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A Review on Detection of Medical Plant Images

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Abstract— Both human and non-human life on Earth depends heavily on plants. The natural cycle is most significantly influenced by plants. Because of the sophistication of recent plant discoveries and the computerization of plants, plant identification is particularly challenging in biology and agriculture. There are a variety of reasons why automatic plant classification systems must be put into place, including instruction, resource evaluation, and environmental protection. It is thought that the leaves of medicinal plants are what distinguishes them. It is an interesting goal to identify the species of plant automatically using the photo identity of their leaves because taxonomists are undertrained and biodiversity is quickly vanishing in the current environment. Due to the need for mass production, these plants must be identified immediately. The physical and emotional health of people must be taken into consideration when developing drugs. To important processing of medical herbs is to identify and classify. Since there aren't many specialists in this field, it might be difficult to correctly identify and categorize medicinal plants. Therefore, a fully automated approach is optimal for identifying medicinal plants. The numerous means for categorizing medicinal plants that take into interpretation based on the silhouette and roughness of a plant's leaf are briefly précised in this article.

Keywords-Medical plants; Classification techniques; Features based on colour and shape

I. INTRODUCTION

Because of its nutrients and therapeutic qualities, traditional medicine has used therapeutic plants for an extremely long time [1]. Because of their bioactive ingredients, including as phenolic, carotenoid, anthocyanin, and other bio-active components, they are well known for their antioxidant, anti-allergic, anti-inflammatory, and antibacterial characteristics [2]. Various plant species, including trees, shrubs, and herbs, are known to have medicinal benefits. The habitat they have evolved to throughout time will determine how quickly their solitary dissemination occurs. Statistics show that between 14 and 28 percent of all plants have therapeutic uses [3]. Additionally, due to the qualities of medicinal plants, which are used to treat ailments in roughly 3-5% of patients in developed countries, over 80% of the rural populace in the nations that are getting developed nations, and about 85% of people in the Southern Desert [4]. Additionally, after thinking about the dangers and side effects of chemical treatments, some individuals in affluent nations have resorted to traditional remedies made from plants used as medicine to treat and manage diseases and ailments. [5]. These plants can be utilized for food, drink, and even cosmetics in addition to their medical use [6]. Unfortunately, a lot of inferior, damaged, or improperly maintained medicinal plants are produced and sold all over the world, which might be harmful to their users [7].Global acceptance and usage of herbal medicine are rising steadily. Similar realizations have been made about the continent of Africa, where more than 60% of the population, particularly in poor countries, relies only on these plants for healthcare [8]. Plants are therefore a major contributor to natural goods and an essential part of healthcare. Traditional medicines are hugely significant to the pharmaceutical industry; in fact, they make up 25% of all prescription drugs globally. Medicinal plants are preferred over synthetic drugs because they are less expensive and have less adverse effects [9]. It is crucial to address this issue since identifying medicinal plants has several advantages for humans [10].

Most often, a plant's leaves, fruits, flowers, or complete body are utilized to identify it. Out of all the identification keys, using the leaves is one of the most effective and trustworthy ways to identify medicinal plants [11]. The use of plants as medicine has made it necessary to identify plants in order to determine whether or not they possess therapeutic properties. Two plants are easily confused when attentively inspected by the inexperienced eye. Since misidentification

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might have disastrous consequences, as a result it is important to consider plant identification while purchasing natural products and medicines [12]. Because of environmental conditions such as climatic change, topographical situation, and others, plants can have different form traits and go through several growth stages throughout the course of various periods [13]. Additionally, understanding plant species is essential for protecting biodiversity. Because it requires the use of scientific nomenclature, using standard keys to identify plants is difficult, time-consuming, and laborious for non-botanists. This presents a significant barrier for freshmen interested in gaining specialised knowledge [14]. It is challenging to distinguish distinct plants using their diverse morphological characteristics. The main challenges are high intraclass variability and low interclass variations [15]. Because plant categories and some of their structural components are closely connected, there are few distinctions across classes. Furthermore, plants exhibit high intraclass variety due to their wide range in size, colour, form, and texture, as well as seasonal changes in appearance [16]. This work suggests using deep learning to identify plants in order to carry out the matching process that allocates a leaf image to a plant group.

The existence of life on earth depends largely on plants. Being that plants are crucial for maintaining natural security, it is much more important to differentiate and accurately define them. Plant categorization is crucial to the science that examines many properties of plants and will be used extensively in horticulture and medicine. When compared to techniques like cell biology or molecular biology approaches for classifying leaf plants, leaf image classification is the method of choice. Previous studies have made an effort to identify the plant using the colour histogram of the picture, edge characteristics, and texture data. The classification of plants as trees, shrubs, and herbs using neural networks has already been studied.

An important aspect of classifying plants is leaf identification. Various plant sections allow for the regular grouping of plants. Three-dimensional things, on the other hand, increase complexity. Therefore, identifying the appropriate leaf picture for the purpose of classifying plants is a straightforward and easier method. The classification of each leaf picture involves a number of connected procedures. A data base is initially generated using example photos of various types of leaves. The related plant information is connected to each photograph of a leaf. When a leaf image is submitted to a system, image processing techniques are used to identify and record the leaf's key properties. The organization of the paper gives a brief overview of datasets available in section 2. The general process of identification of medicinal plant leaf is studied in section 3. Different existing techniques and the results of obtained in existing techniques are described in section 4. Followed by common evaluation metrics in section 5.

II. AVAILABILITY OF DATASETS

A portion of the research's data is acquired from several institutions. The Centre for Plant Medicine Research (CPMR) in Akuapem Akropong, Ghana, has created a medicinal plant leaf dataset for the study. The NIKON D3500 camera is used to capture the photographs, which have the dimensions 6000 4000 3 and are in the uncompressed JPEG format in YCbCr colour [17]. Images are captured on the anterior surfaces of the leaflets of medicinal plants. Relevance, representativeness, non-redundancy, empirically confirmed examples, scalability, and reuse were among the benchmark principles used to develop the dataset [18].

A. Flavia dataset

Yangtze Delta of China with plants that are natural having 33 species are represented by 1907 samples in the Flavia dataset [19–20]. There are no petioles on any of the leaf photos in this collection. The collection contains photos of extremely restricted leaves on a white backdrop in the absence of stems. The leaf image is shown in Figure1.

Figure1. Example of Flavia dataset

B. Swedish Leaf dataset

In [21-22] the authors stated that this dataset consists of 15 species with 75 number of samples from every species. The leaf image of dataset is shown in Figure 2.

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Figure2. Example of leaves from 15 tree classes

C. Mendeley dataset

The National Institutes of Health (NIH) Office of Data Science Strategy (ODSS) GREI project includes the Mendeley Data repository from Elsevier. The NIH has provided funding for the GREI, which consists of seven well-established generalist repositories. These repositories collaborate to create a metadata which is consistent and can create or use the data for sharing, training purpose. The data can also be utilized by the researchers as it is a FAIR data**.** It is a publicly available dataset which is secure and free cloud-based public data archive where you can keep your information, making it simple to share, read, and cite from anywhere. 1835 pictures from 30 species are included in the Mendeley dataset [23].

D. Folio dataset

This dataset is also publicly available for the researchers and the link to download is provided by author in [24].Total 576 number of images are available form 32 species and each species having 18 samples and is discussed by author in [25]. The University of Mauritius' farm and other adjacent areas provided the plants from which the leaves were harvested. The dataset leaves are shown in Figure3.

Figure3. Example of Folio dataset

Some of the leaf image with their scientific name and uses of the medicinal leaf is tabulated in TABLE1.

Image of leaf	**Scientifical name**	**General Name**	**Usage of leaf**
	Melissa officinalis L	Lemon Balm	Used to treat headaches, body pains and also mental disorders
	Stevia rebaudiana Bertoni	Stevia	A very good substitute for sugar and used for diabetic patients, and also treat metal condition of the individual
	Mentha balsamea Wild	Peppermint	Used as an antifungal and antiviral agent
	Aegle Marmelos	Bael	Used to control bleeding, diarrhea and also for intestine problems
	Ocimum sanctum L	Tulsi	Used for skin infections, solving gastro-intestine issues

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TABLE 1: SCIENTIFIC NAME AND USAGE OF LEAF

III. GENERAL PROCESS OF IDENTIFICATION

Data collection and pre-processing are the initial steps in a series of activities that are necessary for the accurate detection of plant diseases from the leaves of a plant. The extraction of characteristics comes after pre-processing in the identification of illnesses. Finally, several classifiers are fitted with the characteristics to do the classification. The general process of leaf identification is shown in Figure 4.

A. Data Collection: The gathering of picture data is the initial stage in the identification of medicinal plant leaves. There are several common plant leaf databases accessible as discussed in section 2.

B. Pre-processing: One of the most crucial processes in the detection of plant diseases is pre-processing. There are several pre-processing procedures, including scaling photos to match the model, eliminating noise, changing colours, performing morphological operations, segmenting the disease region, etc. The noise in the disease-affected picture is removed using a variety of filtering approaches, including different type of filters. In [26] author discussed about the Wiener filter and median filter, in [27] author worked on Gaussian filter. Color spaces used in image processing include RGB, HSV, CIEL*a*b* and YCbCr [28]. The region of interest (ROI)/disease area in the leaf images is identified using a variety of segmentation techniques, including colour thresholding as discussed by author in [29], in [30] author worked on Sobel edge detector, in [31] author discussed Otsu's segmentation, and in [32] K-means clustering is studied.

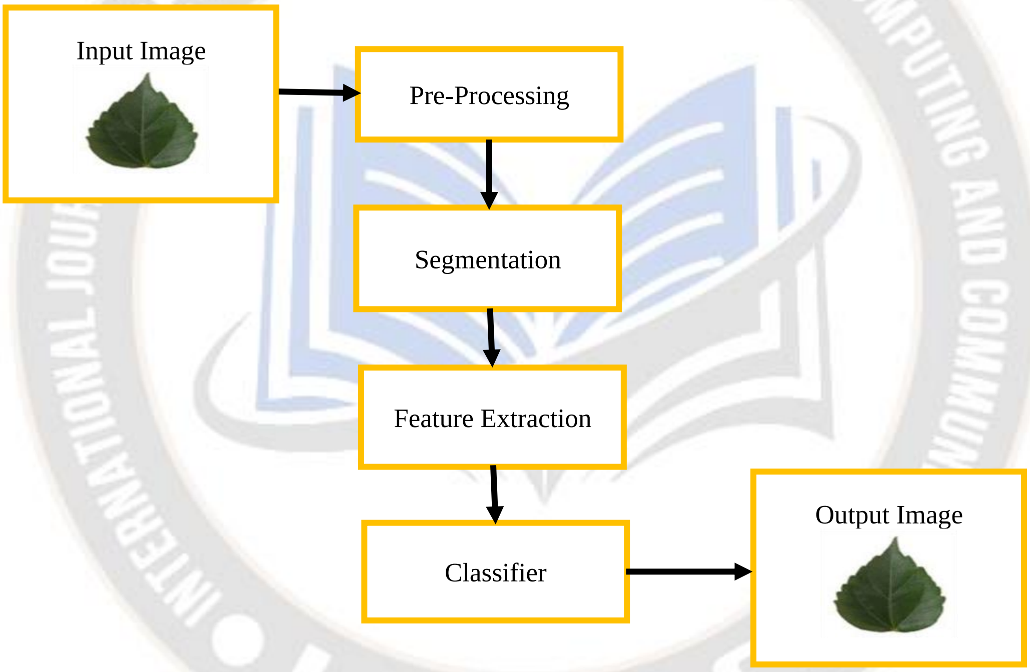

Figure4. General Process of Medicinal Leaf Identification

C. Feature Extraction

A key component of machine learning is features. The mathematical representation of the illness information is done using features, which facilitates categorization. A feature must include the details needed to distinguish between the classes in order for classification to be effective. In order to identify illnesses, many characteristics are utilised.

These features may be categorised as features based on colour, features based on shape [33], features based on texture [34], and features based on deep learning. The various colour values of the illness area are defined by colour characteristics. Some of the form characteristics include the area, perimeter, length in minor/major axis, eccentricity, etc. In [35] author works on local binary pattern (LBP) , in [31] the gray-level co-occurrence matrix (GLCM) is discussed, in [29] author discussed the gray-level run-length method (GLRLM), and Gabor texture features and all these models are categorised into texture-based traits for the identification of diseases. Some of the characteristics that are used to categorise medicinal plants are shown in Figure 5.

D. Classification

Classification, which classifies the numerical analysis of a variety of picture features yields the leaf image data into some of the illness categories. Both supervised and unsupervised categorization are possible. The author in [36] discussed support vector machine (SVM), the author in [37]

discussed decision tree (DT), in [35] author discussed about artificial neural network (ANN) and probabilistic neural network (PNN) are a few examples of machine learning techniques which are frequently used classification algorithms.

IV. EXISTING METHODOLOGIES

The authors in [38] assembled 20 Ayurveda anterior and reverse-sided leaves at arbitrary from 40 diverse species. Weka is a means that discriminates therapeutic plants by means of machine learning approaches. Leaf color and surface properties are obtained from tint and binary photos. SVM and MLP classifiers are used to ascertain the leaves based on the subsequent measures. Some of the features are geometric, centroid-radii (CR) spaces, color and surface appearances, HU invariant moments, and Zernike moments. The authors proposed a method for neural network-based recognition of medicinal leaves [39]. MLP (94.5%) outperformed Support Vector Machine (SVM). Five different plant species' leaves are taken into account. Leaf edges are discovered using the Prewitt Edge detection approach. When compared to other leaves in the data that an artificial neural network (ANN) classifier has learned, the bilva leaf (90.584%) and the castor oil leaf (83.084%) yield good accuracy.

In article [39], the author discussed about categorization and detection techniques for plant leaf diseases. Here, pre-processing is followed by feature extraction. RGB photographs are first made white, then they are transformed into grey-level images to mine the vein image from each leaf. Then, basic mathematical procedures are applied to the image. After that, the image is renewed into a dual image. If a binary pixel's assessment is 0, it is then transformed to the appropriate RGB image significance. Finally, a disease is recognized using a naive Bayesian classifier, a dominating feature set, and Pearson correlation.

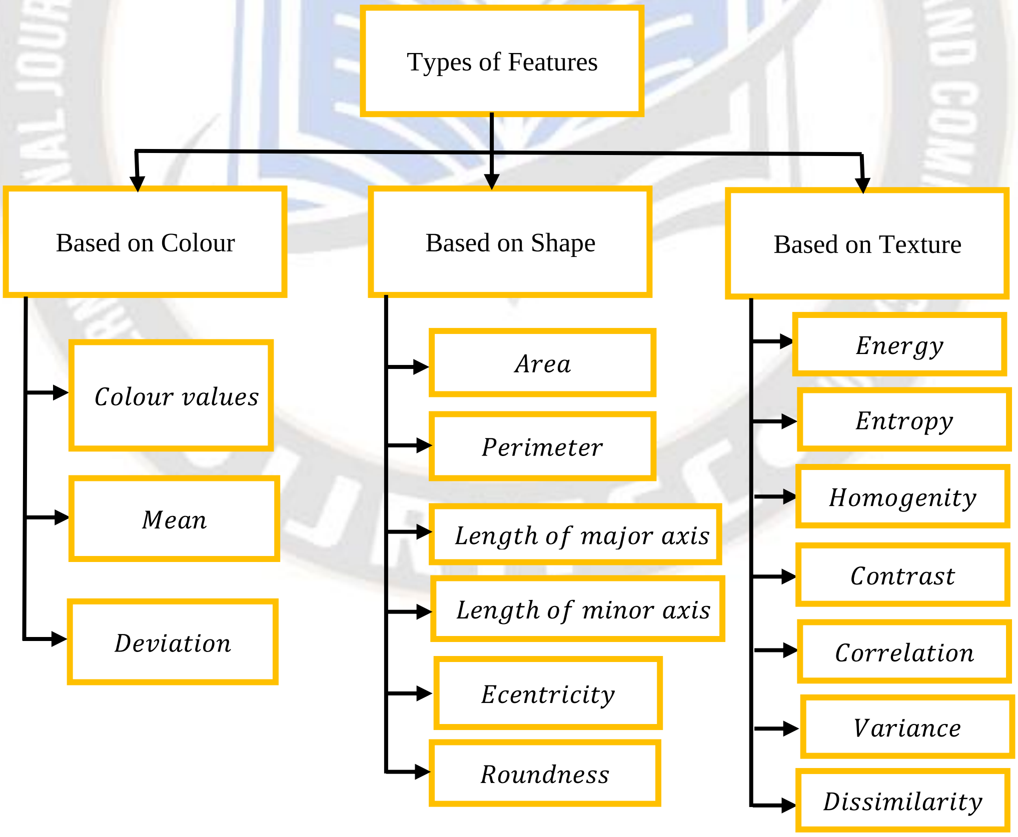

Figure5. Features for Detection of Medicinal Plant leaf

Four steps are described in the study [40]. The first of these involves taking pictures all throughout the country for training and test purposes. In the second phase, Gaussian filtering is used to eliminate all the blare, and thresholding is used to

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acquire the comprehensive green color constituent. K-means grouping is used for separation. All RGB photographs are adapted to HSV in order to extract characteristics from them. In the paper [41], the authors provide a brief outline of the classification techniques of ANN, SVM, and PCA are used to identify medicinal plants. In their suggested work, the authors have estimated the angle proportion, centroid, region, edge, and roundness of neem leaves in order to identify them by their form, color, and vein characteristics. The author classified flowers based on color and features using the Jena Flower 30 dataset, also the data sets 17 and 102 of the Oxford Flower are considered [42]. Various techniques are utilized in botanical combination, pooling, extraction, and recognition. When contrasted with the other two informational indexes, the Jena Bloom 30 dataset has the principal gathering exactness (94%). An involuntary method for classifying mango fruits according to their edges and colors has been developed by students majoring in electronics and telecommunications engineering [43]. Canny edge detection and K-means clustering are two examples of image segmentation methods.

In paper [44] author describes procedures for the detection of diseased plant leaves, including the RGB image capture. altering the response image's RGB to HSI layout. The green pixels were covered up and removed. The parts should be divided into groups using Ostu's method. The genetic algorithm was used to classify the disease after texture features were obtained using the color-co-occurrence methodology. The authors in [45] were able to deconstruct the morphology of leaf edges and create a specific structural signature that quantifies the leaf's form by applying specified structural elements. The difference in feature values between the training and test samples' root mean square errors was used to calculate the identity. They only used a small dataset, which allowed them to achieve an accuracy of 67.5 percent. The Authors [46] used a boundary descriptor known as the Directional Fragment Histogram together with five morphological cues to determine the boundaries. For each result, the Mean Average Precision was employed (MAP). The Authors employed three RGB colour features—red, green, and blue indices—along with four geometry features—solidity, convexity, circularity, and eccentricity—in the experiment [47]. They compared the obtained feature vectors three times to speed up the identification process. They succeeded in achieving a general identification rate of 85%.

The authors of [48] employ colour conversion to convert RGB pictures into grayscale images. Many approaches for enhancing images, such histogram equalisation and contrast correction, can enhance the quality of the images. SVM, ANN, and FUZZY classification are just a few of the classification characteristics used in this. In feature extraction, many types of feature values, such as texture, structural, and geometric features, are utilised. ANN and FUZZY classification are used to identify the paddy plant disease.

In [49] author utilized colour conversion to turn RGB photos into grayscale pictures. An image's quality can be improved using a variety of enhancement methods, such as contrast adjustment and histogram equalisation. This uses SVM, ANN, and FUZZY classification, among other classification qualities. Various feature values, such as texture, structural, and geometric features, are used during the feature extraction process. It can diagnose the paddy plant illness with the aid of ANN and FUZZY classification.

Author devised an automated technique in [50] that uses the leaf to categorise medicinal plants. The Anhui University of Traditional Chinese medicine's medicinal plant specimen bank provided 240 leaves from various plants for the dataset. A 93.3 percent identification rate was attained using the SVM classifier to extract five texture characteristics and 10 form features. In [51], the author extracted several leaf properties, such as the number of vertices, length, width, perimeter, area of the hull, and colour, from a collection of 24 unique plant species from the subtropical island of Mauritius, each containing 30 pictures. The greatest accuracy with 90.1% is obtained using the random forest classifier.

In order to identify Philippine traditional medicine plants using leaf data, the author in [52] experimented with seven different types of classification methods. For varied leaf shape and venation structural parameters, a 98.6% recognition rate was attained. The author of [53] presented a method employing neural networks to categorise and identify herbal medicinal plants using a dataset containing 50 distinct species and also leaves with five hundred numbers. With the help of texture, colour, and form, a total of 21 characteristics were retrieved. In experiments, accuracy was 99.2% when all three characteristics were used and 93.3% when only texture features were used.

The performance of the Extreme Learning Machine (ELM) approach in [54] was compared to that of K-Nearest Neighbor, Decision Tree classifier, Support Vector Machine, Naive Bayes classifier, and a Multilayer Perceptron trained using Backpropagation algorithm when it came to categorising plants. The datasets Fisher's Iris Plant, Wheat Seed Kernels, and 100 count of Plant Leaves were used in this research. A Centroid Contour Curve form signature, a fine-scale border feature histogram, and an interior texture feature histogram were a few of the attributes deduced. The Iris data set with an Ac of 97% and the Seed data set with Ac of 96% produced the

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greatest results for ELM. In [55], the author assessed the effectiveness of several machine learning algorithms for classifying herbal, fruit, and vegetable plants based on their leaves. We utilised 3,150 leaf images from 25 different plant species, including those of herbs, fruits, and vegetables. A Gaussian filter was used to minimise the picture noise after colour shots were converted to grayscale versions. The three feature categories from which 17 features were gathered are shape, texture, and colour. The accuracies obtained using various classification techniques are observed in which SVM with 85%, KNN with 75% and RFC with 80%

In [57], the study shows that an ANN system developed using the morpho-color metric variables as inputs surpassed a visible (VIS)/Near Infrared (NIR) spectrogram with an efficiency of 92.5% when tested on 20 different Chinese traditional medicines whose leaves were gathered. The Swedish Leaf dataset was used by the author in [58]; the Gaussian filtering mechanism was used as a pre-processing approach, and then texture and colour characteristics were retrieved. Multiclass support vector machine classification with an accuracy of over 93.26%. The Swedish Leaf dataset was used by the author in [58]; the Gaussian filtering mechanism was used as a pre-processing approach, and then texture and colour characteristics were retrieved. Multiclass support vector machine classification with an accuracy of over 93.26%. Author compared the Swedish Leaf's Local Binary Patterns—Support Vector Machine (LBP-SVM) technique to the K-NN classifier and the Binarized Neural Network in [59] (BNN) shown in TABLE2.

V. EVALUATION METRICS

Due to its ease of use and capacity to calculate other crucial metrics like accuracy, recall, and precision, the confusion matrix is the most often used assessment measure in predictive analysis. An N×N matrix, where N is the number of class labels in the classification job, indicates a model's total efficiency when deployed to a dataset.

The effectiveness of the employed approaches is evaluated using the metrics listed below: The letters Truely positive (TP) stand for cases that were accurately predicted, falsely negative (FP) for normal or true instances that were incorrectly categorised by the suggested method, Truely negative (TN) for normal or true cases that were correctly classified, and falsely negative (FN) for cases that were incorrectly classified as normal or fraudulent cases.

TABLE 2: ACCURACY EVALUATION USING DIFFERENT DATASETS AND ALGORITHMS

Author	Dataset used	Feature extraction method	Classification Technique	Metric Evaluation
Ken et al., [50]	Database of medicinal plants obtained from anhui university china	Shape features and texture features	Support vector machine	Ac= 93.3%
Begue et al., [51]	Database of medicinal plants obtained from tropical island of Mauritius	Area, perimeter, homogeneity, vertices length and breadth of images	Random forest classifier	Ac= 90.1%
De Luma et al., [52]	Database from Philippine herbal medicine plants	Shape of leaf and structure of veins	KNN, LDA and LR	Ac= 98.6%
Vijayashree et al., [53]	Herbal medicinal plants with 50 different species	Shape, colour and textural features	Neural Networks	Ac=93.3%
S Naeem et al., [56]	Medicinal plant leaves with six varieties	chi-square feature selection strategy	Multilayer perceptron	Ac= 99.01%
J.R. Xue et al., [57]	Chinese medicinal plants with 20 number of varieties	Morpho-colourimetric parameters Visible (VIS)/Near infrared (NIR) spectral analysis	ANN Model	Ac=98.3%

S. Kaur et al., [58]	Swedish leaf dataset	Colour and texture features	Multiclass SVM	Ac= 93.26%

The current BNN and KNN models only yielded accuracy results of 77% and 75%, respectively, whereas the LBPSVM model produced an accuracy result of 84%. The identification of medicinal plants has been frequently used to deep neural networks. Some of the techniques which are been evaluated by various authors are shown in TABLE3.

TABLE 3: DIFFERENT DEEP LEARNING METHODS AND IDENTIFICATION ACCURACY

Author and year	Dataset	Technique	Identification Accuracy
M. Jaiganesh et al., 2020 [60]	Flavia leaf dataset	CNN	86%
C. Zhang et al., 2015 [61]	Flavia Dataset	7L-CNN	94%
H.X Huynh et al., 2020 [62]	Swedish leaf dataset	5L-CNN	98%
M.Sule et al., 2015 [63]	Swedish leaf dataset	ResNet 152	99%
P. Pawara et al., 2017 [64]	Folio dataset	AlexaNet	98%
P. Barre et al., 2017 [65]	Folio dataset	17L-CNN	96%

A. SENSITIVITY

Sensitivity is also termed as the true positive rate, recall, or probability of detection in some disciplines. The accurate detection of truly positive values is termed as sensitivity.

$$Se = \frac{Truely\ Positive}{Truely\ Poitive + Falsely\ Neagative}$$

B. SPECIFICITY

Specificity (also known as the true negative rate) is the percentage of genuine negatives that are accurately identified as such.

$$Sp = \frac{Truely\ Neagtive}{Truely\ Negative + Falsely\ Positive}$$

C. ACCURACY

The mixture of true values and false values and the formula is given as,

$$Ac = \frac{TP + TN}{TP + TN + FP + FN}$$

D. F1 SCORE

It serves as a gauge for test accuracy. It is calculated from the test's recall and precision, where recall is the ratio of true positive findings to all positive results, including those that were misclassified, and accuracy is the ratio of real positive results to all samples that should have been classified as positive. The harmonic mean of accuracy and recall is used to get the F1 score.

$$\mathrm{F1} = \frac{2 * (\mathrm{PPV} * \mathrm{TPR})}{\mathrm{PPV} + \mathrm{TPR}}$$

VI. CONCLUSION

This research focuses on several automated methods that are currently in use for classifying and identifying plants. Using recognition, each unique leaf picture may be connected to the appropriate plant based on common characteristics. Due to a lack of acceptable techniques or representation designs, computer-aided plant recognition is still a challenging task in computer vision. To achieve a high recognition rate, a powerful classifier and an effective feature extraction technique are needed. This essay examines and explains a variety of leaf identification methods. The study demonstrates that image processing is the primary area of research for the identification of medicinal plants. In botany and the food industry, it is crucial to distinguish therapeutic plants from other non-edible plants. The conventional techniques for identifying medicinal plants are laborious, complicated, and call for knowledgeable and skilled individuals. Positive findings have been obtained using current approaches using an automated real-time vision-based system that was utilised to detect widely used medicinal plants with comparable leaves.

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