image is found

The above image shows the error message that no image is found; please upload the image.

Fig. 12 Result of uploaded image

5. Conclusion

The presented method uses ML algorithms to distinguish between healthy and unhealthy lemon leaves. The descriptive properties of the leaf samples are extracted using a variety of methods, including the discrete wavelet transform, principal component analysis, and GLCM. SVM, K-NN, and CNN are three algorithms for machine learning used in order to differentiate between sick and healthy leaves. In comparison to other region methods, the interpretation of the proposed methodology seems to be well suited for CNN's algorithmic classification methodology with the needed precision. Then, finally, we put the model on the webpage "lemon leaf disease identification" that bears that name.

Future Scope

The framework can be enhanced in the future to:

- Identify the disease that a lemon leaf has, if one exists.
- Using computer vision, the condition of a leaf can be determined without downloading an image by utilising the camera on a mobile device or any other camera-equipped device.

Abbreviations

- SVM - Support Vector Machine,
- KNN - K- Nearest Neighbour,
- CNN - Convolutional neural network,
- DWT - Discrete Wavelet Transform,
- GLCM - Gray-Level Co-Occurrence Matrix, • PCA - Principal Component Analysis,
- ROI – Region Of Interest.

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