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A Review on Grape Disease Detection and Classification using Image Processing

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Abstract - *Plant disease has become one of the major concerns for farmers and has now evolved into a significant threat to the quality of food consumed by the people. Hence, it becomes necessary to identify these diseases at the early stages of their growth and find possible solutions to avoid them. This paper focuses on reviewing the different approaches of disease detection and classification for grape plants. This paper will provide a detailed review of the different approaches to detect and classify grape diseases. Significant steps involved in disease prediction using image processing are image acquisition, data pre-processing, image segmentation, feature extraction and image classification are discussed. Standard techniques used in each step of image processing are reviewed along with various detection and classification techniques such as Convolution Neural Network (CNN), Deep Learning, Support Vector Machine (SVM), Fuzzy, K-Nearest Neighbors (KNN), K-Means Clustering, Deep Learning and Backpropagation. By referring to various articles, we identified the differences brought about by classification techniques and the different processes followed to obtain various results, thus helping researchers understand which methods can be selected to improve grape leaf diseases' identification and classification efficiency.*

***Key Words*: Grape Disease Detection and Classification, Image Processing, Convolution Neural Network, Support Vector Machine, K-Nearest Neighbours, K-Means Clustering, Deep Learning, Backpropagation.**

1. INTRODUCTION

In India, Agriculture is considered an essential field of occupation as over 60% of the population relies on this field for employment. It also plays a vital role in contributing to the Indian economy, accounting for about 19.9% of its total GDP. The rise in population demands an equivalently increased growth and production in the agricultural field. Food is required to supply nutritional requirements for labour so that the workforce is fed with energy to work efficiently in industries and other economic sectors. Modern agriculture's main objective is to produce paramount yield with reduced expenditure.

India is one of the world's leading grape producers. Grape is one of India's most commercially viable crops used to make wines and raisins. Grapes are considered very important from a business perspective as they can be exported to different countries or used for table purposes. It has a good amount of nutritional minerals like vitamin C, K, and B. Maharashtra, followed by Karnataka and Tamil Nadu, are the significant contributors to the production of grapes in India, which constitutes about 80% of the grape production. However, grape plant diseases affect their quality and bring an enormous difference in the production rate, which causes a significant loss to farmers and adversely affects the economy and health. To prevent this from happening, an efficient technique to detect diseases early is the need of the hour.

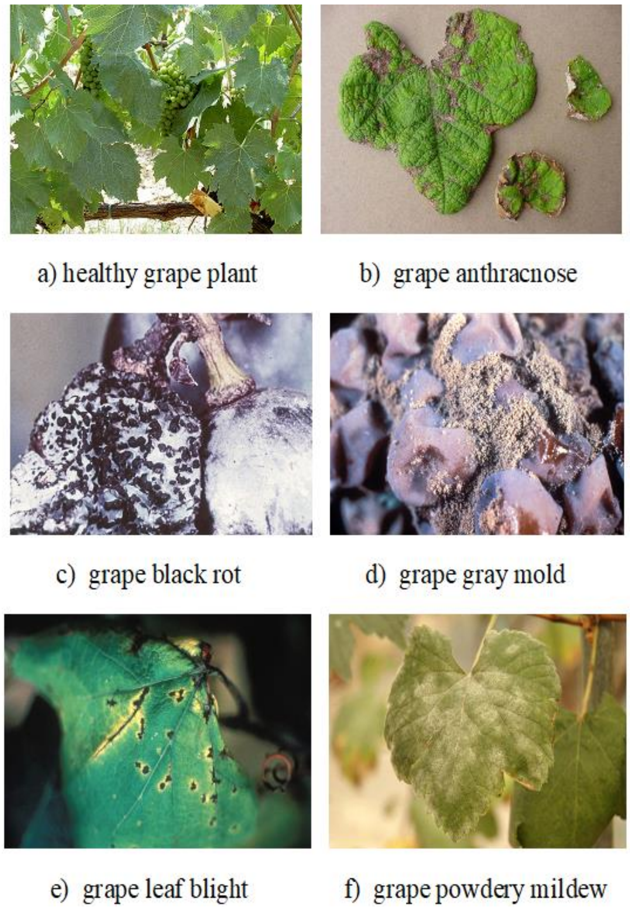
Old traditional methods of detecting diseases through naked-eye are not feasible as they will not always be accurate. Some prefer to use insecticides and pesticides to resist these diseases, but using them may harm human health as they may not be used in appropriate quantities. Recent technologies play a vital role in developing new effective methods to detect and classify grape diseases. Grapes are prone to Downy mildew, powdery mildew, black rot, anthracnose, brown spot, mites, leaf blight, etc.

Timely diagnosis of diseases in grape leaves and accurate suppression of the spread of certain diseases are crucial to ensure the healthy development of the grape. Researchers have come up with various image processing and machine learning-based methods with differing results and efficiencies to overcome the issues. This paper discusses various techniques to analyse and classify diseases in grapes. Various models used to analyse and predict the disease are Convolutional Neural Networks (CNN), Deep learning, and Support Vector Machines (SVM).

A convolutional neural network is a subset of deep learning, and it is seen to be used chiefly to analyse visual imagery. It is composed of several layers of artificial neurons. When an image is given input to the convolutional networks, every layer produces several activation functions passed to the next layer. Initially, it starts from primary feature detections, and as it passes through layers, it identifies complex features such as faces, objects, etc. Some of the models presented are DICNN, Faster-R-CNN, ResNet 50, UnitedModel, DR-IACNN, VGG16 and Inception V3.

One type of classification technique is the Support vector machine, which has received considerable attention. SVM falls under supervised machine learning techniques. In this approach, each data item is plotted to be a point in an M-dimensional space. Then classification is performed by finding the plane that acts as the differentiation factor between the two classes.

Deep learning is considered a branch of machine learning and concentrates mainly on the algorithms stimulated by the working and structure of artificial neural networks. It gradually learns to classify images, and as the name suggests, it can have hundreds of layers, eventually resulting in a deeper network. The SegNet architecture can be used for this kind of approach. VGG-16, ResNet50, Inceptionv3 and EfficientNet are some models which are generally considered for image data processing. The most common approaches or steps used to detect and classify plant diseases are image acquisition, image pre-processing, segmentation, feature extraction and classification.



a) healthy grape plant b) grape anthracnose c) grape black rot d) grape gray mold e) grape leaf blight f) grape powdery mildew

Fig-1: Different types of grape diseases

2. LITERATURE REVIEW

2.1 Convolutional Neural Network (CNN)

Liu B et al. [1] proposed an Improved convolution neural network-based approach to diagnose six general types of grape leaf diseases anthracnose, downy mildew, brown spot, black rot, mites, and leaf blight. Instead of the standard convolution, they applied a deep separable convolution to allay the amount of parameters and abate the Model over-compliance problem. Four thousand twenty-three images were collected from the field. Through public data sets, 3,646 images were collected, and a total data set of 107,366 grape leaf images is generated through enhancement techniques applied on images.

To strengthen the functioning of multi-dimensional extraction of features, an inception structure is applied. From scratch, a novel DICNN model was built and trained to construct the first two convolutional layers. In these two layers, the parameters of the two convolution layers were decreased, which reduced the intake of resources and ameliorated the performance. 0.13% increase in accuracy was observed when compared to other traditional convolutional models. They achieved a precision of 97.22% on the test set and produced better accuracy when compared to ResNet and GoogLeNet.

S. Ghoury et al. [2] aimed at differentiating diseased grapes from healthy grape and grape leaves by performing tasks using a transfer learning approach that uses deep learning models like Faster R-CNN Inception v2 and Single SSD_MobileNet v1, which are pre-trained. Among the image dataset used, 124 were diseased images, and 136 were healthy images.

Faster R-CNN is a Regional Proposal Network (RPN)[2] to detect objects, which rely on region proposal algorithms to envision the locations of objects. For the Regional Proposal Network, a single network is used for generating region proposal operation, and Fast R-CNN classifies regions. “In Faster R-CNN, the RPN shares full-image convolutional features with fast R-CNN” [2]; this allows there to be an almost cost-free region proposal. An RPN is a completely convolutional network that determines object bounds and scores simultaneously, and this makes Faster R-CNN entirely CNN.

An Inception model is a pre-trained deep learning CNN which has a vast number of constraints that is trained on ImageNet dataset using “potent” and computers which are expensive. The training part for this model takes weeks to complete. The very first version of “Inception (inception-v1)” was launched as GoogleLeNet [2]. Later, the construct of inception was improved by [2] using the “batch normalisation technique and other ways”, and the new version (Inception-v2) was introduced.

Classification accuracy of 78% to 99% was obtained through the Faster-R-CNN Inception v2 model; it could classify about 95.57% of the images in the testing part appropriately. Though it gives good accuracy, it has a drawback; it takes longer to process the images.

On the contrary, the SSD_MobileNet v1 model quickly processed the images, but it could only classify about 59.29% of the testing images correctly. This model has poor classification due to the noise and different background resolutions present in the images. If the images were organised, the classification accuracy was much higher (90-99)%. Hence [2] concluded that this model is unsuitable for tasks containing real-time classification, and the “Faster-R-CNN Inception v2 model” could be chosen as a better option for real-time classification.

M. Ji et al. [3] came up with the United Model, a combination of multiple CNN; it helps extract distinct features and mainly aims at distinguishing diseased leaves from typical grape leaves. The basic architecture of the United Model is based on combining the width of InceptionV3 and the depth of ResNet50 so that the proposed model can improve representational abilities and learn more about representational features to provide the best performance in detecting grape disease. The Plant Village dataset is employed to gauge the proposed method. Compared to other basic single CNN models like DenseNet121, VGG16, InceptionV3, and ResNet50, the United Model performed better with a test accuracy of 98.57% and a mean validation precision of 99.17%. The trained model can't be applied for the diagnosis of grape leaf diseases in real-time scenarios within the intricate background as the training dataset utilised consists of samples in uninvolved background scenes.

X. Xie et al. [4] presented a feasible real-time grape disease detector contingent on an advanced deep convolutional network. They constructed a grape leaf disease dataset (GLDD) by applying a technology called digital image processing. To ensure sufficient GLDD 4449 images, both complex and straightforward backgrounds collected in actual vineyards and laboratories are collected. Faster R-CNN and deep-learning-based DR-IACNN model was introduced to obtain efficient feature extraction capabilities. “DR-IACNN model can also detect multi-scale diseased spots and small diseased spots by introducing the Inception-v1 module, Inception-Resnet-v2 module, SE-Blocks” [4]. It achieves 81.1% precision on a dataset of grape leaf diseases (GLDD) and detects at a pace of 15.01 FPS.

K. Thet et al. [5] aimed to overcome the inaccuracy of using the VGG16 Network as the classification of grape leaf diseases was not up to the mark. So, they presented a transfer learning method by improving the VGG16 network, one of the CNN architectures. This system differentiated the healthy leaves from the leaves affected by five common grape leaf diseases such as anthracnose, downy mildew, black measles, etc. Dataset was collected from Myanmar Grapevine Yard, which comprised 6000 images. To improve the correctness of fine-tuning VGG16 for grapes, the Global AveragePooling (GAP) layer is used in place of VGG16’s two entirely associated layers before the final classification SoftMax layer. In comparison to other systems like VGG16, SVM classifier and VGG16 fully connected layers, the proffered system outshined with 98.4% accuracy compared to others [5].

In the paper [6], G. Ghosh starts by using segmentation for finding the first diseased region and then extracts colour and texture features, then resizes them to the pixel intended. The steps implemented were: Data acquisition, Image Processing, and Image Segmentation [6]. Initially, the dataset is augmented, and distorted images in a suitable format are done and saved into the training set. Then these images undergo some preprocessing, such as residing the image and smoothing the images. Following the data preprocessing, extraction methods such as RGB (colour-based features) are applied to extract features in leaf images. Then, converting the labels to categories for model compatibility depending on the images to their respective class is performed [6]. Modeling the classifier is done using 80% of the data for training with the assistance of neural network methods. The model is validated with the remaining 20% of the data. With this kind of technique, an accuracy of 98% was achieved. As a result, the CNN model was able to classify four types of grape leaves diseases [6].

P. Amudala et al. [7] proposed combining multiple CNNs in a United Model to extract additional discriminatory features. The data set to validate this model was the plant village dataset. They developed a mobile application that recognised and distinguished disease indications on plant leaves [7]. CNN architecture is based on Inception V3, which ResNet50 used to classify the diseases of a grape leaf into four different classes, namely esca, Arabidopsis leaf mark, black rot and safe images [7]. The proposed model had achieved a mean validation accuracy of 99.17% and test exactness of 98.57% [7].

2.2 Support Vector Machine:

P. B. Padol et al. [8] used the Support Vector Machine for grape disease classification. The process starts with finding the diseased region using segmentation by K-means clustering [8], followed by extracting colour and texture features. Finally, the SVM classification technique detects the type of disease on leaves [8]. This paper's image preprocessing step consists of resizing, thresholding, and Gaussian filtering [8]. The classification technique consists of two phases, namely, training and testing stages by applying the classifier. The classifier is equipped using feature values and their respective target values [8]. Once the classifier is trained with the training set, it is then validated using the test dataset. The classifier classifies the images based on the training images and classification relative to them. Downy Mildew and Powdery Mildew are the two classes of grape leaves that were classified [8]. For this, a total of 137 grape leaf images were used. The given system accurately assessed 88.89% for Downey and Powderly grape leaf disease [8].

A. Adeel et al. [9] have presented an automated model for grape disease detection centered on notable features selection and saliency estimation. A contrast stretching approach is presented, approximating and extracts the unhealthy regions and extracts other features like colour features. The local contrast haze reduction (LCHR) technique is used in the first step. Extraction of colour, texture and geometric characters is then put together by canonical correlation analysis (CCA). Noise is reduced through Neighborhood Component Analysis (NCA) during the fusion. Classification of the extracted features is done by multiple class SVM. The proposed model is tested on the dataset of grape leaf diseases acquired by Plant Village. The accuracy attained through this M-class SVM is 94.1% which is superior compared to the other classifiers like Q-SVM, ESD, cubic SVM, and cosine SVM. The limitation to this model is that it gives lesser accuracy for complex images. For further enhancements, they plan on building a model using reinforcement learning (RL).

This paper by N. Agarwal [10] focuses on building a system using a multiclass Support Vector Machine (SVM) that will discern the disease of grape plants [10]. The process used is a general procedure involving image processing techniques applied to the data images to extract the essential components for further examination. Further, classification is done using multiclass SVM with the construction of a binary classifier 'k'. For this paper, the k is considered to be four. The data point is allocated to the class with the most prominent decision function value [10]. Three types of diseases have been detected and classified in this paper: Black rot, Leaf Blight, Esca, and a normal healthy leaf of a plant used for training and testing [10]. The results were very accurate for black rot and unaffected cases of the grape leaf disease detection. Still, they gave a considerably average performance, with Esca and L Blight contributing to an overall accuracy of 90% [10]. The paper suggests some future modifications to be made by automatically selecting a few of the features extracted from the K-Means clusters [10]. And also, wavelength-dependent features can be added to the database, which might improve the accuracy [10].

H. Waghmare et al. [11] brought forward a technique for recognising grape plant disease using texture analysis and pattern recognition [11]. The process starts with performing segmentation on the images after the background removal. To spot the diseased parts of the leaf, segmented images are scrutinized through a high-pass filter. A unique fractal-based texture feature is used to retrieve the segmented leaf texture. As the fractal-based features are locally unchanging [11] and hence they provide a remarkable texture model. A multiclass Support Vector Machine method is then used to classify the extracted texture pattern. This paper detects and classifies two significant diseases, namely downy mildew and black rot [11]. "The approach used in this paper consists of four main steps: the acquisition of grape leaves, followed by the extraction of grape leaves background and statistical analysis and disease classification" [11]. The dataset consists of a total of 450 images which comprises healthy, diseased, and pest-infected images [11]. Image preprocessing, such as resizing the images to the required format, makes the image suitable for further processing. The background subtraction is done using the segmentation portion of interest from the image [11]. Feature extraction is performed from the infected region on the leaf according to properties like colour, correlation, congruity, and contrast[11]. The final step is to analyse the features and classify using a Support Vector Machine that categorizes the plant leaves into two classes. With this method accuracy of 89.3% was achieved. However, with a 100: 30 training-testing ratio, an accuracy of about 96.66% was obtained [11].

S. Barburiceanu et al. [12] "proposed new feature extractors for colour texture classification based on Local Binary Patterns (LBP) operators, which are invariant to rotation, illumination, and change of the observation scale, being also robust to Gaussian noise"[12]. The presented model operates in RGB colour space to classify grape leaves containing Gaussian noise and noise-free images by employing a state-of-the-art image de-noising algorithm embedded into a multiscale LBP feature extraction process [12]. The colour increases the ability to classify and discriminate power, increasing accuracy in noise and noise-free conditions. Using SVM, the proposed extractors greatly improve the accuracy of 97-98%in both noise and noise-free images compared to grayscale LBP-based approaches.

This paper by G. Li [13] produced a system to identify and diagnose grape downy and powdery mildew based on image recognition [13] and SVM techniques. The segmentation of disease images is executed using the K-Means clustering algorithm. The Support Vector Machine classification technique [13] was applied to the dataset after converting it to a suitable format. The process applied starts with image acquisition, followed by segmentation, and then the feature extraction is done on the images. Finally, an SVM classifier is applied to these images to achieve results. The dataset consists of fifty images, in a 3:2 ratio of grape downy mildew images to grape powdery mildew images [13] for training. For testing the model, thirty-five images, including twenty grape downy mildew images and fifteen grape powdery mildew, are used. For the thirty-five images, the recognition rate was 91.43% [13].

2.3 Fuzzy Neural Networks

In this paper by D. Kole et al., The proposed system identifies the downy mildew disease [14]. Downy mildew is a serial fungal disease [14]. The technique used is based on a significant fuzzy factor. The dataset used consists of thirty-one images of diseased and healthy images. The technique of image processing used consists of two major stages. The first stage is to lower features in which predominant features are obtained [14]. The next phase is to detect downy mildew disease there in grape leaves [14]. After the feature reduction phase, the values of features chosen for all test images are obtained. Then all the normalised feature value present in the normalised feature matrix generated in the first stage is replaced by a fuzzy value of the nearest cluster of the respective feature [14]. Then the calculation of the mean fuzzy value for each image is done. The images having an average fuzzy values more than or equal to the experimental threshold value are detected as downy mildew disease [14]. The success rate achieved was 87.09%.

2.4 K Nearest Neighbors:

This paper by N. Krithika et al. proposed identifying diseases in a grape plant by using the leaf skeleton of the grape as the focus of detection. The process starts with the identification of leaf skeletons [15]. A tangential direction-dependent segmentation algorithm is presented for the skeletons retrieval [15]. Once the classification of the grape leaf images is done, the colour channels and histograms of H are generated, and the pixel values are noticed to differentiate the healthy and diseased tissues

[15]. Then, the extraction of features and classification of them is done using the KNN classification algorithm [15] in order to detect disease in the grape leaf. In this paper, the image processing is performed by first acquiring the RGB grape leaf images [15] and then finding Hue Saturation Value(HSV) and L*a*b colour spaces helps in the further process [15]. The obtained images are preprocessed for further identification process [15]. Hence, the proposed method mainly detects a leaf skeleton's luminance and characteristic linear image [15]. GLCM features are extracted, and the classification of the diseases is carried out utilizing the images obtained [15]. Further, the classification of grape leaf diseases is done efficiently using the KNN approach.

This paper by A. Bharate et al. gave a system that applies techniques involved in image processing to perform the classification of grape leaves automatically into healthy and unhealthy [16]. The feature extraction is performed to obtain the colour and texture features from the leaf image [16], followed by applying the KNN classification algorithm to classify the leaf diseases. Step one of the given system involves the gathering of data and database creation for the data [16]. The database includes a total of 90 images in which 45 images are termed to be healthy and 45 images termed to be unhealthy [16]. GLCM is used to calculate the texture features. Testing is done using KNN on 30 images. An accuracy of 96.66% was achieved using the KNN classification technique. When the same dataset was classified using the SVM technique, an accuracy of 90% was achieved. Hence it has been concluded that the KNN classifier gives accurate and efficient results when compared to that of SVM classifier.

2.5 K Means Clustering

In this paper, M. S. Utsad et al. proposed a system that processes the grape leaf imagery by applying segmentation and K Means clustering algorithm to detect the image's diseased part [17]. Colour, shape and the other features were extracted from the image segmented based on the most matched features classification of diseases using an SVM classifier. The K Means clustering algorithm is a well-known approach generally applied to solve low-level image segmentation tasks [17]. The paper proposed K Means segmentation method to segment target arrears [17]. A major advantage of using the K Means clustering technique is it works on local and global information of images [17]. The other advantages of using this kind of clustering technique is that it is fast, powerful, flexible and the implementation is simple. With this technique, the accuracy achieved was 91%.

2.6 Deep Learning:

M. Kerkech et al.[18] have presented an optimised detect Mildew disease in vine built on deep learning segmentation method and optimised image registration using multimodal Unmanned.

Aerial Vehicle (UAV) images with a deep learning segmentation procedure that has been used for the detection of vine disease using multimodal UAV images. The model includes three main steps, and the first step is alignment of image, the second step using SegNet architecture to perform segmentation of visible and infrared images in order to identify four classes namely the shadow class, the ground class, the healthy class and symptomatic vine, the last step involves of give raise to an disease map which is performed by fusion of the segmentation results which are obtained from the visible and infrared images [18]. In this case, the method is constructed by integrating infrared images and visible images derived from two different sensors. "The image registration method" was used to enable the combination of images from two different sensors. The proposed model achieved accuracy greater than 92% for disease detection in vineyards. The limitation of this study is the diminutive size of the sample used for training, due to which there was a visible decrease in the performance of segmentation done using deep learning.

The paper [19] proposed a new system for detecting vine diseases like esca in UAV and RGB sensor images. This method integrates the strengths of the deep learning approach (specifically CNNs) with various different "color spaces and vegetation indices" [19]. The obtained images were divided into square grids with varying sizes and pixels. Each block of the grid had to be classified as either healthy or diseased. The model was classified using a deep network and a combination of vegetation indices and colour spaces. Results concluded that "CNNs with YUV colour space combined with ExGR vegetation index and CNNs with ExG, ExR, ExGR vegetation indices" produce optimal results with the value being more than 95.8% accuracy. Some limitations of this system include a recurring problem and the number of labelled data. The Proposed system can be improved by increasing the UAV image database with new vine disease samples.

2.7 Back-propagation Network:

S. S. Sannakki et al. suggested a system in which the input is the images of grape leaves with a complex background. Thresholding is employed to mask green pixels, and anisotropic diffusion is used to remove noise from the images [20]. Then the segmentation of grape leaves is performed using K-Means clustering. Followed by the segmentation process, the diseased fragment is identified. When the feed-forward back propagation neural network is trained for classification [19], Better results were achieved.

[20] The author has considered two types of diseased grape leaves-downy mildew and powdery mildew. Feature extraction is carried out by color co-occurrence methodology that uses an image's texture to arrive at unique features representing the image. The training of neural networks for pattern recognition resulted in 100% accuracy when using hue features alone. Dataset has 33 images; 29 were used for training, the remaining were used for testing and validation [20]. Research can be improved by exploring the benefits of these techniques by including samples of healthy and other diseases of grapes.

J. Zhu et al.[21] have presented an approach to inspect grape leaf diseases automatically using image processing and back propagation neural network BPNN. Diseased images are de-noised using the Wiener Filtering method. The Otsu method is used to segment the grape leaf diseased regions, and to enhance the lesion shape, and morphological algorithms are applied. Further, to extract the entire edge of the lesion region, the Prewitt operator was applied. This system mainly extracted five effective grape leaf parameters: shape, area, perimeter, circularity and rectangularity. The last step was to analyse grape leaf diseases by implementing BPNN. The results showed an average accuracy of 91%, and this method can recognise the five primary grape leaf diseases with high classification accuracy.

2.8 Support Vector Machine and Random Forest Tree:

S. M. Jaisakthi et al. [22] put forward a system to detect grapevine diseases through image processing and machine learning techniques. At first, the region of interest (ROI) is segmented from the rest of the background image by utilizing the segmentation method called grab cut. Then the diseased part identified after segmentation is additionally segmented using global threshold and semi-supervised technique. The extracted attributes from segmentation have been classified into main categories such as healthy, esca, rot and leaf blight using Support Vector Machine, Random Forest Tree and AdaBoost. Compared to other classifiers such as RF and AdaBoost(Decision tree), SVM obtained a superior testing accuracy of 93%.

3. GENERAL ARCHITECTURE

The block diagram of the general architecture is shown in the figure below. The block diagram represents various stages involved in identification and detection of grape leaf diseases. Each stage of the block diagram is described in detail in accordance with the block diagram.

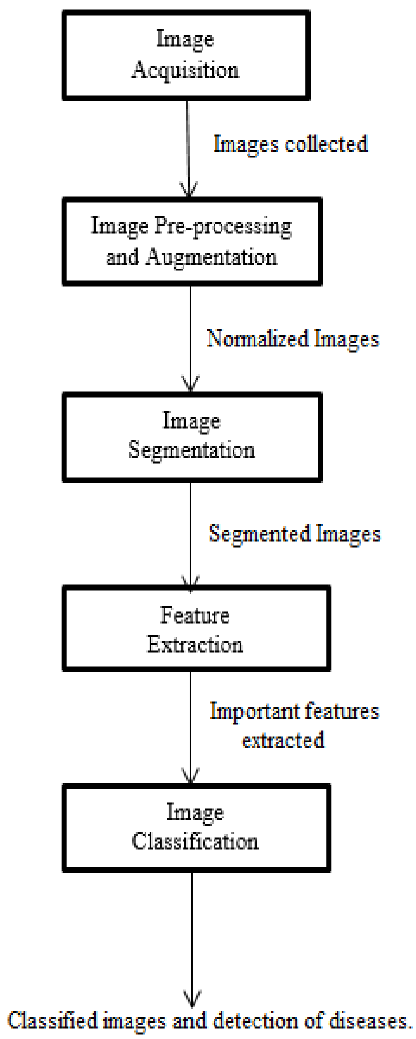


Fig-2: General Architecture for detection and classification of grape plant diseases

3.1 Image Acquisition

To identify and detect diseases in grape leaves, the first step is to collect the data necessary in images. V. Mishra et al. mentioned that the primary motive of image acquisition is to transform optical images (actual data) into an array of numerical data that can later be altered by a computer [23]. Before any processing is applied to the images, the images must be converted to a suitable format, making processing more efficient. In this process, the light energy from an object is converted into electrical signals by combining sensitive sensors to the particular type of energy. These minute subsystems work together to provide a machine vision algorithm with the most accurate representation of the object. The components include:

1. Triggers: For triggering the images at any point in time, the camera has to be configured. This mechanism signals the camera to capture images. Most applications in the modern world use triggered images. This trigger can be in PLCs (Programmable Logic Controllers), sensors and push buttons for manual usage. Triggers can be considered to be used based on the type of camera being used.
2. Camera: The purpose of using cameras is to take the incoming light from an object/scene and convert it into digital signals, i.e. pixels, using CMOS or CCD sensors.
3. Optics: The light front the source must be focused adequately by a lens on the sensor to capture the image with maximum clarity.
4. Illumination: Illumination is one of the most critical factors in a machine vision system. The lighting should be able to illuminate uniformly throughout all the visible surfaces.

In paper [1], paper [8], paper [11], paper [13], paper [16], paper [17] and paper [20], the image acquisition process is incorporated using a digital camera to capture a sum of 7,669 images of grape leaves. For papers [2] and [22], the source of acquisition of images is the internet. And for paper [2], 136 healthy images and 124 disease grape images were considered. In paper [3], paper [6], paper [7], paper [9], paper [10], paper [12] and some of the images from paper [2] were all acquired from the PlantVillage dataset. For the paper [4], the grape disease images from GLDD were collected under various climatic conditions [4], and other leaf images were acquired in Yamethin township. For paper [18], Image acquisition is performed using an Unmanned Aerial Vehicles (UAV) drone, which consists of a high-resolution Survey2 sensor [18]. The drone was used to take continuous images of the vineyard plot. In paper [19], a UAV system with an RGB sensor [19] was utilized for image acquisition. In paper [21], the image acquisition stage is carried out by obtaining images from machine vision inspection system, a CCD, including a lighting system and a computer [21]. The lighting system consists of an LED which helps in noise reduction in the images.

3.2 Image Preprocessing and Augmentation:

Data preprocessing is done to make the data fit into a particular format to be uniform and suitable for further processing. Data preprocessing includes data manipulation and operations on images which aim to reduce undesired distortions and improve the quality of images. Image preprocessing includes resizing, colour corrections, the orientation of the images etc.

The main steps include:

Image Resizing:

The images are resized to achieve uniformity in terms of image and its size[17]. The original images are bigger, due to which it takes a long time to process. Hence images are resized into small sizes to avoid time consumption. In [6],[7], and [11], images were resized into 256 x 256. Similarly, images are resized to size 300 x 300 and then thresholding to obtain green colour parts [8]. [3] VGGNet, DenseNet and ResNet images were resized to 224 x 224 and 229 x 229 for GoogLeNet. Images were compressed to 800 x 600, retaining the proportion to make the resolution of images invariant by applying the Interpolation Method [13]. To enter VGG16 network resizing of images to 150 x 150 were carried out by Linear Interpolation method [5] is

$$y = ((y2 - y1)/(x2 - x1))(x - x1) + y1 \qquad (1)$$

Image Colour Transformation:

The input “RGB images” are converted to “Hue Saturation Value (HSV) color space” and this conversion is what is called a color transformation. HSV is closer to human perception [11]. After transformation, the Hue component is generally considered for further process. As it is the dominant color [11] and does not consider the saturation and intensity component because it doesn’t provide any helpful information [17]. The color spaces represented by grayscale images are enhanced by

$$N\,\mathrm{p},q = \frac{F\mathrm{p},q - \min(F)}{\max(F) - \min(F)} \qquad (2)$$

F and N represent the original and new pixel values and indexes of pixels are represented by p and q.

Otsu's technique is employed to grayscale images. The images obtained have a region of interest called disease spots and hence RGB image is modified into different lab colour spaces and HSI model [10]. Multilevel Otsu thresholding segments the images into different regions by choosing threshold values based on the biggest inter-class variance between the background and foreground [11]. This technique improves accuracy when applied to transformed images.

Image Background Subtraction:

To remove undesired backgrounds from the images and to extract the required region of the image, "background subtraction" techniques are adopted [17]. Colour based background subtraction techniques are used for achieving more accuracy. In this technique, based on RGB intensity values, unwanted backgrounds are removed. As green coloured pixels consist of healthy parts, only these are kept as it is whereas the other pixels are colored black [11].

3.3 Image Augmentation:

The process of combining operations such as image shifting, rotation, shear and flips etc. in order to generate more training images is called image augmentation. It is an essential technique as it helps to overcome the overfitting problem and helps to generalise better [5]. This helps the model learn more variety of patterns during training, avoid overfitting problems and helps to attain greater performance during detection. In the view of the weather's impact during shooting, intensity factors like contrast, sharpness and brightness are considered [4]. The corresponding positions of the camera and diseased leaves are simulated using rotation (90, 180 and 270 degrees), horizontal and vertical symmetry operations [1]. Gaussian noise is utilized to mimic the effects of equipment factors. Furthermore, PCA jittering is applied to augment the input dataset and ameliorates the quantity and diversity of grape leaves.

[21] The Wiener filtering method drawn on wavelet transform (WT) was applied to de-noise the images. Since Grayscale images include a certain amount of noise. This is to be removed before segmentation can be performed on the images. In signal de-noising and image processing, WT has been broadly used because of its time-frequency, de-correlation, localization property, flexibility and multi–resolution [21]. WT also has simple computation, exhibits convenience and effective de-noising effect in de-noising images. The calculation formula of the dimensional Wiener filter is expressed as:

$$g(i,j) = E + \frac{\sigma^2 - v^2}{\sigma^2[f(i,j) - E]} \qquad (3)$$

Where g(x, y) is the grey value of pixel (i, j); E is the local grey mean of pixel (i, j); the local. The region is the neighborhood of pixel (i, j), which is generally a 3×3 or 5×5 neighborhood; σ2 is the local variance of pixel(i, j); v2 is the noise variance; and g(x, y)is the de-noising gray estimate of pixel(i, j) [21].

The advantages of image preprocessing are stated as follows:

1. It helps to improve the images in human interpretation.
2. Images can be stored and retrieved easily.
3. The pixels of the image can be manipulated at the desired density and ratio.
4. The digital image can be made available in any desired format.

3.4 Image Segmentation

Image segmentation divides the images into smaller subgroups of images or pixels to reduce the complexity of images, and image analysis can be done easily. The splitting and grouping of pixels to form a sub-image can be done using various image segmentation algorithms. In paper [9], the segmentation technique used is colour segmentation which follows the colour features and a saliency method extracting only valuable objects from the image and discarding the rest. This method involves four steps:

1. LAB colour transformation.

2. Selection of appropriate channels based on weighted function is carried out.
3. Refinement using morphological operations.
4. Map and draw Region of Interest [9].

In the paper [8][13] [10] [20], K-Means clustering is the technique being applied for segmentation . The clustering technique can be defined as a procedure by which huge data sets are grouped to form clusters of homogeneous segments or sets of data. K-means clustering is used to segment the target area (diseased parts) from coloured parts of the leaf by optimising the partitions based on the user-defined initial set of clusters. It groups objects or pixels based on the number of attributes into K number of clusters.

The steps required to carry out the K-Means algorithm is:

1. First, partition the dataset into K number of groups or clusters and assign data points randomly.
2. For every data point, Euclidean distance from each data point has to be calculated by $\sqrt{((x1-x2)^2+(y1-y2)^2)}$ (4) and (x1,y1) (x2,y2) are two data points.
3. If a data point is in close proximity to its cluster, then leave it unchanged.
4. If a data point is away from its cluster, shift it near its cluster.
5. Repeat all steps until all data points are catered.
6. Clustering will stop when all clusters are stable [8].

After enhancing the pixels in the skeletons, segmentation of skeletons was performed using color and smooth segmentation. Smoothness Segmentation is defined as:

Smooth (c) = $1/N\sum m \in D(|\psi(c)-\psi(m)|)$ (5)

Here N constitutes the number of pixels and D is the side length. If the smooth degree of pixels is greater than the threshold, it will be termed as noise and eliminated from the image [15].

Another segmentation technique includes threshold segmentation, as described in the paper [21]. Otsu threshold segmentation is adopted to segment the diseased regions of grape leaf, and minimum infraclass and maximum interclass variance are optimal criteria for the otsu method. This area was expanded to fill a small hole and connect the ends separated by standard morphological manipulation. The Prewitt operator is the first derivative operator used for edge detection in images [21]. Grab cut segmentation algorithm has been used in paper [22]. This algorithm uses a Gaussian mixture model (GMM) to label pixels as foreground or background, having the first rectangle, which is the approximate segment between the background and the foreground. From the background or foreground, the diseased leaf parts are extracted with the help of the Global threshold method, which is used to convert grayscale image to binary image. For segmentation, the RGB image is converted to a BGR image so that the blue pixels of the affected area are excluded. Filtered image thresholding is applied, and finally the lesion is determined [22].

3.5 Feature Extraction

The creation of a collection of features from the raw data provided initially is known as feature extraction. The data that is being dealt with in the modern-day consists of data with enormous amounts of features. If the number of features available becomes as big as the data considered or even reaches numbers beyond the data considered, this may lead to a machine learning model suffering from model-overfitting. Feature extraction can generally be viewed as a method provided that can get around major problems yet describe the data efficiently. Most of the papers considered adopt techniques to extract various features such as shape, colour and texture features.

In paper [8], color and texture features are extracted to attain the best accuracy as color features are suitable for Downy Mildew, and texture features are needed for Powdery Mildew.

Steps to extract color features for an image [8]:

1. The RGB image is converted in HSV color space.
2. Uniform subdivision of the image into 3x3 blocks is done.
3. For every block of the nine blocks, mean colour is evaluated applying the formula
4. $x' = \left(\frac{1}{N}\right) x_i$ (6)
   Where xi is the pixel intensity and N is the total number of pixels.
5. Variance for every block is evaluated by the formula
   Variance $= \frac{1}{N}\sum_{i=1}^{N}(xi-x')^2$ (7)
6. Skewness is used to find the surface of the image for each block.

Another important feature is extraction based on shape characteristics to describe the geometrical properties of the lesion irrespective of the grey values. Some of the major parameters in shape characteristics are target area, target regional circumference; Lesion circularity, rectangularity and shape complexity are computed by formulas:

Lesion circularity $C = 4\pi A/L^2$ (8)

Lesion rectangularity $R = A/Ar$ (9)

Lesion complexity $e= L^2/A$ (10)

The image parameters of the lesion can be passed as a feature vector for classification. This extraction method is effective for separating lesion areas in leaf images.

Texture features are used as discriminators when images don't have well-defined colours or shapes. Local pattern formation describes the texture formed. Local Binary Pattern (LBP) is a capable feature as it is invariant to illumination conditions. LBP uses simple primitives to describe complex structures in images. Opposite colour LBP feature extraction is used to analyze the texture [11]. To address the noise sensitivity and obtain distinctive features MRELBP (Median Robust Extended Local Binary Patterns) was proposed, and BM3DELBP (Block Matching and 3Dfiltering Extended Local Binary Patterns) descriptors were employed to reduce Gaussian noise [12]. In the paper [12], the MRELBP and BM3DELBP operators are extended to colour using the relative color scheme. Here, the operator is individually applied to each color channel, collecting the colour pattern of the opponent.

In papers [16] and [22], features like texture and colour are extracted and used as input for sorters to improve results. Gray Level Co-occurrence Matrix (GLCM) is a good approach because Grape leaves have a repeating pattern.The GLCM approach was developed through spatial grey-level dependent matrices (SGDM's) [20]. Co-occurrence matrices

Measure the probability of a pixel at one grey level occurring at a different distance and orientation from another given pixel of the second grey level [20].

Texture Feature Extraction through GLCM:

1. Begin
2. Read colour images and find varioust intensity levels in the image.
3. Compute GLCM image by identifying the GLCM's size. Find intermediate matrix A by determining how often a pixel p appears in a particular spatial relationship with pixel q.
4. By dividing every element of the matrix by the sum total of elements in the matrix GCLM is calculated.
5. Calculate properties like contrast, correlation, energy and homogeneity for images using GLCM.
6. End

Color Feature Extraction [20]:

1. Begin
2. Read colour images.
3. Determine the percentage of red, green and blue colors in a data image which can be termed as extraction of the three components.
4. Conversion of colour image to HSV image is to be performed.
5. Extract hue, intensity and saturation of an image
6. Calculate the mean, variance, and range for each component extracted in steps 3 and 5.
7. End

So far, most studies have been extracting statistical features of RGB and converting them to LAB format. Therefore, the paper [10] added several properties of the HSI image format to increase the feature set and improve accuracy. It is known that the HSI image does not change even when the background illumination changes [10].

To extract skeleton information, luminance characters are essential as the light intensity of the skeleton should be more than other pixels. Hence Tangential Direction (TD) method is adopted to extract skeleton pixels.

The luminance difference is calculated by [15]:

$$d(e, An) = mLAn\,(|(c) - (m)|) \qquad (11)$$

Where x is the pixel, c is the center, An is the angle, and the short line is LAn, and the function () is used to find the brightness value of the pixel. Then the angle with the smallest brightness difference is selected as TD of e. Then, de-noising is performed on the selected candidate pixels from the skeleton image [15].

3.6 Image Classification

Classification techniques are applied to classify data based on decisions. The theory describes that the classification problem relies on the training data set containing the observation value and its category membership to identify which category set a new observation value belongs to.

CNN is part of a deep learning neural network that is primarily used for image identification and processing and specially designed for processing pixel data. CNN technique involves multilayer perceptrons which are designed to result in low processing requirements. Each neuron present in the CNN layers takes several inputs, and then it considers a weighted sum over the taken inputs, where it is made to go through an activation function which further responds back with the output achieved. The layers of CNN are composed of hidden layers, including input layers, output layers, and multi-convolutional layers, pooling layers, fully connected layers and normalization layers. CNN can be viewed to be prone to overfitting data as there is full connectivity between the layers. The reduced limitations and increased image identification and processing efficiency lead to a highly efficient system, simpler to train the model, yet limited to image processing and natural language processing.

Some of the models proposed by the researcher are DICNN which trains the first two layers separately so that the intake of parameters is reduced and the performance is better. Faster R-CNN is based on a Regional Proposal Network (RPN) [2]. It has a single and fully convolutional network. It is called Faster-R-CNN because RPN predicts object bounds and scores simultaneously as the combination of the width of InceptionV3 and the depth of ResNet50 United Model was introduced for better accuracy and representational abilities. To detect multi-scale diseased spots and small diseased spots, the DR-IACNN model was presented by including the Inception-v1 module, Inception-Resnet-v2 module, SE-Blocks. Shortcomings in VGG16 were overcome; the Global AveragePooling (GAP) layer is used instead of VGG16's two completely connected layers before the ending classification SoftMax layer, which increased if efficiency compared to VGG16 fully connected layers, SVM classifier and VGG16. CNN architecture is based on Inception V3, which ResNet50 used to classify the diseases of a grape.

Support Vector Machine has gained considerable attention as a classification technique. Support Vector Machine could be preferred as it tends to work with high dimensional data and avoid the curse of dimensionality. This classification technique's approach is considered unique as it uses a subset of training examples to represent the decision boundary. This classification method aims to find a hyperplane in the M-direction space (M - number of features) where data points can be clearly classified. SVM technique helps in global optimum solutions, whereas the artificial neural networks (ANN) and rule-based classifiers tend to find only locally optimum solutions. Capacity control can be performed by SVM by maximising the margin of the decision boundary. SVM works with high efficiency on small sample sets as training time incorporated in this type of classifier is high.

The fuzzy set theory concept was invented by Zadeh. The concept of fuzzy set theory is a research approach that can handle subjective, ambiguous and inaccurate judgments and quantify the linguistic aspects and assessments of data that can be used for individual or group decision making. It has proven itself to be considered as a powerful tool for helping in the decision making process. For a fuzzy classification technique, a certain set of fuzzy rules are applied to the linguistic values of its features. An object can be classified. All rules considered have a number weight between 0 and 1, which applies to the number given by the former. There are two distinct parts involved in this. The first part includes the background evaluation, and Input should be fuzzified, and the necessary fuzzy operators are applied. The second part involves applying the result achieved in the first part to the consequent, generally known as inference. The fuzzy output can be achieved when the inference applies the fuzzy reasoning mechanism.

KNN is based on the supervised learning method and is a machine learning algorithm. In KNN, when a test sample is given, first, the computation of proximity with the rest of the data points in an N-dimensional space is performed where N is the number of attributes.

The algorithm for 'k' number of nearest neighbors and D set of training examples works as follows:

1. For each test sample $e = (x', y')$ do
2. Compute $d(x', x)$, the distance between and every example $(x, y) \in D$
3. Select $D_e \subseteq D$, the set of k closest training examples to e.
4. $y' = argmax_v\, \Sigma(x_i, y_i) \subseteq D_e\, [I(v = y_i)]$ (12)
5. End For.

The algorithm specifies to start by computing the distance (or similarity) between each test sample and all the examples used in training to determine the nearest neighbor list. This kind of computation may be costly if a large number of training examples are considered. But the number of computations needed for finding the nearest neighbor can be reduced using certain efficient indexing techniques. Once the closest neighbor is determined, the next step is to classify the test samples based on the number of classes to which the closest neighbor belongs. KNN can be considered advantageous over the other classification technique as no model building is required to be done based on the fed data. But as it is an instance-based classifier, i.e. it uses specific training samples to make decisions without any model building, classifying a test sample may be costly as the computation of proximity should be performed between the test example and all the training examples. The nearest Neighbors classification technique can produce wrong predictions unless the appropriate data preprocessing and proximity values are considered.

K Means is an algorithm based on unsupervised classification that is also called clusterization. Unsupervised classification specifies that the data set either does not have any labels or the labels are not used. Here, the classification of data is done using the properties and characteristics of the data. The K- Means algorithm involves three steps. K Means classification technique involves grouping objects into 'k' different groups, which is done based on their characteristics. This grouping minimises the final sum of the distances between the cluster and each data object. Euclidean distance is generally considered and used for this distance.

The algorithm involves three steps:

1. Initialisation.
2. Assignment of the data objects to the centroids.
3. Updation of centroids.

In this algorithm, the first step involves choosing the number of clusters (k) and creating k centroids in the data space, which can be chosen randomly. The second step in the algorithm suggests that a centroid should be assigned for each centroid. The centroid position is updated considering the new centroid, the average of the positions of objects which belong to the particular cluster. The second and third steps are repeated until there is no more movement in the centroid or it moves below the specified threshold value of distance in each step.

Deep learning can be viewed as a subset of machine learning. Deep learning uses an ordered level of artificial neural networks (ANN) to carry out machine learning processes. Deep learning systems allow machines to process the data in a non-linear approach. Deep learning models consist of multilayers of neural networks for processing data and performing certain computations on a huge amount of data. As in the modern-day, most machine learning algorithms work on data with thousands to millions of features. The efficiency of certain algorithms may be degraded due to a large number of features for a single data object. In the case of deep learning techniques, the algorithm progressively learns more about the data object as it goes through every layer in the neural network. Hence deep learning algorithms become important to process or classify data objects with a large number of features. Deep learning acts as a powerful tool for unstructured data. But deep learning can easily fall into the "over fitting" problem resulting in a failure to generalise the data objects well, and applying deep learning to less complex data might result in overkill. Hence, deep learning needs access to extensive data and is considered to be less effective when compared to linear models or boosted decision trees for less complex data. But deep learning can also act as the most effective tool when a complex data set is considered.

An artificial neural network is a set of connections composed of I/O units, each associated weight. Back propagation neural network is a standard method for training artificial neural networks.

The main functionality of BPN is to calibrate or make minor adjustments to the weights of a particular neural network depending on the error rates obtained in the previous iteration. Accurate adjustments of the weights lead to the depreciation of error rates and results in a dependable model as it increases the generalisation.

For a single weight in the neural network, the backpropagation algorithm evaluates the gradient (change in the weight concerning change in error) of loss function for that weight by the chain rule.

Backpropagation algorithm:

1. Inputs X shows up through the pre connected path.
2. Input is geared using actual weights W. Usually, the weights are selected randomly.
3. Outputs are calculated for every neuron, starting with the input layer, the hidden layers, and finally, the output layer.

4. Evaluation of errors in the outputs is done.

$$Error = Actual\ Output - Expected\ output \quad (13)$$

5. From the output layer, move back to the hidden layer to tune the weights to reduce the error.

4. CONCLUSIONS

Detection and classification of grape leaf disease can be done using various techniques. In this paper, we have studied the various approaches used by researchers to find an optimal and effective solution for identifying and detecting grape leaf diseases. Each approach has a distinctive quality. With each paper, there are differences in the dataset, the kind of disease to be identified by the particular approach and then the approach itself. This article outlines recent research methods, and it helps in future research work. The five main steps in image processing are image acquisition, image pre-processing, image segmentation, feature extraction and image classification. Some image acquisition sources were digital or mobile cameras, internet, Plant Village, Grape leaf Disease dataset (GLDD) and Unmanned Aerial Vehicles (UAV) like drones. Some of the main steps in data pre-processing are Image Resizing, Image Colour Transformation, Image Background Subtraction and Image Augmentation. Some commonly used image segmentation techniques are K-Means clustering and the Otsu threshold segmentation method. Feature extraction is based on color, texture and shape. Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM) and Tangential Direction (TD) are a few texture-based feature extraction methods. The classification techniques reviewed in this paper are Convolutional Neural Networks (CNN), Support Vector Machine (SVM), the fuzzy set theory, K Nearest Neighbor (KNN), Deep Learning and Backpropagation neural networks. This paper presents an overview of different techniques used in grape leaf disease detection and classification, which can be helpful in further research.

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