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Plant leaf vein and outline feature extraction using fractal and computer vision approaches

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ABSTRACT:

The study focuses on utilizing plant leaf characteristics for plant identification and disease detection. Leaves are pivotal for gathering information about plants. The proposed model uses computer vision and smart agricultural technologies to discern venation and texture features in various plant leaves. This research utilized a modified dataset derived from the Flavia leaf image dataset, comprising images of 32 plant species. The dataset was divided into two subsets (one with 1907 images and another with 1000 images) to differentiate between tuned and untuned image processing. Techniques such as GLCM, LBP, Gabor filters, Fractal Dimension, and box-counting were employed to extract leaf texture features, including venation patterns. The study conducted four experiments with training and testing splits of 70/30 and 80/20. A novel method combining SVM with fractal dimension analysis was benchmarked against six classifiers (Random Forest, KNN, DNN, Naïve Bayes, Decision Tree, and SVM), achieving an impressive accuracy of 88% and a Fractal Dimension of 1.8709. This research holds significant potential for advancing digital and modern agriculture, particularly in the early detection of plant diseases and accurate plant identification.

KEYWORDS: Fractal Dimensions, SVM, Fusion Feature, Texture Feature of Leaf, Classification.

1. INTRODUCTION

Computer vision approaches has discovered many unhide in different fields of life and even agriculture. Computer vision has changed approaches and dimensions of agriculture with every aspects and brings positive change. Leaves are a significant part of plants with various features in their distinct structures. By studying these attributes of plant leaves, we can extract useful information from them which can be used in plant morphology and several other fields. Different techniques can extract and utilize these features for classification and recognition purposes [1]. Plant leaves comprehend distinct and complicated vein patterns which play a critical role in plant physiology and morphology. The extraction of veins and outline attributes from plant leaves is vital in plant biology and agriculture research because it enables plant recognition, classification, and analysis of plant morphology. This field includes a study that mainly focuses on observing and recognizing a plant based on its distinct features [2]. Retrieval of these features can be done using manual approaches. However, utilizing these methods involves more chances of errors in the results and are also time-consuming.

Moreover, experts need to utilize manual techniques to get accurate results. To address this problem, an alternative automated approach must extract veins and outline features from plant leaves using some computational procedures and classify them. Automatic classification and plant recognition plays a significant role in solving various problems in agriculture fields [3]. In plant classification, the leaf is the most common part, and it is used to extract distinct features and classify them based on their attributes. Several features can be extracted and utilize in classification task like shape, texture, color or combination of all these attributes. Texture features can be extracted using different filters like GLCM, LBP, and Gabor [4]. Fractal dimension on the other hand, is used to measure the complexity of leaf structure. Box counting method can be used to extract fractal dimensions from plant leaf varying the sizes of boxes [5]. In this study, the dataset was preprocessed first, and different texture features from leaves images, including homogeneity, dissimilarity, contrast, and energy, were extracted using GLCM, Gabor, and LBP. In addition, fractal analysis techniques were used to identify the complexity in texture and, combine this value with other texture features and observe the classification performance. This work identifies fractal dimensions using the box-counting method from our plant leaf dataset. Afterwards, combine fractal dimension values with prominent texture features and identify how it will affect the classification process. After extracting all these attributes, Six different classifiers were used to classify different leave images based on these attributes in different classes. It was observed that the proposed results were based on the performance of different classifiers by identifying accuracy, precision, recall and F1-score.
Different classifiers (KNN(K-nearest neighbour), CNN, SVM (Support vector machine), Decision Tree, Naïve Bayes and DNN, were used [6]. The dataset was divided into two chunks, one portion consists of 1000 images and another split consists of the 1907 images. The 1000 images dataset is a fragment from the same dataset but with a limited Number of images from each class while the 1907 image dataset or second part is same as the Flavia offers the dataset. After the experiment Nine "9" features based on the texture of leaf image also including the fractal dimension value as the feature, were derived. The proposed study used the special libraries (Filters) for eight texture features and implemented the fractal dimension method using box counting to calculate the fractal dimension value of each image in every class. The different tests and training sets were used in the proposed study, and the performance of every classifier was based on texture features and fractal dimensions. In the whole classification process, the feature scaling of all the feature values is applied first to make the data appropriate for the algorithms. After partitioning the data into the train, test classifiers were used to observe the performance of the outcomes in accuracy, precision, recall, and f1-score. Different classifiers perform differently with distinct test train data. Moreover, parameter tuning was used to find the best parameter for the given data with feature values and observed the classifier's performance on these parameters.

2. LITERATURE REVIEW

In earlier studies of plant leaf veins and features, the focus was describing the structure and function of veins and their part in the photosynthesis process. Different methods have been used to extract leaf veins and their features in past years to classify different species. Various applications of computer vision algorithms help enhance ampelography's capabilities by providing more accurate techniques for plant classification using its leaf veins and features. [5], utilized computer vision methods named artificial neural network model and fractal dimension for cultivar classification. The auto extraction of Morpho-colorimetric data and DL modelling proved to be more precise, fast, and non-destructive methods that can be used in cultivar classification. The study [7] proposed an automated system for identifying ayurvedic medicinal plant species from images of leaves utilizing computer vision and machine learning techniques. The proposed system combined SURF and HOG attributes and classified them using the KNN classifier. It gave promising results and proved the system a practical approach. Computer vision techniques for plant species identification has been done for examining their results, and determining is one of the best techniques [8]. In [9], they developed a technique for processing, attaining, and investigating hemispherical images of sessile oak, tree crowns. They determined that it was feasible to identify a constant dimension variance of the crown structure by calculating the fractal dimension of tree crown images. Plant leaf identification is a vital computer vision technique that automatically distinguishes plant species from their nominated attributes. The paper [10] proposed a multiscale fusion convolutional neural network technique (MSF-CNN) to identify plant leaf at multiple scale. After down-sampling the images, fed into MSF-CNN architecture was to identify distinct leaf features. In this study, the proposed technique was superior to multiple state-of-the-art in plant leaf identification techniques. Plant leaf image recognition mainly relies on the features that are extracted from the leaf. In [11], a fractal analysis technique has been used to extract the leaf features. Utilizing this approach, it identified that recognition accuracy was better than other existing methods. In the study [12], they calculated the fractal dimension utilizing box counting algorithm of fractal analysis for vigorous and repeated functions. They showed that images can be compressed easily using fractal image compression technique that is multifractal analysis. In the paper [13], 10 common classifiers were evaluated in leaf species classification with distinct leaf attributes such as texture, margin, and shape. In conclusion, the most accurate and robust classifiers in leaf identification were Sparse representation, logistic regression, LDA, and random forest. On the other hand, SVM, KNN, and Nu-SVM performed better when there was a small number of species. The study [14] proposed a new classification scheme utilizing only leaf texture feature extraction technique. In the experiment, they included the structure composition of leaf veins as a part of the texture analysis approach, and they analyzed how the two different shape feature extraction methods responded to this. The results demonstrate that the above process gives better results in species classification task. In [15], plant leaf classification uses GIST texture features. They utilize machine learning algorithm principal component analysis to extract suitable attributes. They applied the proposed method on famous dataset and found that it performed well in the case of both accuracy and time. For plant species classification, several researchers initially adopted manual methods. However, these methods prove to be more time-consuming. In [16], four different transfer learning models for DNNs plant classification were investigated on different datasets. The results proved that transfer learning can be a significant approach for plant recognition. In the study [17], a quantitative structure model was developed for all the trees to illustrate their branching architecture. The box-dimension fractal analysis technique measured structural complexity and its architectural self-similarity. In the study [18], they used crack resistance technique for plant leaf to enhance crack resistance of aluminum alloy aircraft skin. They utilized fractal analysis and image detection methods for this purpose. They found that the stress intensity ahead of crack tip was reduced by implementing a bio-residual stress field. They presented the potential technique inspired by plant leaf crack resistance. In the study [19], they used the fractal theory to determine the structural complexity of 3D surface roughness of leaf using measurements named atomic force microscopy. The outcomes showed that image processing utilizing fractal theory can efficiently identify plant species by their leaves. In study [20], the fractal analysis method was used to characterize soybean leaves. They utilize the box-counting method to determine the fractal dimensions of leaf shape in the two different genotypes. Using the fractal analysis technique, they characterize the leaf geometry concerning specific foliar parameters for soybean leaves. The paper [21] proposed a fully automated approach for medicinal plant identification utilizing machine learning and computer vision techniques. Several machine-learning algorithms has been used to classify the leaves. In conclusion, the highest accuracy was achieved by a random forest classifier. Image processing techniques are widely used in plant leaf recognition or its disease identification. Computer vision and machine learning have become progressing fields that are competent to identify and comprehend information from digital images. In [22], they proposed a plant leaf disease identification prediction model utilizing computer vision and deep learning techniques. They found that the proposed approach performed well with the random forest model compared to other classifiers. Deep learning provides automated approaches for plant species identification and classification which improves the results and accuracy. In [6], a CNN-based approach named D-leaf was presented in order to perform plant leaf classification. Leaf images were preprocessed, and CNN models extracted attributes. After this, these features were then classified using five different algorithms. They found that D-leaf provided more accuracy in classifying these leaves and proved to be an effective automated system. The paper [23] proposed a methodology for recognizing the plant leaf images with the help of several attributes, including GIST and Local binary pattern (LBP) features. They extracted three types of color moments, geometric attributes, vein and texture features based on lacunarity. After this, the classification of these attributes was done through different classifiers. The study's results demonstrated that the decision tree algorithm was most accurate. The leaf shape geometry was analyzed using fractal dimension parameter for a species found in alluvial forests. They developed mathematical models between the indices and fractal dimensions. [24]. Automated plant leaf recognition plays an important role in the classification of plant using computer vision techniques. Leaves of plants are the most vital identification parts. In the paper [25], the image is analysis in order to extract plant leaf attributes and identify plant species. For classification of these plant leaf features utilizing SVM and KNN algorithms. The result showed that the proposed approaches had the smallest identification time and highest accuracy. Automated techniques perform better than manual methods that are used for feature and vein extraction from plant leaves. The study [26] utilises an automated technique for classifying medicinal plants. They implement K-nearest neighbor a deep learning algorithm to design an automatic classifier and classify the Indian medicinal plants. They utilize the texture features that play an important role in leaf recognition. As a result, they designed an automated classification system for medicinal plants. One of the deep learning algorithms, named gradient descent tree algorithm (GDBIT) was used in the plant re process. They used this algorithm on binary images of 100 different kinds of leaves and found that accuracy rate with all attributes was 93.5%. They proved that this model performed great, in contrast to other deep learning algorithms. [27]. Identifying and evaluating leaf vein patterns and its densities is very important in several plant species classification and identification applications. In [28], a fast and automated approach for recognising leaf attributes and its vein types was presented. In result, the proposed method proved to be an efficient technique for leaf vein extraction. Several researchers have widely done venation network analysis as it provides new insights into the origins of plant characteristics. In [29], a novel approach was introduced capable of identifying leaf vasculature. Outcomes proved that the proposed approach was best in both quantitative and qualitative investigations. In [30], an automated plant recognition system was proposed for recognizing the plant species from their leaf. They utilized the convolutional neural network to gain the maximum accuracy. As results, the performance was improved and more effective than other existing methods. Convolutional neural network algorithms have been widely used in various fields. In the paper [31], CNN framework has been used for automated recognition of grapevine species using leaf images in the evident spectrum. This improved DL model and could identify distinct grapevine species with an average classification accuracy. In [32], a novel model for plant species identification based on morphological attributes identified from the images of leaves utilizing a support vector machine(SVM) with the AdaBoost method was presented. In conclusion, the proposed technique provided accurate and better results than existing approaches. In [38] the study is about the feature extraction and feature fusion techniques of guava plant images. The 12 classes of guava leaf has been used for the self-oriented dataset of 12 guava varieties from the orchard of Pakistan. Different identifiers has been used for the classification of leaf. The Instant base Identifier (IBI), the latest variant of Instant base learner (IBL), is the best identifier with overall accuracy of 93%.

The Fractal Fragmentation Index (FFI), and Local connected fractal dimension (LCFD) technique have been used for the succolarity and proved useful, for the analysis of ecosystems worldwide for the identification of dense forest regions [39].

3. MATERIAL AND METHODS

The proposed procedure includes feature extraction of leaf by their images, applying different classification methods on the fractal

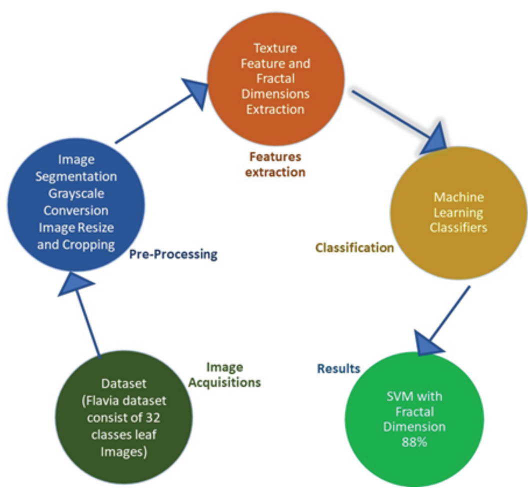


Figure 1: Proposed Model with SVM and Fractal Dimensions

dimension values and some texture features values. The following steps are involved in the proposed approach. The basic procedure of leaf classification was divided into preprocessing of dataset, feature extraction, feature scaling, and classification utilizing six classifiers. The following steps for proposed approach were used in Figure 1.

3.1. *Dataset*

The Flavia dataset of Leaf with 32 types were used for the experiments. The dataset of 1907 leaf images having 32 types. All the images contain distinct features like shape, texture, and edge. The experiments were performed on the dataset, and the best performance of classifiers with Fractal Dimension Features was observed.

3.2. *Preprocessing*

The first step was to preprocess the data to make it able to be used for classification and recognition tasks. Different image preprocessing techniques were utilized to extract distinct features. The image was converted to greyscale to extract some texture features. Furthermore, for fractal analysis the value of fractal dimensions were extracted using the box-counting method and the image was transformed to greyscale and for threshold, it was converted to binary image and the box-counting technique applied to the image. The value of the fractal dimension was determined by varying the box sizes.

3.3. *Feature extraction*

The study retrieved significant information by experimenting with the dataset, which had distinct features like shape, texture, and edge. The Flavia dataset containing different leaves images with 32 classes has been used in the experiment. The proposed study extracted texture features include Homogeneity, GLCM Energy, LBP Entropy, LBP Energy, Gabor Mean, Gabor std, Contrast, Correlation and Fractal Dimension for fractal analysis of plant leaves are extracted.

- ***Gray-Level Co-occurrence Matrix (GLCM) Features***

Some feature extraction techniques were applied.

- ***Homogeneity***

Homogeneity is considered for the inverse difference moment, which was used to measure the proximity of scattering of components diagonal to GLCM in the proposed model.

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} S \tag{1}$$

- ***Contrast***

The contrast of pixels in the image was measured by the local differences in intensity between pixels of nearest neighbours.

$$\sum_{i,j=0}^{N-1} P_{i,j}(Li - Lj)^2 \tag{2}$$

- ***Correlation***

The correlation texture feature was used to measure the linear dependency of the gray levels in the image between the neighbouring pixels.

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(Li-\mu_i)(Lj-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{3}$$

- ***Entropy***

Entropy was used to measure the vagueness of the scattering of pixels in the image. It identified the image texture's disorder where there was high value of entropy, which represented the more intricate textures in the experimental dataset image.

$$\sum_{i,j=0}^{N-1} P_i\,, j\left(-\ln P_{i,j}\right) \tag{4}$$

- Local Binary Pattern (LBP) Features

The experiments used a local binary pattern operator to attain texture details. Different texture features were extracted from local binary patterns where LBP texture energy measured the variation in energy of texture in the proposed dataset image and the randomness of local binary patterns were identified by using LBP equation as:

$$LBP(P,R) = \sum_{P=0}^{P-1} s(Lg_P - Lg_C)2^P \tag{5}$$

- ***Gabor Filter***

Gabor Filter was utilized for texture analysis, feature extraction and edge detection in computer vision. Several Gabor texture filters extracted texture features from the data like Gabor energy, Gabor mean, and Gabor std. In the experiment, two features were extracted using the Gabor filter, which are Gabor Std and Gabor mean as

- ***Gabor Mean***

$$\mu = \frac{1}{MN}\sum_{x=1}^{M} \sum_{y=1}^{d} G(x,y) \tag{6}$$

- Gabor STD

$$\sigma = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(G(x,y)-\mu)^2} \quad (7)$$

- ***Fractal Dimension***

Fractal contains self-similarity, which mainly identifies the complexity and intricate structure of any object [36]. Fractal dimension was used as a numeric value of the object that gave the structure of the image with different features. The fractal dimension values was extracted using the box-counting method as:

$$D(r) = \lim_{r \to 0} \frac{\log_N(r)}{\log_r -1} \quad (8)$$

- ***Feature Scaling***

After extracting values of texture features and fractal dimension from the leaf image dataset was analyzed and the feature scaling technique was applied to preprocess the data and ensure that all features contribute equally to the learning process in classification algorithms.

- ***Classification***

The six classifiers were utilized in the proposed approach: SVM (Support Vector Machine) DNN, KNN (K-nearest neighbor), Decision Tree, Random Forest, and Naïve Bayes. The performance of all these classifiers were observed on two different training and testing sets. first learners were trained on the extracted features set and then tested with respect to the class labelled. The best classifier was found based on higher accuracy and optimized parameters.

- ***Performance Evaluation Parameters***

For the performance, different metrics were used to evaluate the proposed model performance, which was Recall, Accuracy, Precision, and F1-score as:

Accuracy = (TP+TN)/(TP+FN+TN+FP) (9)

Precision = TP/(TP+FP) (10)

Recall = TP/(TP+FN) (11)

F1score = 2x ((precision x recall)/ (precision + recall)) (12)

- ***Parameter Tuning Performance***

The different parameters were used for tuning to identify the best parameter for the dataset that provides the best outcomes. The Proposed method used the GridSearchCV module for hyperparameter tuning and defining the parameters. The Proposed model classifies test , and train set based on the parameters and cross-validation set to 5 for all classifiers. GridSearchCV then classified the data and gave a classification report on the best parameters retrieved from cross-validation. These parameters increased the performance of learners and provided improved accuracy.

- ***Experimentation***

The experiments were conducted to observe the performance of different classifiers on the extracted texture features and fractal dimension values. All experiments were done under Python Environment, and the computer specifications were Lenovo ThinkPad T456ps and HP Core I7 Processor, 8GB RAM, and 4GB Graphics NVidia Card. The experiment focused on identifying how the fractal dimension's value affects the accuracy of different classifiers with other texture features. Six classifiers were employed to obtain accuracy using two testing and training sets. The Flavia dataset in the proposed study was used, and it contained images of leaves from 32 different plants. The Nine basic features were in the pixel of the images were derived by the correlation, Contrast, Homogeneity, glcm_entropy, lbp_energy, lbp_entropy, gabor_mean, gabor_std and Fractal Dimension. Figure 2 shows the image of a portion of Flavia dataset images. In the proposed technique for experiments, the Author divided the Flavia dataset into two splits one part contains whole dataset with 1907 images with 32 classes, and the other subdivision consists of 1000 images with 32 classes but limited Number of images. The distribution of the dataset is shown in Table 1 as:

Table 1: Dataset Distribution and Total Features and Per Image Features Used in Experiments

Total Classes	Train/ Test Split	Images Per Class	Total Images	Per Image Derived Features	Total Derived Features in Images
32	70/30	31	1000	9	9000
32	80/20	31	1000	9	9000
32	70/30	59	1907	9	17163
32	80/20	59	1907	9	17163

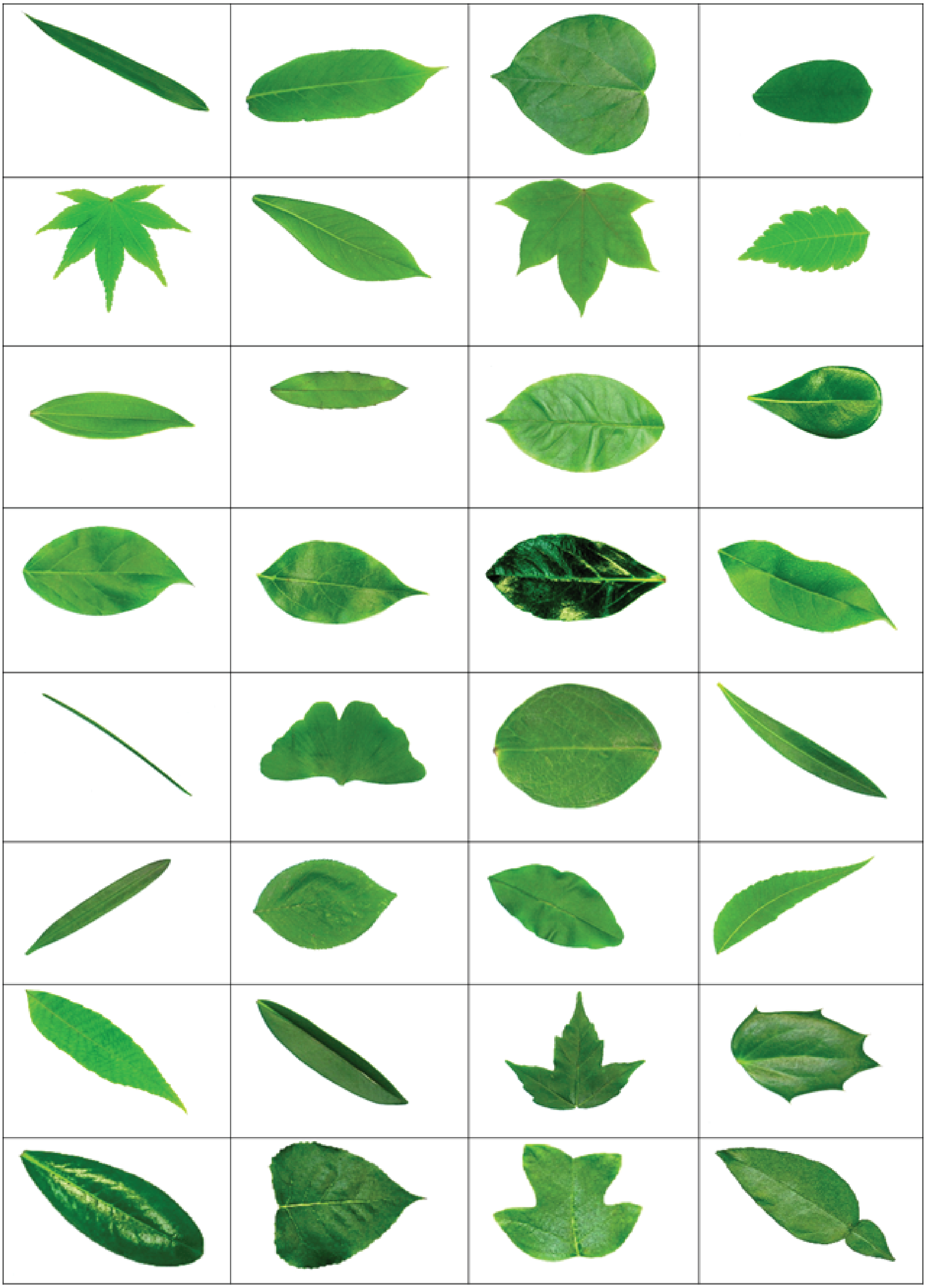


Figure 2: Flavia Leaf Dataset of 32 Species used in the Proposed Study Experiments

Four experiments were conducted on the above dataset, and the best results were obtained. These experiments were as follows:

- ***Experiment 1***

The Flavia dataset, containing 1907 images of 32 different classes, was used in the Experiment.

The eight texture features were extracted using GLCM, LBP, and GABOR filters for this dataset and the fractal dimension feature using the box-counting method. Afterward, feature scaling was applied to these values to make them appropriate for the classifiers, and they were split into test and training sets. The first experiment divided data into a 70/30 test train set and applied six different classifiers. By doing this, accuracy, precision, recall, and f1-score were derived as given below, and the performance of all classifiers was evaluated.

- ***Experiment 2***

In this experiment, the same dataset containing 1907 images was used, and all eight texture features and fractal dimension values were extracted using the box-counting technique. At this time, a dataset was changed as a test train set to 80/20, applying six classifiers on this set. In doing so, we got the classification report containing accuracy, precision, recall, and f1-score. On these results, the study evaluates the performance of all the classifiers and compares the outcomes with the outputs of the experiment with 70/30 test train set.

- ***Experiment 3***

In this, the Author split the same Flavia dataset into a smaller set containing 1000 images of leaves by limiting the number of pictures of each class. This experiment gives values to evaluate how the small dataset affects the performance of classifiers. Afterward, eight texture features were used using different filters and fractal dimension values, utilizing the box-counting technique for this dataset. Then, feature scaling and divided it into test train set. In this experiment, the data was into a 70/30 test train set and six classifiers on it. Then, we evaluate the performance of all the classifiers based on the classification report we got as accuracy, precision, recall and f1-score results.

- ***Experiment 4***

Here, the same dataset of 1000 images was applied and the same eight texture features and fractal dimension feature were extracted using the box-counting method. The proposed method modified and split the data into 80/20 set and applied six classifiers. Afterwards, the performance of all the classifiers was derived based on their accuracy, precision, recall, and f1-score. The results were compared with the outcomes of 70/30 test train set of the same dataset features. In Figure 3, there is the processed image, which we convert into binary, grayscale and binary threshold images during feature extraction as:

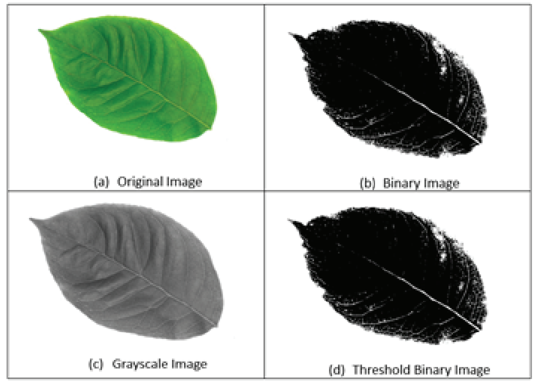


Figure 3: Processed Image with different Format

4. RESULTS AND DISCUSSION

In the proposed study, six different classifiers were implemented. They evaluated the performance of learners based on the accuracy, precision, recall, and f1-score on a dataset containing 1907 images as well as a dataset consisting of 1000 images. The Author compared the accuracies obtained from all the classifiers with two different test train sets for both datasets. First, Let's discuss the results of all the classifiers for the dataset comprising 1907 images. Here, the initially proposed method split the data into a 70/30 test train set and trained all the classifiers on it. In Table 2, the results show that SVM is the best learner which gives the best accuracy. Afterward, the experiment was performed with parameter tuning on all the learners, and classification was applied with the best parameters. By doing this, the classifier performance was more precise and increased in accuracy. In the next experiment, the train, test was 80/20 and train all the classifiers with the whole dataset features. There was a clear change in the results of these learners. The comparison of the results of both test train sets for the whole dataset features is in Table 2. Results show that the best classifier that performs the best in both test train sets with parameter tuning was the SVM. It gives 0.81 accuracy with 70/30 test train set and 0.88 with 80/20 test train split for the dataset feature values. Detailed accuracies of all the classifiers for whole dataset features are shown in Table 2. Also, a detailed accuracy graph for all the classifiers is shown in Figure 4.

Table 2: Comparative Accuracy of Fractal dimensions applied on dataset of leaf images 1907 with and without tuning using multiple classifiers.

1907 Images Leaf Dataset With/Without Tuning	Train/Test split	Random Forest	KNN	Naive Bayes	DNN	Decision Tree	SVM
Without Tuning	70/30	0.71	0.65	0.53	0.79	0.65	0.65
After Fine Tuning	70/30	0.73	0.64	0.53	0.81	0.64	0.81
Without Tuning	80/20	0.71	0.62	0.48	0.81	0.59	0.75
After Fine Tuning	80/20	0.71	0.63	0.48	0.81	0.61	0.88

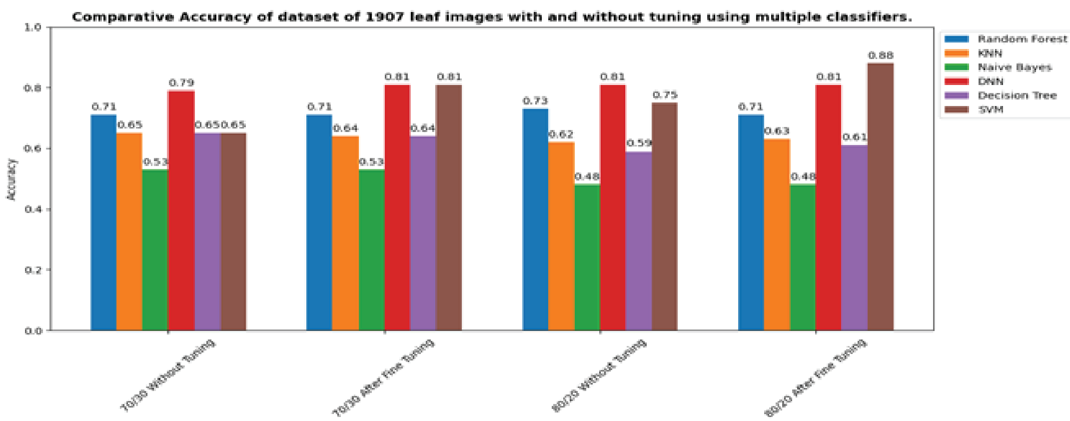


Figure 4: Comparative Accuracy of Dataset with 1907 Images

In the next experiment, six classifiers were used on the dataset containing 1000 images to evaluated their performance. Firstly, the dataset was split into the test train set to 70/30, and accuracies were obtained from all six learners. Afterwards, parameters with tuning were used and classification with the best parameters results. The results with better accuracies were derived after parameter tuning and identified that SVM was the best classifier, which performed well with an accuracy 0.83 after parameter tuning, as shown in Table 3. On the other hand, when we split the test train set to 80/20 and apply classifiers on a dataset of 1000 images there were different results. We also performed parameter tuning for this experiment and identified that SVM performed well with an accuracy of 0.88. The SVM performs better with the fractal dimensions feature for identifying leaf texture and shape feature identification. Detaileddaccuracies of all the learners are shown in Table 3. A detailed accuracy graph of all the classifiers is also shown in Figure 5.

Table 3, shows the results with tuning and without tuning of different classifiers with specific features used and shows the better results after the fine-tuning and SVM classifiers with overall 88% accuracy.

Confusion matrix was used to describe the performance of the classification model based on the test set for data where the true values were identified. In this matrix, each row represents the features in the actual class and each column represents the features in the predicted class. Here is the confusion matrix for both the datasets with the highest accuracy in the SVM classifier, which are shown in Figure 6 and Figure 7.

Table 3: Comparative Accuracy of Fractal dimensions applied on dataset of leaf images 1000 with and without tuning using multiple classifiers

Tuning Status	Train/Test split	Random Forest	KNN	Naive Bayes	DNN	Decision Tree	SVM
Without Tuning	70/30	0.56	0.65	0.63	0.78	0.62	0.68
After Fine Tuning	70/30	0.75	0.66	0.63	0.83	0.64	0.83
Without Tuning	80/20	0.56	0.69	0.64	0.82	0.58	0.72
After Fine Tuning	80/20	0.56	0.69	0.64	0.84	0.57	0.88

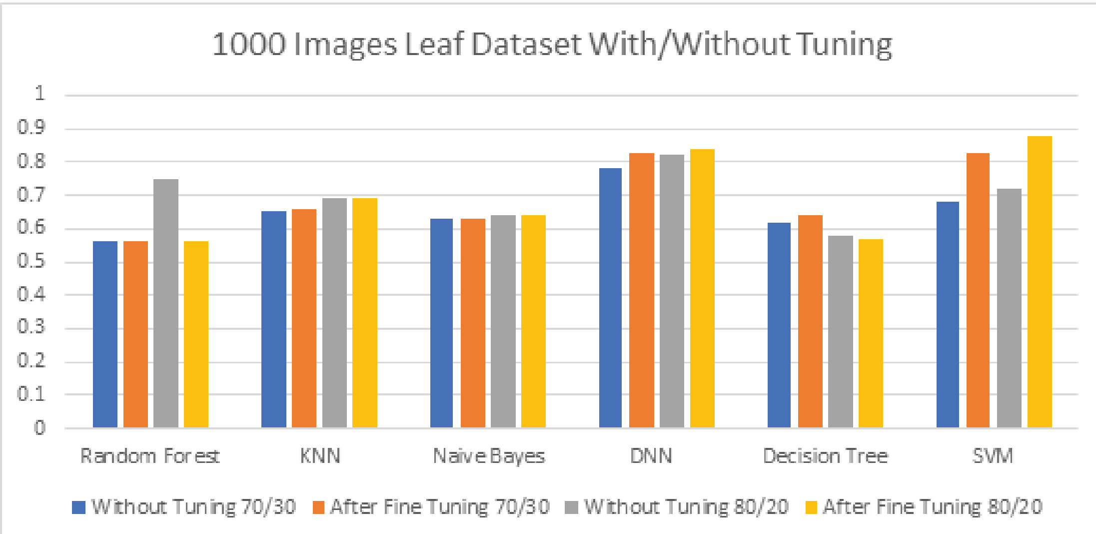
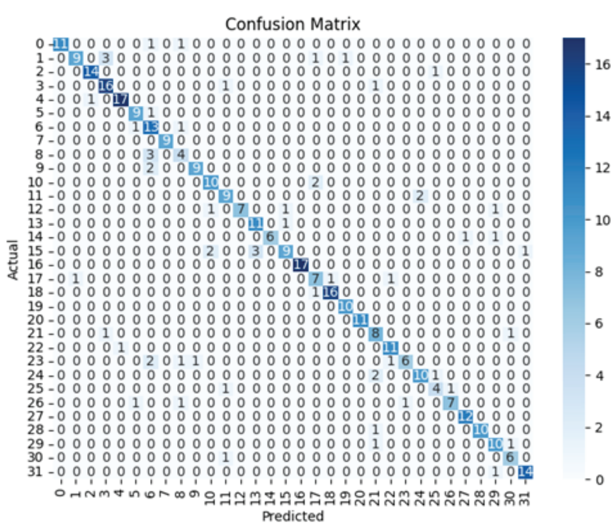
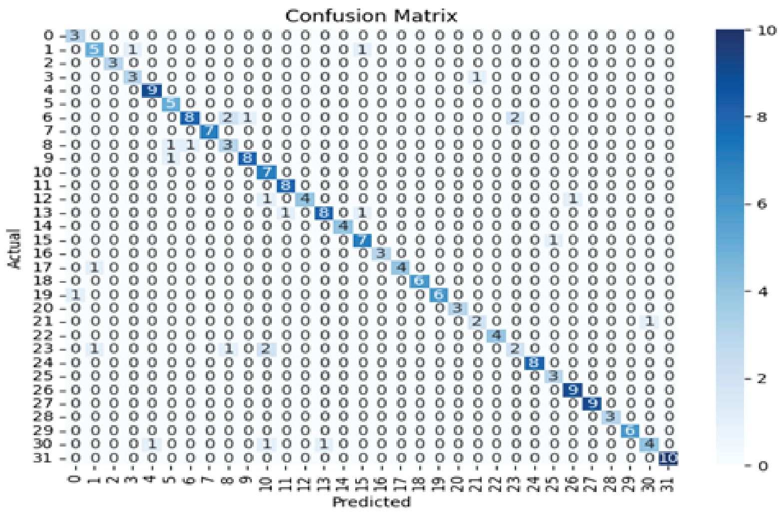


Figure 5: Comparative Accuracy of dataset with 1000 images





FFigure 7: confusion matrix of 1907 images

Evaluating the performance of all the classifiers based on the accuracy, precision, recall, and f1-score results, we identified that SVM performed well with the best accuracy for both datasets. The best accuracy of both datasets is shown in Table 4.

Table 4: Performance of SVM with Fractal Dimension Feature with Dataset of 1000 and 1907 images

After Fine Tuning	Train/Test split	Total Number of images	Classifier	Accuracy
After Fine Tuning	70/30	1000	SVM	0.83
After Fine Tuning	80/20	1000	SVM	0.87
After Fine Tuning	70/30	1907	SVM	0.81
Proposed Method	80/20	1907	SVM	0.88

In figure 8 SVM accuracy is shown here with tuning and without tuning. With tuning, the results improved. Figure 8 illustrates the accuracy of Support Vector Machine (SVM) models with and without hyperparameter tuning. The x-axis represents different tuning configurations or iterations, while the y-axis shows the corresponding accuracy scores achieved by the SVM models.

Figure 8 illustrates the accuracy of Support Vector Machine (SVM) models on different dataset splits, comparing the performance with and without hyperparameter tuning. The x-axis represents the various dataset splits used for training and testing, such as 70/30, 80/20 train-test splits. The y-axis shows the corresponding accuracy scores achieved by the SVM models.

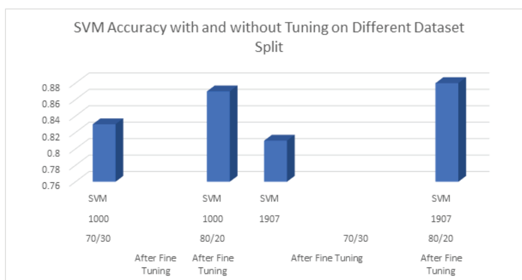


Figure 8: SVM Accuracy with and without Tuning

5. CONCLUSION

Plant leaf classification is a widely used technique for several years to classify leaves based on their specific attributes like shape, color, size, and texture. In the proposed study, four experiments with the Flavia dataset are divided into two sets, one containing whole data of 1907 images and the other consisting of 1000 images dataset. Data mining techniques and classification were applied in the experiment with the proposed model and the texture features plant leaf using different filters like GLCM, LBP, and GABOR. The fractal dimension feature is also extracted with the box-counting technique. The feature scaling technique was applied to these feature values and split them into two different test and train-derived datasets. The two distributions were experimented on the derived datasets as 70/30 and 80/20. Six classifiers were applied for a dataset with 1907 images with 70/30 test train split. The test and train split was changed to 80/20, then, six learners were again applied for better results. Both the results were compared to identify which classifier performs well with best accuracy. The same procedure is repeated with the extracted features of the dataset with 1000 images and derived results were compared for both test train split. The SVM was the best classifier that performs well with the best accuracy for both the dataset with the combination of texture features and fractal dimension feature. The proposed model with SVM classifier gave the best results when dealing with the texture feature values and fractal dimension values for plant leave dataset with over all accuracy of 88% percent. The consequence from this proposed study is the introducing and implementation of external factors of the plant from the leaf images. The proposed study can identify the stomata index (SI) and green color intensity level (GCIL) for the nutrients identification of plants.

REFERENCES

[1] P. S. Kumar et al., "Leaf classification based on shape and edge feature with k-NN classifier," *Proc. 2016 2nd Int. Conf. Contemp. Comput. Informatics, IC3I*, pp. 548–552, doi: 10.1109/IC3I.2016.7918024, 2016.

[2] M. I. Sarwar et al., "Data Vaults for Blockchain-Empowered Accounting Information Systems," I*EEE Access,* 9, pp. 117306–117324, doi: 10.1109/ACECCESS.2021.3107484, 2021.

[3] A. Aakif and M. F. Khan, "Automatic classification of plants based on their leaves," Biosyst. *Eng.,* 139, pp. 66–75, doi: 10.1016/j.biosystemseng.2015.08.003, 2015,

[4] J. Chaki et al., "Plant leaf recognition using texture and shape features with neural classifiers," *Pattern Recognit. Lett.,* 58, pp. 61–68, doi: 10.1016/j.patrec.2015.02.010, 2015.

[5] S. Fuentes et al., "Automated grapevine cultivar classification based on machine learning using leaf morpho-colorimetry, fractal dimension and near-infrared spectroscopy parameters," Comput. Electron. Agric., 151, pp. 311–318, doi: 10.1016/j.compag.2018.06.035, 2018.

[6] J. W. Tan et al.,, "Deep Learning for Plant Species Classification Using Leaf Vein Morphometric," *IEEE/ACM Trans. Comput. Biol. Bioinforma.,* 17(1), pp. 82–90, doi: 10.1109/TCBB.2018.2848653, 2020.

[7] A. Sabu et al., "Recognition of ayurvedic medicinal plants from leaves: A computer vision approach," *2017 4th Int. Conf. Image Inf. Process. ICIIP 2017*, pp. 574–578, doi: 10.1109/ICIIP.2017.8313782, 2018.

[8] J. Wäldchen and P. Mäder, "Plant Species Identification Using Computer Vision Techniques: A Systematic Literature Review," 25(2). *Springer Netherlands,* doi: 10.1007/s11831-016-9206-z, 2018.

[9] J. Murray et al., "Using fractal analysis of crown images to measure the structural condition of trees," *Forestry,* 91(4), pp. 480–491, doi: 10.1093/forestry/cpy008, 2018.

[10] J. Hu et al., "A multiscale fusion convolutional neural network for plant leaf recognition," *IEEE Signal Process. Lett.,* 25(6), pp. 853–857, doi: 10.1109/LSP.2018.2809688, 2018.

[11] T. W. Harjanti and S. Madenda, "Development of feature extraction on leaf image for medicinal plants identification," *Int. J. Recent Technol. Eng.,* 8, pp. 163–168, doi: 10.35940/ijrte.B1040.0782S719, 2019.

[12] S. Khaitan and R. Agarwal, "Multi-Fractal Image Compression," *2019 Int. Conf. Mach. Learn. Big Data, Cloud Parallel Comput.*, pp. 340–345, 2019.

[13] Q. Zhang et al., "Initial investigation of different classifiers for plant leaf classification using multiple features," 1117922, pp. 44, doi: 10.1117/12.2539654, 2019.

[14] C. Arrasco et al., "Leaf Venation Enhancing for Texture Feature Extraction in a Plant Classification Task," *2018 IEEE Lat. Am. Conf.Comput. Intell. LA-CCI 2018*, pp. 1–4, doi: 10.1109/LA-CCI.2018.8625221, 2019.

[15] F. Mostajer Kheirkhah and H. Asghari, “Plant leaf classification using GIST texture features,” *IET Comput. Vis.,* 13(4), pp. 395–403, doi: 10.1049/iet-cvi.2018.5028, 2019.

[16] A. Kaya et al., “Analysis of transfer learning for deep neural network based plant classification models,” *Comput. Electron. Agric.,* vol. 158, no. January, pp. 20–29, doi: 10.1016/j.compag.2019.01.041, 2019.

[17] Y. Dorji et al., “Response of beech (Fagus sylvatica L.) trees to competition-new insights from using fractal analysis,” Remote Sens., 11(22), doi: 10.3390/rs11222656, 2019.

[18] L. Wu et al., “A method for improving the crack resistance of aluminum alloy aircraft skin inspired by plant leaf,” *Theor. Appl. Fract. Mech.,* 106, pp. 102444, doi: 10.1016/j.tafmec.2019.102444, 2020.

[19] G. Q. Ramos et al., “Advanced Microtexture Study of Anacardium occidentale L. Leaf Surface from the Amazon by Fractal Theory,” Microsc. Microanal., 26(5), pp. 989–996, doi: 10.1017/S1431927620001798, 2020.

[20] A. L. Agapie et al., “Fractal analysis for soybean leaves characterization,” *AIP Conf. Proc.,* 2293, doi: 10.1063/5.0026508, 2020.

[21] A. Kumar and D. B. Kumar, “Automatic Recognition of Medicinal Plants using Machine Learning Techniques,” *Gedrag Organ. Rev.*, 33(1), pp. 166–175, doi: 10.37896/gor33.01/012, 2020.

[22] N. Ganatra and A. Patel, “A multiclass plant leaf disease detection using image processing and machine learning techniques,” *Int. J. Emerg. Technol.,* 11(2), pp. 1082–1086, 2020.

[23] M. Keivani et al., “Automated analysis of leaf shape, texture, and color features for plant classification,” *Trait. du Signal,* 37(1), pp. 17–28, doi: 10.18280/ts.370103, 2020.

[24] F. Sala et al., “Fractal dimension and causality relationships with foliar parameters: case study at Alnus glutinosa (L.) Gaertn.,” *Ann. West Univ. Timisoara, ser. Biol.,* 23(1), pp. 73–82, 2020.

[25] J. Huixian, “The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network,” *IEEE Access,* 8, pp. 68828–68841, doi: 10.1109/ACCESS.2020.2986946, 2020.

[26] B. R. Pushpa et al., “Comparision and classification of medicinal plant leaf based on texture feature,” *2020 Int. Conf. Emerg. Technol. INCET 2020,* pp. 1–5, doi: 10.1109/INCET49848.2020.9154155, 2020.

[27] Z. Tang, “Leaf image recognition and classification based on GBDT-probabilistic neural network,” *J. Phys. Conf. Ser.,* 1592(1), doi: 10.1088/1742-6596/1592/1/012061,2020.

[28] J. Zhu et al., “A Fast and Automatic Method for Leaf Vein Network Extraction and Vein Density Measurement Based on Object-Oriented Classification,” *Front. Plant Sci.,* 11, pp. 1–15, doi: 10.3389/fpls.2020.00499, 2020.

[29] M. Rapacz and R. Łazarz, “Automatic extraction of leaf venation complex networks,” F*ront. Artif. Intell. Appl.,* 325, pp. 1914–1921, doi: 10.3233/FAIA200309, 2020.

[30] D. Bisen, “Deep convolutional neural network based plant species recognition through features of leaf,” *Multimed. Tools Appl.,* 80(4), pp. 6443–6456, doi: 10.1007/s11042-020-10038-w, 2021.

[31] A. Nasiri et al., “Automated Grapevine Cultivar Identification via Leaf Imaging,” 10(8), pp.1628, 2021.

[32] S. Mahajan et al., “Plant recognition using morphological feature extraction and transfer learning over SVM and adaboost,” *Symmetry (Basel).,* 13(2), pp. 1–16, doi: 10.3390/sym13020356, 2021.

[33] M. Held and T. I. B. Committee, “Momentum Method to Measure the Blastcontour,” *17th Int. Symp. Ballist.,* 2, pp. 267–274, 1998.

[34] H. A. Elnemr, “Feature selection for texture-based plant leaves classification,” *ACCS/PEIT 2017 - 2017 Intl Conf Adv. Control Circuits Syst. 2017 Intl Conf New Paradig. Electron. Inf. Technology,* pp. 91–96, doi:

10.1109/ACCS-PEIT.2017.8303025, 2018.

[35] S. E. Grigorescu et al., “01042386.Pdf,” 11(10), pp. 1160–1167, 2002.

[36] A. Barcellos, “The Fractal Geometry of Mandelbrot,” *The College Mathematics Journal,* 15(2). pp. 98. doi: 10.2307/2686514, 1984.

[37] M. Asim, “Classification of Microscopic Malaria Parasitized Images Using Deep Learning Feature Fusion,” *Lahore Garrison Univ. Res. J. Comput. Sci. Inf. Technol.*, 7(2), pp. 7, doi: 10.54692/lgurjcsit.2023.0702473, 2023.

[38] M. Asim et al., “Varietal Discrimination of Guava (Psidium Guajava) Leaves Using Multi Features Analysis,” *International Journal of Food Properties* 26(1), pp.179-196, 2023.

[39] I. Andronache, “Analysis of Forest Fragmentation and Connectivity Using Fractal Dimension and Succolarity,” *Land,* 13(2), pp. 138, 2024.