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Automated Recognition of Medicinal Plant Leaves using Genetic Algorithm

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ABSTRACT **- Automated plant identification plays a crucial role in agriculture, botany, and biodiversity conservation. Traditional plant recognition requires expert knowledge and is often time-consuming. This paper presents an automated leaf-based plant identification system using Digital Image Processing (DIP) and Machine Learning (ML). The methodology involves preprocessing of input images, extraction of shape, color, texture, and vein features, selection of optimal features using Genetic Algorithm (GA), and classification using Recurrent Neural Network (RNN) and Support Vector Machine (SVM). Experimental evaluation using the Flavia leaf dataset demonstrates that the proposed system achieves an accuracy of 91.30% with RNN and 77.27% with SVM. Comparative analysis confirms that RNN outperforms SVM in sensitivity, specificity, and overall accuracy. This work can be further extended into an Android-based application for field-level medicinal plant identification.**

Keywords: Leaf identification, Genetic Algorithm, Digital Image Processing, Plant Classification, SVM, RNN, Feature Extraction.

I. INTRODUCTION

Plants play an essential role in sustaining ecological balance, supporting life, and serving as a primary source of food, medicine, and industrial resources. Identifying plant species accurately is crucial for applications in agriculture, healthcare, botany, and environmental conservation. Traditional plant identification relies heavily on expert botanists and manual observation of morphological features, which is time-consuming and prone to human error. With the advancement of digital technologies, computer vision and machine learning have emerged as powerful tools for automated plant recognition.Digital Image Processing (DIP) enables the extraction of meaningful information from leaf images, which are easier to obtain compared to flowers or fruits, making them a reliable basis for classification. However, existing plant recognition methods often face challenges such as sensitivity to lighting variations, specific growth stages, imaging conditions, and limited feature generalization. Additionally, many approaches use complex algorithms without optimizing feature sets, resulting in overfitting or reduced accuracy.To address these challenges, this work proposes an automated plant identification system that uses leaf images to extract shape, color, texture, and vein features. A Genetic Algorithm is employed to select the most discriminative features, reducing complexity and improving accuracy. The selected features are then classified using Support Vector Machine (SVM) and Recurrent Neural Network (RNN) models. The system aims to provide an efficient, accurate, and user-friendly solution for identifying medicinal plants, enabling faster decision-making in research and field applications.

II. LITERATURE REVIEW

Plant species are commonly identified through characteristics such as leaf shape, flower color, odor, bark pattern, seedling structure, and overall morphology, all of which link the specimen to its scientific name. When a plant is affected by pests or diseases, the leaf structure often undergoes deformities, making visual identification more challenging. Among various plant parts, leaf images are widely preferred for species recognition because they are easy to collect, two-dimensional, and simple to process using computer vision techniques. By feeding leaf images into computational models, features can be extracted automatically for classification. Previous research on automatic plant identification has explored multiple feature extraction methods—some relying on a single feature type, while others combine shape, color, vein, and texture information for improved accuracy. Ghasab et al. [1] introduced an Ant Colony Optimization (ACO) method with SVM to classify leaves from the Flavia and FCA datasets, achieving 95.53% accuracy. Abdul Kadir et al. [2] extracted shape, color, vein, and texture features and classified them using Probabilistic Neural Networks (PNN), reporting 93.75% accuracy. Chaki et al. [3] analyzed leaf shapes using Moment Invariants and centroid-radii models, followed by neural-network-based classification, obtaining accuracies between 90–100%. Brendon et al. [4] developed an adaptive SVM–Otsu segmentation technique for apple grading that successfully handled variations in lighting conditions. Tang et al. [5] applied Gabor wavelet features with neural networks to classify grass and broadleaf weeds. Wu et al. [6] used PNN with 12 leaf architecture features to classify 32 plant species with accuracy above 90%. Oncevay et al. [7]

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incorporated boundary shape, Haralick texture features, and color moments, achieving 90.41% accuracy on the Image CLEF dataset. Pallavi et al. [9] used shape, vein, color, and texture features with neural networks for precise tree-leaf identification. Kadir et al. [10] reaffirmed the effectiveness of PNN for classifying 32 leaf species in the Flavia dataset. Arribas et al. [11] used RGB segmentation, feature selection, and a Generalized Softmax Perceptron with PPMS for sunflower leaf classification, reaching 85% CCR and AUC above 90%. Wang et al. [13] extracted 21 color, 4 shape, and 25 texture features for wheat and grape disease detection using PCA and multiple neural-network variants. Sandeep Kumar et al. [17] proposed a simple method using leaf area, color histogram, and edge features to identify medicinal plant species. Ravishankkar et al. [18] applied neuro-fuzzy classifiers and multilayer perceptrons to classify 28 leaf classes using B and T algorithms. Finally, Tsolakidis et al. [19] employed Zernike moments and HOG features with SVM for robust leaf classification.

III. METHODOLOGY

Plant identification involves recognizing a specimen and associating it with its correct scientific name based on characteristics such as size, form, leaf shape, flower color, and odor. Accurate identification is essential for understanding plant growth, maintenance, and protection from pests and diseases. In botanical studies, plant systematics traditionally relies on reproductive structures, especially floral parts, as they exhibit strong taxonomic features. However, many horticultural and woody plants lack visible flowers, making leaves the most practical basis for identification.

The proposed method extracts unique features from leaves by slicing along the major and minor axes and normalizing the resulting measurements. These features form the input to an SVM classifier trained using samples from multiple plant species. New leaf images are compared against the trained model to determine the closest match. The system displays processed test images, extracted features, and the top five matching leaves from the database. Additionally, detailed information about the best-matched species is presented through an automatically generated webpage, enabling efficient and user-friendly plant identification.

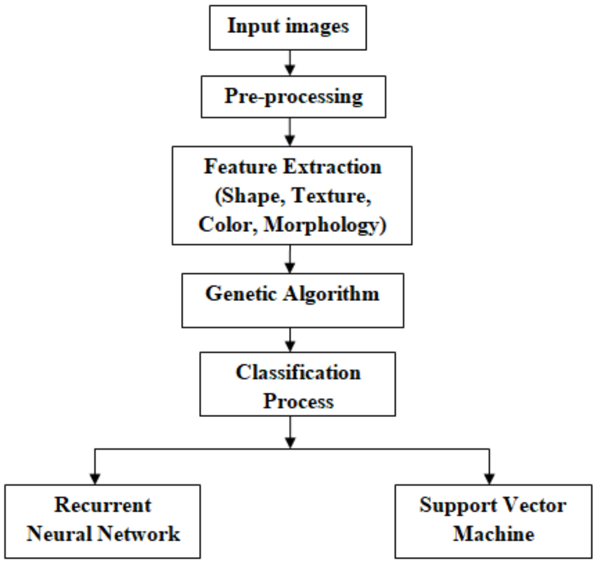

Figure 1 Block Diagram of Medical Plants Identification

A. Pre-Processing

The preprocessing step begins by resizing the input color images and converting them into grayscale to reduce complexity. Grayscale images preserve brightness levels and offer 256 intensity values, making them easier to process than RGB images. Thresholding is then applied to convert the grayscale image into a binary form, containing only black and white pixels. Binary images store each pixel as a single bit, enabling fast and efficient shape-based analysis. Although they contain minimal detail, they are ideal when only object boundaries are required. This conversion ensures efficient processing for subsequent feature extraction steps. The figure 2 shows that pre-processing steps like resized image, gray-scale image and binary image.

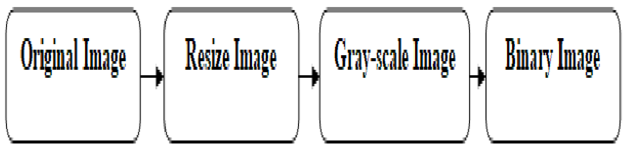

Figure 2 Detailed Block Diagram of Pre-Processing

Figure 3: Original Image

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The above figure 3 shows that original image is obtained from the flavia dataset

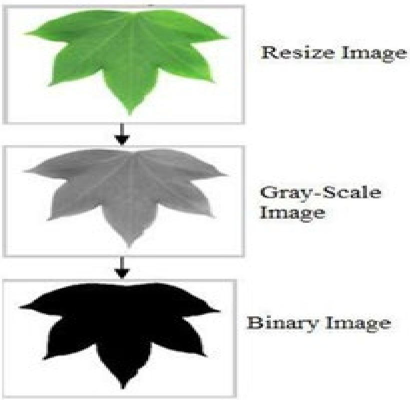

Figure 4: Image Pre-Processing Steps

B. Feature Extraction

Four categories of features are extracted:**Shape features** such as area, perimeter, aspect ratio, and roundness;**Color features**, including mean, standard deviation, skewness, and kurtosis;**Texture features** derived using Gray-Level Co-occurrence Matrix (GLCM) descriptors such as contrast, entropy, correlation, and homogeneity;**Vein features**, extracted using multi-scale morphological openings to quantify vein density and distribution. These features collectively represent structural, chromatic, and textural characteristics of leaves.

C. Feature Selection Using Genetic Algorithm

A GA is used to select the most discriminative subset of features. The algorithm initializes a population of random feature subsets and evaluates their fitness using preliminary classification accuracy. Selection is based on roulette-wheel probability, followed by crossover and mutation operations to form new subsets. The iteration continues until an optimal feature subset with minimal redundancy and maximum discriminative power is obtained.

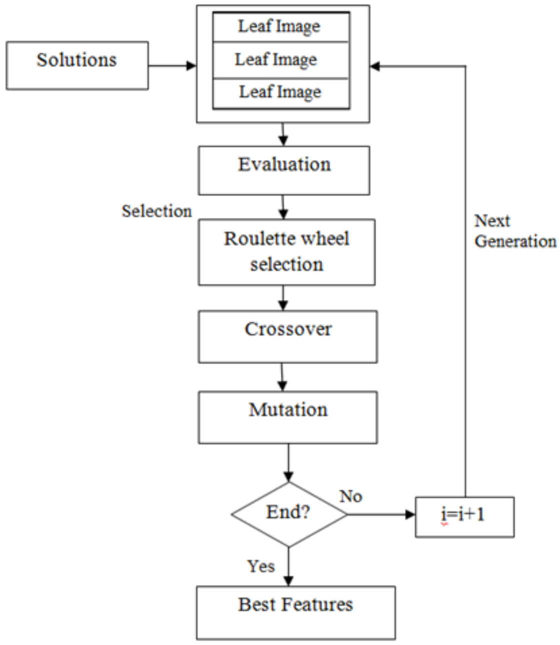

Figure 5: Flow Chart of Genetic Algorithm

D. Classification

Two classifiers are implemented.

- RNN, which models nonlinear dependencies among features and adapts weights through Backpropagation Through Time (BPTT);
- SVM, which constructs a maximum-margin hyperplane for class separation. Both classifiers are trained using GA-selected features, and the resulting performance is compared using metrics such as accuracy, sensitivity, and specificity.

IV. RESULTS AND DISCUSSION

Input Leaf Image

First step is the pre-processing steps include coloured images after rescaling are converted to gray-scale and pre-processing method gray-scale image converted to binary.

Figure 6: Input Images

In figure 6(a) and figure 6(b) shows that Input images get from flavia dataset in that given leaf image name is amirda valli and betel.

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Output Images

Pre-Processing

Pre-Processing step include gray-scale image and binary image described below.

Gray-Scale

A gray-scale image is composed of different shades of gray color.

Figure 7: Gray-Scale Images

In figure 7 shows that input images are converted into Gray-Scale images.

Binary Image

In figure 8(a) and figure 8(b) shows in that grayscale image apply to threshold to create binary images.

Figure 8: Binary Images

Feature Extraction

Table 1 Feature Extraction for various leaf image

Features	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7	Image 8
Contrast	0.1082	0.0862	0.1633	0.0569	0.1729	0.1590	0.1964	0.2388
Correlation	0.9838	0.9879	0.9813	0.9908	0.9768	0.9805	0.9839	0.9785
Entropy	0.3153	0.2609	0.2505	0.3147	0.2454	0.3037	0.2013	0.2561
Homogeneity	0.9553	0.9571	0.9321	0.9735	0.9309	0.9408	0.9259	0.9243
Perimeter	999.2360	1.2329e+34587	1.0446e+5674	999.9060	999.2360	1.8148e+8976	1.7943e+78654	2.3860e+96213
Area	32710	14400	24463	28974	27868	25912	25554	29714
Energy	4.9273	6.4874	5.9196	5.1383	5.4986	5.3963	5.8356	6.4902
Kurtosis	-1.8829	-1.0385	-0.8506	-1.7857	-1.9809	-1.7264	-1.6380	-0.2388
Skewness	23.5181	2.5909	169.8876	11.7634	23.6092	31.9061	28.6552	0.9785
Roundness	0.4117	0.1190	0.2817	0.3642	0.3507	0.0656	0.0989	0.0997
Mean	189.3736	146.0170	159.4828	183.4100	173.6757	166.0761	150.9453	161.1944
Standard Deviation	20.6262	17.8475	17.5933	17.2908	21.9353	19.0520	16.1179	25.4109
Aspect Ratio	32.7350	11.6794	23.4182	28.9767	27.8893	14.2778	14.2415	12.4534

In above table 1 shows that represent the shape, morphology, texture and color feature values extracted in eight different leaf image.

Feature Selected Using Genetic Algorithm

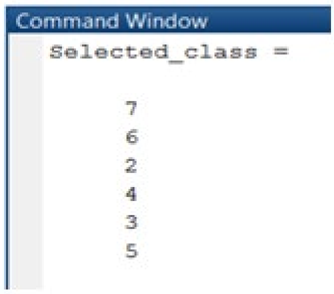

Figure 9 Selected Feature Classes

In figure 9shows that Genetic Algorithm used to feature selection process. Purpose of genetic algorithm, it will not consider all the features it is selected only particular features.

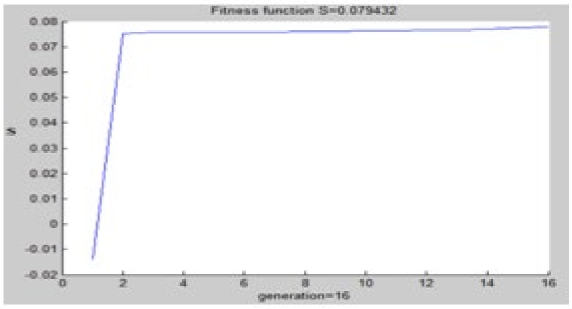

Figure 10 :Calculate Fitness Function

In figure 10 shows that calculation of fitness function. Two main classes of fitness functions exists one where the fitness function does not change as in optimizing a fixed function or testing with a fixed set of test cases and one where the fitness function is mutable as in position differentiation or co-evolving the set of test cases.

CLASSIFICATION OUTPUTS

Recurrent Neural Network

In figure 11 represented amirda valli leaf identified using RNN Classifier and their uses also display in command window.

Figure 11(a) Input Image, (b) Display Leaf Name and its Uses using RNN Classifier for Amirda Valli leaf

In figure 12 represented betel leaf identified using RNN Classifier and their uses also display in command window.

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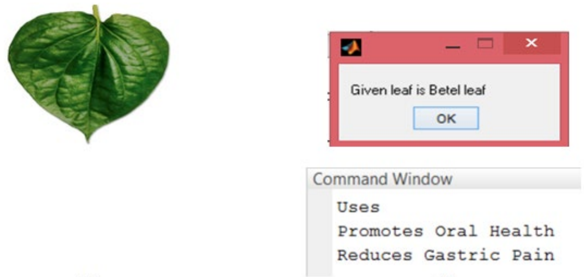


(a) (b)

Figure 12(a) Input Image, (b) Display Leaf Name and Uses using RNN Classifier for Betel Leaf

Support Vector Machine

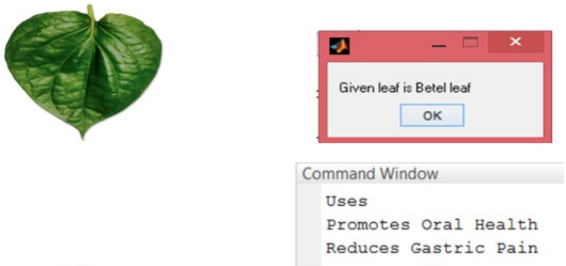
In this proposed method two classifiers used first classifiers already tested. Second Classifier is SVM classifier.

(b)

(a)

Figure 13(a) Input Image, (b) Display Leaf Name and Uses using SVM Classifier for Amirda Valli leaf

In figure 13 represented the amirda valli leaf identified using SVM Classifier and their uses also display in command window.



(a) (b)

Figure 14(a) Input Image, (b) Display Leaf Name and Uses using SVM Classifier for Betel Leaf

In figure 14 betel leaf identified using SVM Classifier and their uses also display in command window.

Comparison results of RNN and SVM

Table 2 Comparison of RNN and SVM Classifier

CLASSIFIER	ACCURACY	SPECIFICITY	SENSITIVITY
Support Vector Machine	77.2727	66.6667	84.6154
Recurrent Neural Network	91.3043	90.9091	91.6667

Accuracy of SVM Classifier is 77.2727% and RNN is 91.3043%. Specificity and Sensitivity of SVM Classifier is 66.6667%, 84.6154% and RNN Classifier is 90.9091%, 91.6667%. Compared to all the values Recurrent Neural Network Classifier is best.

V. CONCLUSION AND FUTURE ENHANCEMENTS

An automated technique for identifying medicinal plants has been developed using Genetic Algorithm (GA)–based feature selection, followed by RNN and SVM classification. GA plays a key role in selecting the most discriminative features from leaf images, improving the separation between species. After feature extraction and selection, the classifiers predict the plant name, with experimental results showing 91.30% accuracy using GA-based methods. Comparatively, ANN/RNN outperforms SVM in recognition accuracy.

Future enhancements include improving the system's robustness, expanding the dataset to include more leaf types, and adding information such as plant family and origin. The desktop application can be extended into an Android-based system using a client–server model, where images captured on smartphones are processed on a high-performance server via HTTP. This technology can also benefit industries such as food packaging and pharmaceuticals by detecting spoilage or decomposition without expert intervention, making it accessible even in remote or developing regions.

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