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Classification of Medicinal Plants Leaves Using Deep Learning Technique: A Review

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Abstract: Pharmaceutical companies are increasingly using medicinal plants since they are less costly and have less adverse effects than current drugs. As a result, a lot of academics are very interested in studying automatic medicinal plant classification. A powerful classifier that can accurately categorize therapeutic plants in real time must be created. This article reviews the effectiveness and predictability of many machine learning and deep learning algorithms deployed in recent years to categorize plants using pictures of their leaves. This study contains image processing techniques for some classifiers that are used to recognize leaves and extract important leaf characteristics. Early plant disease identification is essential because plant diseases have an impact on the growth of their specific species. There are several Machine learning models that are used to identify and classify the signs of plant diseases, but recent advancements in Deep Learning, a subset of ML, seem to offer tremendous promise for improved accuracy. The ML and DL models used to categorize different plant leaves are thoroughly reviewed in this article.

Keywords: Medicinal plants classification, Machine learning, Plant disease, Deep learning, Leaf pattern recognition.

I. INTRODUCTION

Plants create oxygen, which is essential for all living organisms on the planet. Although plants come in many different forms and sizes, they all have a significant role in conserving diversity of life on earth by providing oxygen and water [1]. Herbs known as medicinal plants are utilized to cure particular human diseases and problems. [2]. There are various sorts of herbal treatments available for several human diseases [3]. From the roots to the foliage, these plants offer significant therapeutic effects. Humans have used plants in medication, food preparation, and cosmetics sector in everyday activities. Numerous medicinal plant species exist, and some of them are difficult to classify due to their similarities, therefore herb users must employ categorization. In several countries, most specialists still use traditional methods for classifying herbs manually. Medical plants have qualities that are useful to human and animal health. They were first referred to simple plants in ancient medicine, and now they are referred to herbal plants. The plant is rarely utilized in its whole, at least one of its components can be used to make herbal medicines [4] Different portions of same plant might be used for different purposes. Plants having therapeutic characteristics can also be utilized as a meal or even in the manufacture of hygienic beverages. Since ancient times, people have looked for cures for their illnesses in the natural world. The use of medicinal herbs treats a variety of human disorders. Before the development of iatrochemistry in the 16th century, treatment and prevention of many diseases were provided by plants [5–6]. However, the use of natural medicinal plants has come back into the spotlight due to the declining effectiveness of synthetic drugs and the rising number of side effects associated with their use.

Plants are most fundamental natural habitat for many creatures. Furthermore, today many people who use fuels like coal and conventional gas were created from plants that have existed for a long time span, however humans have significantly damaged herbal ecosystem in recent years, causing numerous crops to fall short. The environmental disaster that followed, on the other hand, had a number of catastrophic effects, including land desertification, climate anomaly, earthquakes etc, all of which put people's life and growth in jeopardy. The herbal medication industry is flooded with not so good quality substances, endangering human wellbeing and threatening global expansion. As a result, developing techniques to categorize herbal medications has been a hot field of research. It is now well acknowledged that the plant's leaf possesses features that are simple to remove and evaluate. As a result, it is naturally utilized as the primary means of identifying all therapeutic plants. Automatic computer picture identification is increasingly frequently utilized in this area, thanks to the rapid advancement of image processing.

II. Implication of Image Processing in Plant Recognition

Automatic plant picture identification [7] is most promising option for bridging gap, and it is receiving a lot of interest in botany and computing fields. An image represents most valuable information in various applications like plant recognition, facial recognition, and so on. In contrast to people, computer/device extraction of characteristics is extremely challenging. To obtain

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excellent accuracy, computer/system must be adequately taught using training datasets. The training data set provides more extracted characteristics in extraction procedure. It also improves the accuracy of the recognition mechanism. The most important requirement for detecting related items and distinguishing between them is recognition accuracy. For applications like facial recognition, this setting only enables approved users. These variable only permits approved users in applications like face recognition, but it recognizes medicinal plant that is vitally important for patient to preserve life in applications like medicinal plant reconnaissance system.

The leaf pictures are identified using image processing methods [8-9]. The context for this allegation is provided below. To begin with, remedial flora is tough to distinguish as the majority of them grow in deep forests and have similar-looking leaves. If you chose the wrong plant by accident, you might develop a major health condition that could result in death. A plant can be identified in a variety of ways. Plants are currently recognized by hand, which is prone to human mistake [10]. Several researchers have created an automatic system identification mechanism [11] to prevent this. Plant leaf categorization, segmentation, and quality assessment are the focus of many researches. Below figure represents medicinal plant recognition which entails a few basic image processing stages to identify and classify plant. This approach includes the phases of picture acquisition, image preparation, component extraction, and classification.

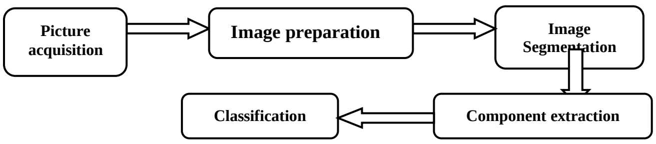

Figure 1.1: Basic concepts of plant recognition [4]

III. Classification Approaches Based on Machine Learning

Various models for medicinal plant classification have been proposed as a result of advances in machine learning technology. The proliferation of cell phones and the introduction of online apps have resulted in the acquisition of millions of plant photos. Automated recognition of plants is vital for real-world environmental monitoring [12], exotic plant surveillance [13] etc. Improved efficiency of mobile plant classifiers is gaining attention from academics and researchers. Ordinary people are frequently entrusted with the task of collecting plants from woods. Due to a variety of human blunders, rare and vital plants are occasionally misidentified. Due to a variety of human blunders, rare and vital plants are occasionally misidentified. These uncommon plant species are critical in saving a patient's life. Furthermore, these individuals are prone to ingesting dangerous plant species. In such instances, an automatic plant recognition system is necessary. This strategy enables the ordinary individual to distinguish between different plant species. Such devices are also highly useful for people who want to gather plant species when hiking in the mountains.

This section covers machine learning classification techniques that are used to diagnose illnesses in plant leaves [14]. Its precision is determined by amount of samples taken and classification methods utilised. Supervised and Unsupervised are mainly 2 kinds of classification techniques [15]. Few of the classification techniques for medicinal plant recognition are depicted in following figure.

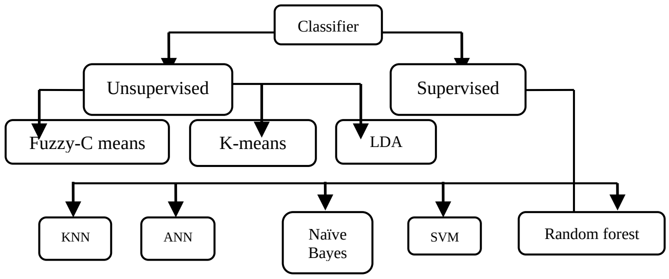

Figure 1.2: Classification algorithms in ML

A. **Unsupervised Classification:** Even with unsupervised learning, generated model captures relationship, but there is no output connected with inputs. In this learning process, similar patterns are clustered together. Fuzzy C-means is an iterative technique that aids in the discovery of cluster centers that minimize a dissimilarity function and the efficient handling of overlapping data. It produces better results when data is partial or ambiguous, but it takes longer to compute and is susceptible to noise. K-means is an iterative learning technique that helps identify cluster centers for each group, although it cannot guarantee the optimal outcome. It's simple to set up and computationally quicker. However, predicting no. of clusters is not easy. An unsupervised method called principal component analysis [16] helps identify the most variable and trustworthy information display. The projections to a straight line are calculated for various classes, and component axes are maximized.

B. **Supervised Classification:** A variety of inputs and outputs are provided, and relationship between them is identified during training phase. The main objective is to forecast intended outcome and to create a model that captures relationships and dependencies between incoming data.

   K Nearest Neighbor is pattern identification and arithmetical evaluation algorithm. It is easy, adaptable, and resilient to noisy training information, however it has a greater computing cost. Probabilistic Neural Networks are a find of feed forward technique which is much quicker and precise than multilayer perceptron networks. The instances with the greatest margin are picked and divided by hyper plane in Support Vector Machine. The input, hidden, and output layers make up the Radial Basis Function. It's used to approximate functions that are simply dependent on their distance from the origin. Random Forest is an ensemble ML technique which does both classification and regression. It adopts the divide-and-conquer strategy for improving efficiency. It builds a forest having many decision trees that aids in accurate forecasting.

IV. Classification Approaches Based on Deep Learning

Accurate prediction or diagnosis of sickness or anomalies in the medical field is a difficult Endeavour. As a result, deep learning approaches based on automated computer-aided diagnostic systems can help medical specialists forecast or diagnose disease or anomalies, allowing them to make informed decisions or plan appropriate treatment schedules [17]. With the advancement of technology, deep learning-based systems work admirably, and the system's output assists specialists in making appropriate selections. To eliminate complicated backgrounds and improve intended functions, classification methods rely significantly on pre-processing. Furthermore, feature engineering for artistry is incapable of handling large-scale, uncontrolled images. Plant classification is a mechanism for appropriately assigning plants to their belonging categories based on certain features. According to data analysis, there exists 4,00,000 kinds of plants. Out of these 2,70,200 have been recognized and acknowledged by botanists. Plant identification is becoming difficult in biology and agriculture, as novel plant discovery is common these days. Also, in order to assist farmers in plant multiplication, it is necessary to recognize a plant by its classification.

A. **Deep neural networks:** These are fundamentally composed of an input layer, several hidden layers, and an output layer. The output of DNNs is computed successively throughout layers of network when input data is delivered to them. To generate the weighted sum, input vector (which contains outcomes for every unit in previous layer) is multiplied by weight for all units, in current layer at every level. Then, non-linear functions like sigmoid or rectified linear unit are applied to value of weighted sum for computing each layer's final output [18].

B. **Convolutional neural networks:** CNNs are based on visual cortex of brain and are meant to analyze a variety of data kinds, particularly two-dimensional pictures. Simple cells respond to rudimentary trends in sub areas of visual inputs, while complex cells synthesize input from simple cells to recognize other complicated variants. CNNs are used to mimic three fundamental concepts: local connection, position invariance, and local transitional invariance. The fundamental structure of CNNs is made up of convolution layers, non-linear layers, and pooling layers. To employ strongly associated sub region of input, groupings of local weighted summations, known as feature maps can be computed by performing computation among local patches and weighted vectors known as filters. B because identical characteristics might exist everywhere in data, filters are applied repeatedly throughout whole dataset, lowering no. of parameters to learn and improving training effectiveness. Non-linear qualities of features map are then enhanced by non-linear layers. Maximum sub sampling of non overlap areas in feature maps is conducted at every pooling layer. The non overlapping sub samples allow these networks to accommodate features that are slightly varied but semantically similar, allowing them to combine local features to find more advanced structures.

C. **Recurrent neural networks:** RNNs have basic structure with cyclic link and are designed to use sequential information. Recurrent computing is accomplished in hidden neurons where cyclic connections exist because input data is handled progressively. As a result, previous knowledge is effectively preserved in hidden units known as state vectors, and result for current input is calculated using these while evaluating all previous inputs [19]. Bidirectional RNN have been constructed and utilised frequently because there are numerous circumstances when both previous and upcoming inputs impact output for present input. Although RNNs don't have as many layers as DNNs or CNNs, they can have deeper architecture if unrolled over time. Replacing basic perceptron hidden neurons with more complicated units that operate as memory cells, like LSTM or GRU considerably reduces difficulty.

D. **K-Nearest Neighbors:** When the number of test photos grew, both the recognition and classification systems' identification accuracy improved. The study in [59] shows that the Principal Component Analysis (PCA) algorithm and the Cosine k-Nearest Neighbors (KNN) classifier have been improved compared to SVM and the Patternnet neural network. The KNN classifier provides 83.5% accuracy [60]. Such low accuracy is too weak to be acceptable, even the feature extraction process is quick and simple. The KNN classifier is not capable of handling sample distortion and could cause inaccuracy in the classification process. A method proposed for this classifier with a specific color histogram increases the accuracy by up to 87.3% [60].

E. **Support Vector Machine (SVM)**: It is a fundamental machine learning method used in SVM to learn data and address classification and identification issues. The study in [61] proposed to use the leaf contour and the centroid to propose the leaf image recognition systems. The proposed method aimed to use image processing techniques as well as SVM used as a classifier. Flavia's data set was used to take 70 patterns with their shape and geometric characteristics. Their findings indicate that 97.7 percent accuracy was their finest success. A comparative analysis for leaf recognition and categorization is given by the authors in [62]. This system uses SVM as a classifier and a form detector to extract features from 14 sheets. 16 distinct plant species from Flavia's database were used in the training data set. The findings demonstrate that SVM can get the greatest accuracy of 90.9%.

F. **Artificial Neural Network (ANN):** The leaf pattern recognition system suggested in [39] demonstrates the dependability of using ANN as a classifier. According to one study, identification accuracy may be improved by employing more data sets and reached 98.6 percent [63]. The findings in [64] can be improved by using ANN as a classifier to detect and classify the leaves of medicinal plants. The color, shape, and texture that were retrieved from photographs of leaves were trained using the ANN classifier. The outcomes demonstrate that the system uses 63 leaf pictures to offer an accuracy of 94.4 percent. When RNA was used as the classifier together with threshold determination in [65], the precision of the extracted leaf vein was increased by around 10%. The findings indicate that when ANN and threshold were combined, accuracy increased to 97.3%. Simple statistical tests may be supported by ANN, which can identify dependent/independent variable associations. In terms of its drawbacks, ANN is computationally intensive and has a propensity to over fit data.

G. **Probabilistic Neural Network (PNN):** PNN is used as a classifier in recognition and classification techniques because to several benefits, including strong distortion resistance, flexibility to adjust data, and the specimen's ability to be categorized into many outputs.

V. LITERATURE SURVEY

Kumar et al.,(2021) introduces novel CNN architecture for identifying mango Anthracnose disease using deep learning. The verification is based on data acquired in real time on farms in Karnataka, Maharashtra, and New Delhi. There are photographs of both normal and diseased mango tree leaves included. The proposed technique, in contrast to previous cutting-edge methodologies, yields an accuracy of classification of roughly 96.16% [1].

Maibam et al., (2021) Plants are essential for human life, according to this theory. Herbs, in particular, have long been used as traditional remedies by indigenous peoples. Clinicians usually recognize herbs depending on their personal sensory or olfactory experience. Latest advancements in logical technologies have made identifying plants based on scientific data considerably easier. Many people benefit from this, especially those who aren't used to identifying herbs. A quick and accurate method for detecting herbs is needed. The use of a mix of computers and statistical analysis is expected to help with herbal identification. This nondestructive method will be preferable for swiftly identify herbs for those who don't have access to costly logical apparatus. This paper discusses many ways for recognizing plants, as well as their benefits and drawbacks. Enhanced ML classifiers with pre processing and attribute selecting models would be employed in future plant identification research to tackle accuracy difficulties and boost performance [7].

Samreen Naeem et al., (2021) Using multispectral and texture dataset, they created ML based medicinal plant leaves categorization. Main goal is to gather refined and standardized dataset, identify edges and lines, extract fused features, optimize retrieved features, choose the most important feature, and select efficient ML classifiers. Tulsi, Mint, Bael, Lemongrass, Catnip, and Stevia are among six medicinal plants represented in multispectral and textured feature collection, which were acquired using computer vision lab setup. The acquired dataset is well polished and standardized due to comprehensive laboratory model. Chi-square feature extraction identifies 14 most important traits for improving classification outcomes. Multi-layer perceptron, LogitBoost, Bagging, Random Forest, and Simple Logistic regression are among five classifiers studied. For starters, categorization of medicine plant leaves information is conducted using ROO's size (220 220). For MLP, LB, B, RF, and SL, it was achieved well-organized accuracy of 95.87%, 95.04%, 94.21%, 93.38%, and 92.56% respectively. Secondly, same method is used on dataset of medicinal plant leaves with ROO sizes of (280 280). 99.01%, 98.01%, 97.02%, 96.03%, and 95.04%, respectively, are highly encouraging outcomes. Furthermore, authors found that MLP model functioned better when contrasted to certain other models that have been built. This research brings up new frontier in categorization of medicinal plant leaves. It can assist pharmacists in identifying proper medical plant and aid in process of manufacturing medication [8].

Nayana et al., (2020) To identify proper species of medicinal plant, ensemble supervise ML method based on color, texture, and geometrical aspects was used to build strategy for medicinal plant recognition. Combination of form, color, and texture factors results in 94.54% accuracy in leaf recognition. Outcomes of this approach are quite encouraging, indicating that this algorithm is well suited for medicinal plant recognition system. In future, this approach might be expanded to greater no. of Plant species with higher accuracy [9].

Ajra et al.,(2020) uses image processing and two CNN models, AlexNet and ResNet-50, to present strategy for detecting and preventing plant leaf disease in agricultural field. To begin, this approach is used to study signs of sick leaves using Kaggle databases of potato and tomato leaves. Then, utilizing AlexNet and ResNet50 models and image analysis, feature extraction is done on dataset pictures to identify leaf illnesses. The suggested technique achieves general 97% and 96.1% accuracy of ResNet50 and 96.5% and 95.3% accuracy of AlexNet for categorization of better and healthier leaf and its illnesses, respectively, according to experimental data. Finally, graphical structure is shown to give preventative measures strategy for identified leaf diseases as well as broad understanding of plant health [10].

Moyazzoma et al.,(2021) To conduct categorization, CNN is employed. Authors employ MobileNetv2, pre-trained extracting features strategy, because no method can accurately acquire properties of accessible data. MobileNetv2 has lot of advantages for mobile devices. Study has 90.38% validation accuracy rate. This syndrome manifests itself in agricultural sector, assisting farmers in discriminating between sickness and harvest. Our model's main purpose is to restore damage caused by encountering plants, which can help in growth of companies. Farmers can save money by taking care of this problem themselves. Our goal is for them all to be possible to treat their crop when it is needed. Authors collect a large number of cucumber leaves. Following that, our model was able to taste any leaf. Using the recommended design, authors hope to reduce leaf disease [11].

Muhamad et al.,(2021) CNN has been used to create an identification model for citrus plant diseases, which divides diseased citrus leaf pictures in 4 categories: cancer, greening, blackspots, and healthy. The data is collected from Kaggle website. Suggested technique has 95.6% accuracy in collection of six hundred citrus leaves pictures, according to test utilizing 5-fold cross validation. This work exceeds prior research that employed M-SVM prototype and weight segmentation with 90.4 % accuracy. [12]

Pushpa et al.,(2021) Plant patterns that are apparent to the naked eye are investigated. Individually observing plant illnesses is highly tough and time-consuming, requiring a lot of work, understanding of plant diseases, and a lot of time. As a consequence, plant illnesses are detected using image processing techniques. In the illness detection phase, different DIP stages are employed. To extract plant disease features from photos of leaves, the proposed system employed a special type of segmentation. The data was gathered from Plant Village, Kaggle, and Mendeley sets, and contained diverse plant leaf photos of varying shapes, margins, and feature descriptors for diagnosing the illness that affected them. After being sliced using data classifiers for training and testing sets, acquired dataset is processed. An indices-based histogram method segmented data with 92.06% accuracy. [13].

Pham et al.,(2020) Early illness on plant leaves with little symptom blobs is identified using ANN technique, that could be spotted with high resolution photos. Every contaminated blob for entire dataset is fractured following pre-processing phase with visibility restoration approach. The accomplishment of model is determined by selecting features from a collection of measurement based characteristics. These features depict blobs using a wrapper-based attribute selection methodology as per hybrid metaheuristic. An ANN is fed with specified characteristics. The authors' findings increased with transfer learning when compared to those obtained using another strategy that uses well-known CNN classifiers (AlexNet, VGG16 and ResNet-50). ANNs outperform CNNs with simpler network layout in terms of performance (89.41% versus 78.64% , 79.92% and 84.88% respectively). It depicts that suggested technology may be used on lower cost gadgets like cellphones that would be immensely valuable to farmers on ground [14].

Adedoja et al.,(2019) Through transfer learning, conducted case study employing DL-based analysis to detect sick plants using leaf photos. CNN is built using NASNet framework. This framework is then developed and tested using data from PlantVillage project, which includes photos of plant leaves with varied infection levels. Accuracy rate of model is 93.82 % [15].

Singh et al.,(2019) For categorizing Mango leaves infected with fungal illness Anthracnose, a new version termed MCNN has been proposed. To identify various illnesses in mangoes and divide these from healthier pieces, image classification algorithm is used. To artificially increase dataset size, image augmentation is used on initial photos, along with image cleaning and preprocessing. These classifications are encoded and supplied into CNN that categorizes mango pictures into distinct classes. Proposed technique is empirically validated for best results. When contrasted with existing methodologies, the proposed system outperforms them all, with an accuracy rate of 97.13 %. In addition, suggested framework is both scalable and simple [16].

Venkatesh et al.,(2020) V2IncepNet is revised VGGNet method that combines greatest aspects of both VGGNet and Inception components. VGGNet collects standard features, while Inception retrieves high-dimensional attributes and classifies pictures. The following terms are used: leaf color, venation, petiole situation, tip structure and circumstances, leaf outline and edge, black spots on leaf cutting edge and midrib, boundary of burn on leaf and its sharp edge, midrib, and petiole. In our database, authors have 2268 color photographs of mango leaves, including 1198 self clicked color pictures shot in field and 1070 color images uploaded from Plantvillage. Proposed framework might categorize level of Anthracnose based on findings of experiment. The proposed framework could identify Anthracnose infection on Mango leaves with an accuracy of 92%, as per findings of experiment. The structure given is simple yet effective [17].

Trongtorkid et al.,(2018) provides knowledge-based expert approach for identifying plant illnesses based on mango leaf diagnostic analysis. In knowledge-based obtained via DM approach, decision tree algorithm was applied. There are 129 attributes of leaf's figure in file, that are divided in three response groups (Normal leaf, Anthracnose, Algal Spot). After implementing J48 method on Weka 3.8, DT algorithm comprises six critical characteristics to employ for identifying leaf symptoms. The accuracy of model is around 89%. Scholars may conclude from research that proposed model can be employed as precision framework in software platform for characterizing diseases in plants [18].

Zheng and Wang (2009) To describe leaf lamina, they suggested visual consistency-based feature extraction approach that extracts essential aspects such as aspect ratio, vertically eccentricities, rectangularly, convexity, horizontally symmetric, and form complexity. Authors also used Inertia Axis approach to execute leaf rotation, which required leaf to be turned to certain orientation. This is done to mimic human behavior when looking at an entity. Results demonstrate that characteristics from similar plant have higher degree of consistency with little differences in laminas, and that aspect ratio, vertical eccentricity exhibit noteworthy differences in laminas from dissimilar flora [20].

Patil and Manza (2015) In photos, statistical characteristics like leaf's largest diameter, breadth, lengthwise measurement, aspect fraction, and form factor were retrieved. Scientists also collected morphological characteristics from leaves like smoothing and thinning factor, boundary part of diameter, physiologic breadth, and vein elements are most relevant traits, according to authors, since they may accentuate differences between leaves [21].

Wang et al. (2019) The scientists used curvature scale space algorithm to obtain plant dental data, such as total no. of tooth, ordering, space among them, sinus and tooth shape, which is necessary for detecting species of plants. When employing extracted characteristics to categorise plants, authors were able to attain accuracy of 88.33% [22].

Begue et al. (2017) Using RF classifier, authors were able to identify 24 different medicinal herbs with 90.1% accuracy. The classifier is made up of large no. of discrete decision trees, and its choice depends on ensemble forecasts. Classifier is selected because of capacity to analyse non linear characteristics and higher dimensionality instances, like photos of plants having many attributes like forms and outlines. Multiple characteristics were used in classification, including lengths, breadth, bounded box region, leaf area and boundary, hull area and boundary, horizontal and vertical distance maps, 45° radial map, and RGB readings of every pixel [23].

Jeon and Rhee (2017) They looked at GoogleNet's plant identification performance. Using Histogram of Oriented Gradient and Scale-invariant Feature Transform, characteristics that underwent luminance or shape modification were retrieved from different forms of leaf, including lanceolate, light oval, acupuncture, long oval, elongated and long leaf. SIFT is scale and rotational invariant description in which algorithm places key-points inside image and assigns values to those key-points. Results demonstrated encouraging findings by obtaining 90% accuracy rate [24].

Table 1: Comparison of ML and DL Techniques

Authors, Reference	**Classifier**	**Accuracy reported**	**Drawbacks**
A. Kadir et al, [26]	PNN	95%	There isn't any real-world testing. Both for training and testing, just 95 leaves photos were utilised.
Bin Liu et al, [27]	Deep Convolution Neural Network	97.62%	Identifying model's structure is challenging.
Z. Husin et al, [28]	ANN	98.9%	Slow process of detection
Z. Husin et al, [28]	ANN	98.9%	Slow process of detection

H. Mattila et al, [29]	SVM	96.4%	The centre vein of TAROF leaf was occasionally misidentified as oat using a texture-based technique.
J. Chaki et al, [30]	Neuro Fuzzy Controller	50.16%	Using Gabor filter only, or one feature, was not adequate to achieve acceptable accuracy.
Sun et al, [31]	Deep Learning Model	91.78%	Lesser Scalability
A. Bhardwaj et al, [32]	KNN	91.5%	This research contains limits in terms of how to identify leaves with inadequacies and recognition rate, as well as how any changes in nearest distance affect the derived texture feature's value.
Santanu Phadikar et al [33]	Self-Organizin g Map	92%	The frequency domain modification of image does not improve categorization.
Sandika Biswa et al [34]	FCM clustering and neural network	93%	Segmentation is complex.
Harshal Waghmar e et al [35]	Multi class Support Vector Machine	96.6%	Only by enhancing testing and training data proportion, accuracy can be improved.

The following graph shows accuracy reported for various classifiers:

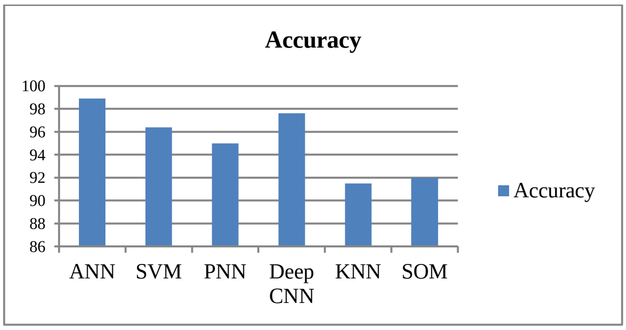

Figure 1.3 Accuracy Comparison of ML and DL techniques

Among the above mentioned machine learning and deep learning techniques classifiers, ANN have the highest accuracy with 98.9%, whereas KNN have the least accuracy of 91.5% and the rest of the techniques lies in between them such as: SVM have 96.4% of accuracy, PNN have 95%, DeepCNN and SOM(Self Organizing Map) have 97.62% and 92% accuracy respectively. Deep learning model have 91.78% accuracy, whereas FCM clustering and multiclass support vector machine have 93% & 96.6% accuracy respectively.

Table 2:-PNN Based Leaf Classifications

Authors, Reference	Dataset	Year of Publish	Features	Accuracy rates
L. Huang et al,[36]	900 images	2008	Shape, Texture	93.70%
Y. Herdiyeni et al, [37]	2448 images	2012	Texture, Color	74.51%
J. Hossain et al, [38]	1200 images	2010	Shape	91.41%
S. Wu et al, [39]	1800 images	2007	Texture, Color, Shape	90.00%
K. Mahdikhanlou et al, [40]	Flavia dataset Swedish dataset	2014	Shape	Flavia = 82.01% Swedish = 80.01%

Table 3:-SVM Based Leaf Classifications

Authors, Reference	Dataset	Year of Publish	Features	Accuracy rates
V. Srivastava et al, [41]	Flavia dataset	2018	Shape	90.90%
R. Nesaratnam et al, [42]	300 images	2015	Shape	86.70%
A. Khmag et al, [43]	Flavia dataset	2017	Shape	97.70%

Table 4:-ANN Based Leaf Classifications

Authors, Reference	Dataset	Year of Publish	Features	Accuracy rates
R. Janani et al, [44]	63 images	2013	Shape, Color, Texture	94.40%
H. Fu et al, [45]	2940 images	2007	Color, Vein	97.33%
Q. Wu et al, [46]	180 images	2006	Shape,Vein	94.40%

Table 5:-KNN Based Leaf Classifications

Authors, Reference	Dataset	Year of Publish	Features	Accuracy rates
P. Kumar et al, [47]	Flavia dataset	2016	Shape	94.37%
F. Kheirkhah et al, [48]	Image CLEF dataset Leafsnap dataset Flavia dataset	2019	Texture	ImageCLEF = 88.80% Leafsnap = 74.50% Flavia = 98.70%

Table 6:-CNN Based Leaf Classifications

Authors, Reference	Dataset	Year of Publish	Features	Accuracy rates
Y. Zhong et al, [49]	2462 images	2020	Color, Texture, Shape	92.29%
W. Jeon et al, [50]	Flavia dataset	2017	Shape	99.70%
B. Anami et al, [51]	6000 images	2020	Shape	92.89%
S. Wang et al, [52]	1443 images	2020	Texture	93.27%
P. Zhang et	2816	2020	Color,	96.00%

al, [53]	images		Texture, Shape	
B. Hang et al, [54]	6108 images	2019	Color, Texture	91.70%
R. Akter et al, [55]	3570 images	2020	Shape, Vein	71.30%
Y. Toda et al, [56]	ImageNet dataset PlantVillage dataset	2019	Color	97.14%
M. Sibiya et al, [57]	54306 images	2019	Texture	92.85%

VI. ANALYSIS

The evaluation of current classification techniques focuses on a number of issues, such as the features and classifiers in widespread use and their effects on classification accuracy, the testing data sets, and research trends on leaf sorting techniques. Color, form, texture, and vein are just a few of the elements that researchers have included in their techniques. Additionally, we have discovered that some studies integrate many criteria to increase accuracy ratios. In their approaches for classifying objects, most studies concentrate on the properties of forms. The inclusion of numerous characteristics in the classification technique aids in improving the accuracy ratios of leaf classifications, according to an analysis of the accuracy ratios of these approaches. The state of the art includes a number of classifier approaches. Most accuracy ratios indicate that approaches based on CNN perform better than those using alternative classifiers. On the other hand, ANN classifiers are gaining popularity because to their high accuracy rates. The accuracy ratio attained by various classifiers is shown in Fig. 1.4.

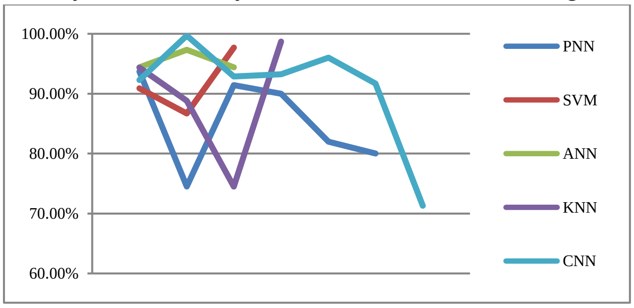

Fig 1.4 Accuracy ratio attained by various classifiers

Our investigation reveals that the majority of researchers (about 57 percent) have created their data sets for their tests when it comes to test settings. Less than 30% of the research made use of well-known standard data sets, such Flavia and Swedish. The usage of several data sets for leaf categorization techniques is depicted in Fig. 1.5.

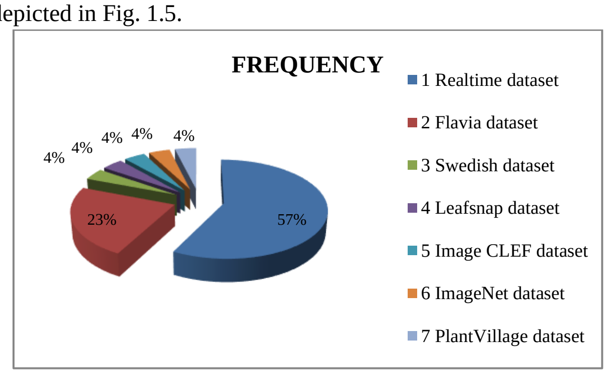

Fig 1.5 Datasets used to categorize leaves

Among the currently used classification methods, CNN makes up around 39% of the methods, while PNN and SVM make up about 26% and 13% of the methods, respectively. The frequency of the various categorization techniques now in use are shown in Figure 1.6.

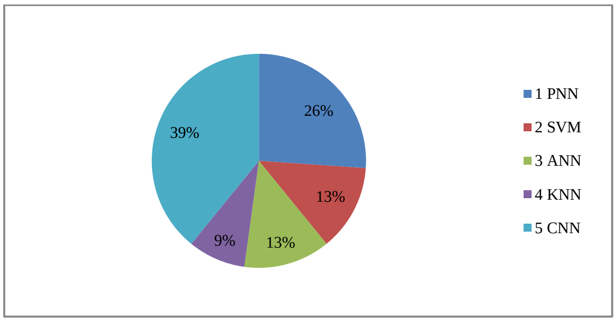

Fig 1.6 Techniques for classifying and identifying leaves

VII. CONCLUSION

Manually identifying medicinal plants takes a large amount of time and is prone to human mistake. Automatic plant identification may be a solution to these issues, however developing an automatic identification system necessitates a huge amount of resources, including a vast database, extensive understanding of plant morphology, and computer programming abilities. To recognize leaf patterns, many automated procedures are used. ML and DL methods that take into account image context completely speed up the classification procedure, which is suitable for extremely complex plant leaf samples. The majority of research on plant identification systems is conducted using pre-existing datasets created in a controlled setting. As a result, greater study is needed into photos with diverse lighting situations and complicated backgrounds. Apart from that, dataset must be huge in order to permit the models for better preparation. This would improve accuracy of the established classification system. Higher accuracy might have an influence on the advancement of medicinal plant use in medical field, and upgrading automatic plant identification system would have significant impact on environmental conservation and preservation.

AUTHOR'S CONTRIBUTION

The author Himanshu Chanyal conducted the research, analyzed the data, proposed the methodology and wrote the initial draft, Dr. Rakesh Kumar Yadav supervised the research and modified the initial draft and Mr DilipKumar J Saini has written the final version of the manuscript. All authors had approved the final version.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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