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A Comparative Analysis of AI Methods for Flower Classification and Chemical Fingerprint Creation

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Abstract: Plants have long been recognized as natural sources of therapeutic compounds, with their various parts, including flowers, being used in traditional treatments for centuries. Flowers, in particular, have captivated humans with their beauty. However, the classification and identification of specific flowers for therapeutic use can be challenging using conventional methods. Researchers have turned to modern tools like cameras and computers to aid in this process. Despite their limitations, the need for more efficient and accurate methods has led to the exploration of artificial intelligence (AI). This study seeks to evaluate various AI-based methods utilized by researchers in the field of flower analysis, highlighting their strengths and weaknesses to inform future research. The advanced analytical tools available today are instrumental in creating a chemical fingerprint of flowers. Chromatographic and spectroscopic techniques, used to determine precise chemical composition, offer valuable scientific insights into traditional medicine. Plant part identification often commences with feature extraction. Any plant part is digitally captured multiple times and subjected to different feature extraction methods. Common basic features include color, texture, and shape, while deep learning features like CNNs are also employed. We analyze and review diverse approaches reported in recent literature, examining their advantages and potential applications.

Keywords: Flower Identification, Machine Learning, Convolutional Neural Network, Artificial Intelligence, Chemical Finger Print Analysis

1. Introduction

Since ancient times inclusion of medicinal flowers has been a fundamental element of traditional medicine. The World Health Organization (WHO) found that traditional medicine is practiced in low economic countries and vivid range of illness has been cured using the medicinal qualities of various plant species [1]. Still, it is very challenging to identify the medicinal flowers as many individuals lock expertise in the field [2-4]. In addition difference in climate, soil conditions and the timing of harvesting may influence the chemical composition of medicinal flowers [5].

Artificial Intelligence can play a vital role in identifying medicinal flowers and analyzing their properties and chemical values. Through active research and with help of Artificial Intelligence this can be achieved. A thorough identification system can be built up gathering information about therapeutic flowers, including pictures, descriptions and chemical values. This database wills helpful to train a deep learning system to that it can differentiate between various plants based on their visual traits such as color, texture and shape [4]. The elaborate study about classification of Chinese medicinal flowers with the aid of Convolutional Neural Network (CNN) was reported by Meiling Huang *et. al* [6].

The deep learning model presented here consists a two parts model, the first part is Convolutional Neural Network [7] block is utilized for characteristic extraction, followed by a classification block that uses these extracted features for accurate identification [8]. There has been a significant rise in the popularity of deep learning in recent years, mainly due to its application in different tasks related to form automation, such as object detection and image categorization [9-12]. The algorithm learns to analyze picture of fresh or new plants and identifies them by their visual characterizes after undergoing the training. In, addition the algorithm can also identify the specific chemical compound that leads to these properties and identify their interactions with other compounds. Nowadays, in developed countries, the use of traditional medicine, prepared by using various medicinal plants and their natural sources, to treat and manage various illness has been surged. The major reason for this shift may be the negative side-effects of chemical medications [13, 14]. Apart from their medicinal uses, these plants also have various applications in the food and beverage industry, as well as in cosmetics. They can be used as ingredients in food and drinks to add flavour and aroma, or as natural colorants in cosmetics and personal care products [15, 16]. The flourishing of flowers holds importance not just for their decorative appeal, but also for their value in nutrition, medicine, culinary arts, cosmetics, and aromatherapy [17]. Flowers act as abundant reservoirs of diverse compounds that play essential roles in a range of metabolic processes within the human body. The inclusion of edible flowers can stimulate a worldwide demand for more appealing and delectable food, enhancing the nutritional content of gourmet cuisine [18]. In the current regulatory frameworks and pharmacopoeias, the evaluation of herbal medicines' quality, both in terms of their characteristics and quantity, typically involves sensory assessments, such as visual inspections at both macroscopic and microscopic levels, along with quantitative analysis of specific intrinsic marker compounds [19]. The utilization of various analytical techniques yielded a substantial array of variables in the fingerprint data. This not only presented a valuable chance to extract pertinent chemical insights from the initial dataset but also posed a challenge in harnessing this valuable chemical information through conventional univariate analysis [20]. In nowadays, rapid advancements in computer science, the utilization of Chemo metrics methods for multivariate statistical analyses of chemical fingerprint data has gained significant traction in the field of quality research for HM (Herbal Medicine) [21]. Medicinal flowers offer therapeutic properties, including anti-inflammatory and antioxidant effects. They are utilized in traditional medicine for ailments, promoting digestive health, and aiding in stress reduction. Some flowers have antimicrobial properties, contributing to skincare and respiratory support. Beyond physical benefits, medicinal flowers often hold cultural and ritual significance. Accurate identification of edible flowers is crucial since only a few varieties are suitable for consumption [22].

The major challenge in identifying medicine flowers is that often they have a striking resemblance, especially the variations that occur during the growth cycle. This can be a precious tool for experts, botanists and pharmacists who need to find and analyze the medicinal flowers for their therapeutic use. The project "Identification of Comprehensive Medicinal Flowers, Properties and Chemical values based on Artificial Intelligence" presents opportunity to overcome these challenges by forming a system that use artificial intelligence to identify medicinal flowers, examine their properties and determine their chemical composition. This initiative has the capability to aid in the development of large database of medicinal flowers through the growth of this system. This database can be used to identify, authenticate and guarantee the quality control of medicinal flowers, amongst other things.

2. Study Design and Procedures

2.1. Sampling Methodology and Collection Techniques

The Sampling Methodology and Collection Techniques involved a series of steps, with the outcomes of each step visually illustrated in Figure 1. Samples from capturing plant and flower identification can be a valuable supplement to traditional methods, giving visual documentation that helps in species identification and verification. The samples of leaf images were taken with an imaging setup high resolution Camera or Smart phone, lighting box and a Computer. RGB images with a resolution 3456x4608 pixels and utilized for macro mode, close up shots of flower morphology and leaf traits, Stem structure saved as JPEG file on a personal computer. This imaging system features a ring of LED lamps emitting low-intensity infrared light (450 lm) with adjustable intensity levels (low, medium, and high).The leaf samples were captured at a distance of 250 mm noted in many studies provides good image clarity. The detailed account on image processing was discussed elaborately by Azadnia and Kheiralipour [23].

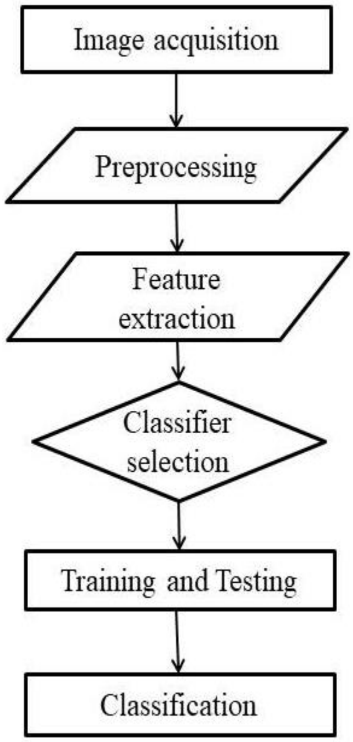

Figure 1. Protocol for Flower Recognition

2.2. Pre-Processing of data

Image processing has been conducted using software codes written in multiple programming languages, notably Python, in numerous documented studies. Typically, the code automatically imports and processes images, utilizing libraries such as OpenCV2, Python Image Library (PIL), and Numpy. Otsu's thresholding technique was employed in this investigation to identify the most suitable threshold value for separating the background [24]. Each steps in Figure 2 illustrated the pre-processing for background removal involved a series of steps. Firstly, the obtained images were resized to facilitate for further processing. Subsequently, the images were optimized using Otsu's thresholding method to determine the appropriate threshold for background separation. Following this, any empty pixels within the leaf images were eliminated through a dilation operation employing morphology techniques. The binary mask generated in the previous step was then inverted. Finally, the inverted mask was applied to substitute the pixels corresponding to the plant's main images, effectively removing the background [8].

The primary determinants affecting the speed and precision of image processing within deep learning networks primarily revolve around the dimensions of the pixels in the images [25]. Aim was to enhance recognition accuracy and reduce computational time through image pre-processing. Perform image cleaning and pre-processing on the gathered images to enhance dataset quality and ensure its consistency [26-28]. This step may involve resizing, cropping, and standardizing the images. Preserving the integrity of floral characteristics is crucial during pre-processing. Image analysis pre-processing typically encompasses a range of operations, including denoising, enhancing content, and segmentation.

2.3 Classifiers

Classifiers are algorithms used to assign objects to predefined categories. In the context of flower recognition, they are employed to identify different flower species based on their visual features. Here are some commonly used classifier in flower recognition is discussed in Figure 3.

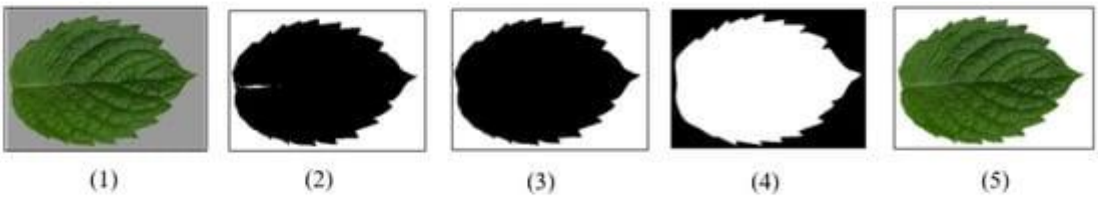

Figure 2. Show the step-by-step image pre-processing for background removal from an original image [8].

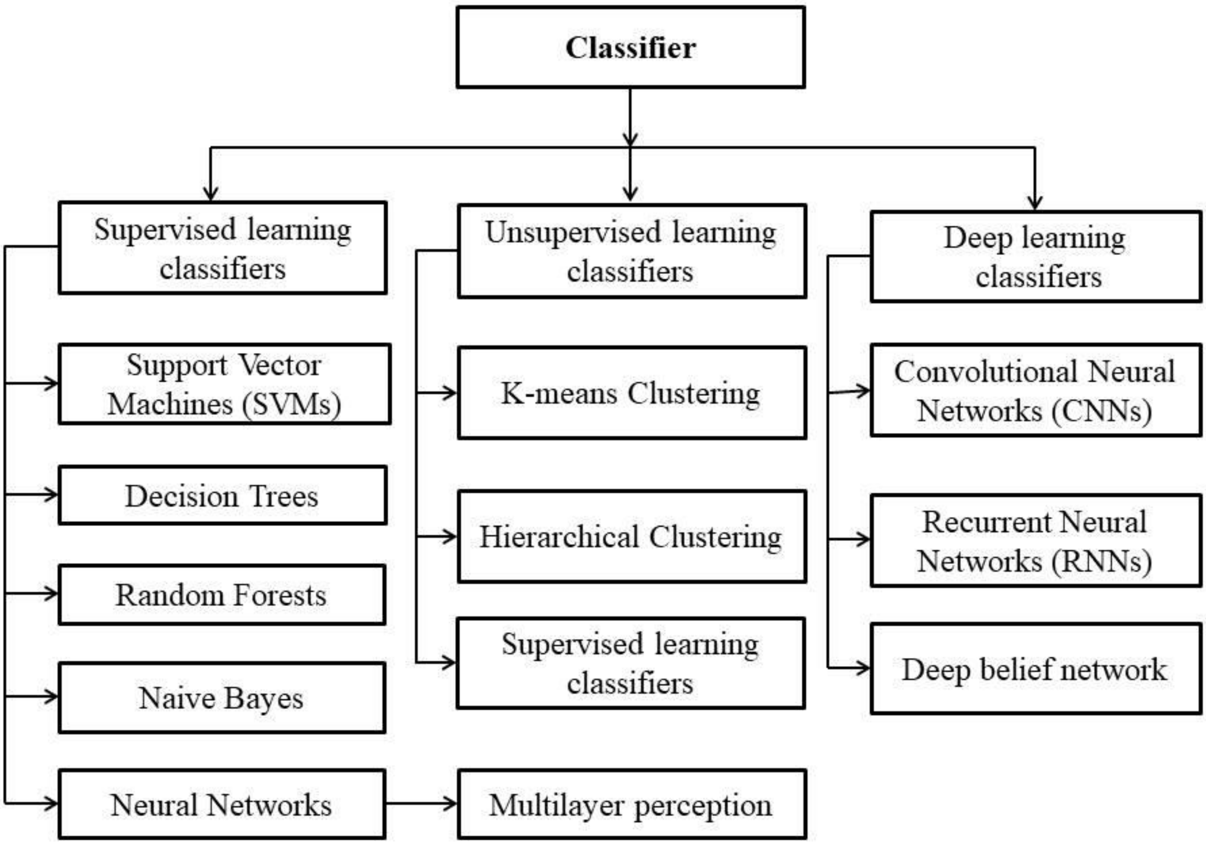

Figure 3. Commonly used classifiers in flower identification

They were broadly classified into supervised and unsupervised classifiers, for better results are reported by combined approaches. Each classifier showed its own advantages and also disadvantages.

The best classifier for flower recognition depends on various factors, including the specific dataset, desired accuracy, computational resources, and the complexity of the problem. However, some classifiers have consistently shown strong performance in flower recognition tasks. CNNs are particularly effective for image recognition tasks due to their ability to automatically learn and extract relevant features from images. They have achieved state-of-the-art performance in many flower recognition benchmarks. Secondly SVMs are powerful classifiers that can handle non-linear relationships and high-dimensional data. They are often used in flower recognition tasks. For large datasets, deep learning classifiers often outperform traditional methods.

2.4 Feature Extraction

Feature extraction is a crucial step in the analysis of medicinal flowers, as it involves identifying and quantifying specific characteristics that can be used to differentiate between species, assess quality, or predict therapeutic properties. This review explores various feature extraction methods commonly employed in the study of medicinal flowers. Figure 4 shows the various features and extraction strategies which are used flower and plant identification process.

Feature extraction is a fundamental step in the study of medicinal flowers, enabling researchers to characterize plant diversity, assess quality, and predict therapeutic properties. By combining morphological, chemical, and molecular approaches, it is possible to obtain a comprehensive understanding of the biological and chemical features that contribute to the medicinal value of these plants. Currently researcher focuses on developing new feature extraction methods and integrating data from multiple sources to improve the accuracy and efficiency of plant analysis.

2.5. Architecture of the CNN Model

The architecture of a Convolutional Neural Network (CNN) is designed to efficiently process and analyse image data. It consists of several layers, each serving a specific purpose in extracting and processing features from the input images. It contains input layers, convolutional layers, activation function, pooling layers, fully connected layers and output layer. Input layer receive image, in the form 3D tensor and its pixel value represented as numerals. Convolutional layer contain filters, which extract features of the flowers, each filter is a small matric and extract particular patterns of the flower. Activation function is a nonlinear function to the output of each convolutional layer. Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh and it introduces nonlinearity into the model, enabling it to learn complex patterns. Pooling layers downsize the feature maps to reduce computational complexity and over fitting.

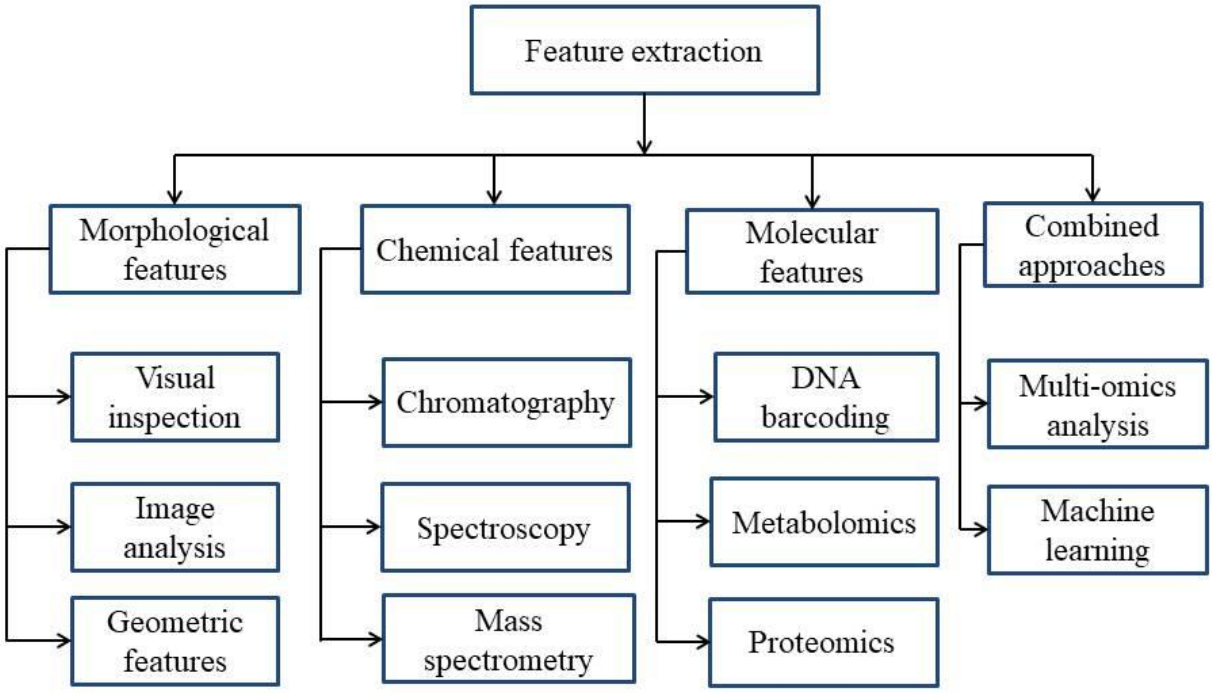

Figure 4. Commonly used feature extraction methods in flower identification

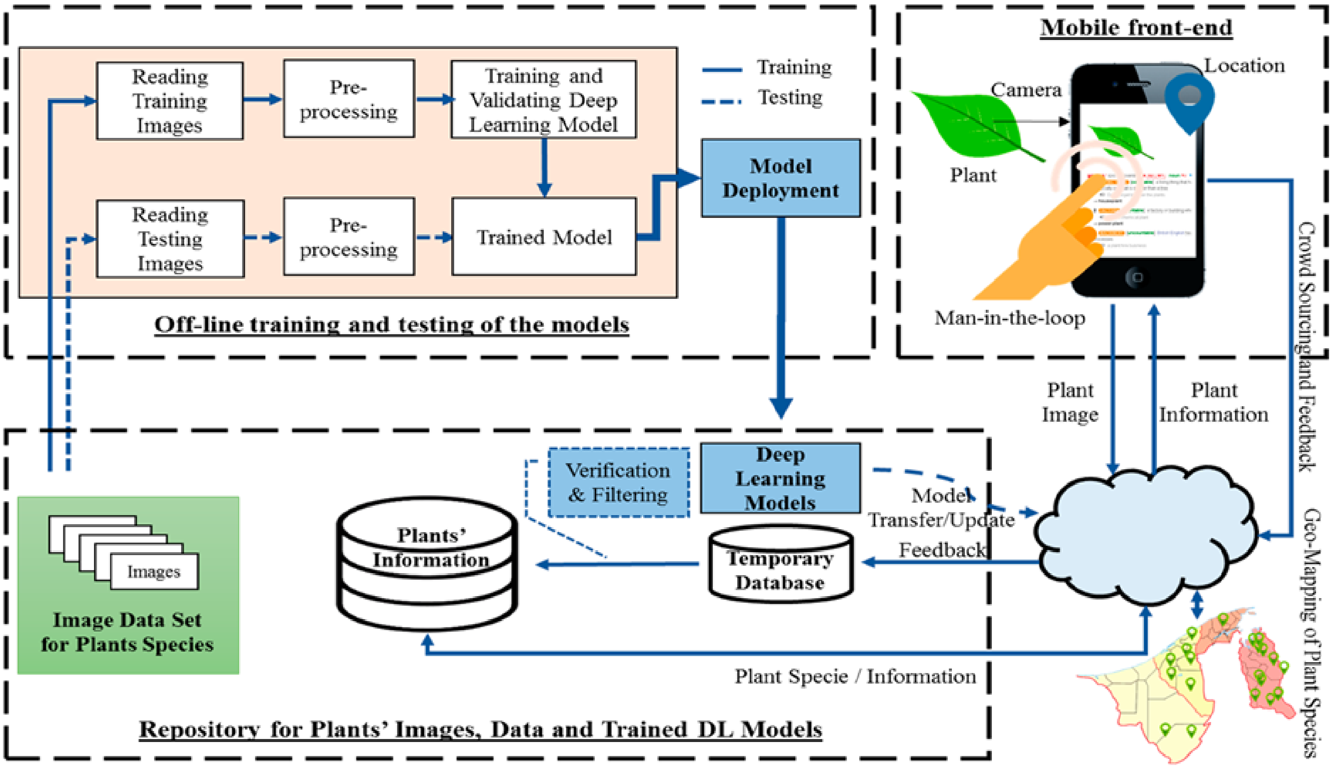

Figure 5. Mobile Application System's architecture [29]

Max pooling and average pooling are normally used to select maximum value from the feature map and average pooling determines average value. Fully connected layers covert feature map into one dimensional vector, connect each neuron in the flatten vector to the every neuron in the next layer. These layers are similar to traditional neural networks and are used to combine and classify the extracted features. The number of neutron in the output layer depends on task. Each neuron in the output layer represents a class, and the output with the highest activation is considered the predicted class.

The detailed explanations of Figure 3 for each component are provided in the following subsections [29].

In the previous study, Jahagirdar [30] introduced a categorization approach based on Convolutional Neural Networks (CNN) for medicinal plant identification. CNN, a well-established technique [31], is employed in this method, utilizing a labelled dataset as a supervised learning approach. The reported CNN model is visually represented in Figure 5 and comprises several key components: Image capture, pre-processing, model architecture, training, and testing. During image capture, a black background is employed. The pre-processing stage involves operations such as resizing, rotation, zooming, and flipping. The selected model comprises two convolutional layers followed by a 2x2 max-pooling layer and Rectified Linear Units (ReLU) activation function.

Identifying medicinal plants heavily relies on analysing the characteristics of their leaves, including shape, colour, and texture. Both the sides of the leaf, with their colour and texture, play vital roles in distinguishing various plant species. This study explores feature vectors extracted from both the front and back sides of green leaves, alongside morphological attributes, to ascertain the most effective combination of features for optimizing plant identification accuracy [32]. Priyanga *et.al.* [33]. utilization of a CNN classifier, classifying multiple classes of medicinal plants but extended to handle multinomial logistic regression, demonstrates the model's adaptability and scalability for classification.

2.6 Chemical Analysis

The chemical analysis can provide information about the active compounds, potential therapeutic applications, and any known side effects. Finding chemical value by comparing them with expert knowledge or additional laboratory experiments continuously validate and predictions.

2.6.1. Chemical fingerprint techniques

Chemical fingerprints are unique patterns of chemical compounds that characterize a specific substance or organism. In the context of medicinal flowers, chemical fingerprints can be used to identify and authenticate species, assess quality, and detect adulteration.

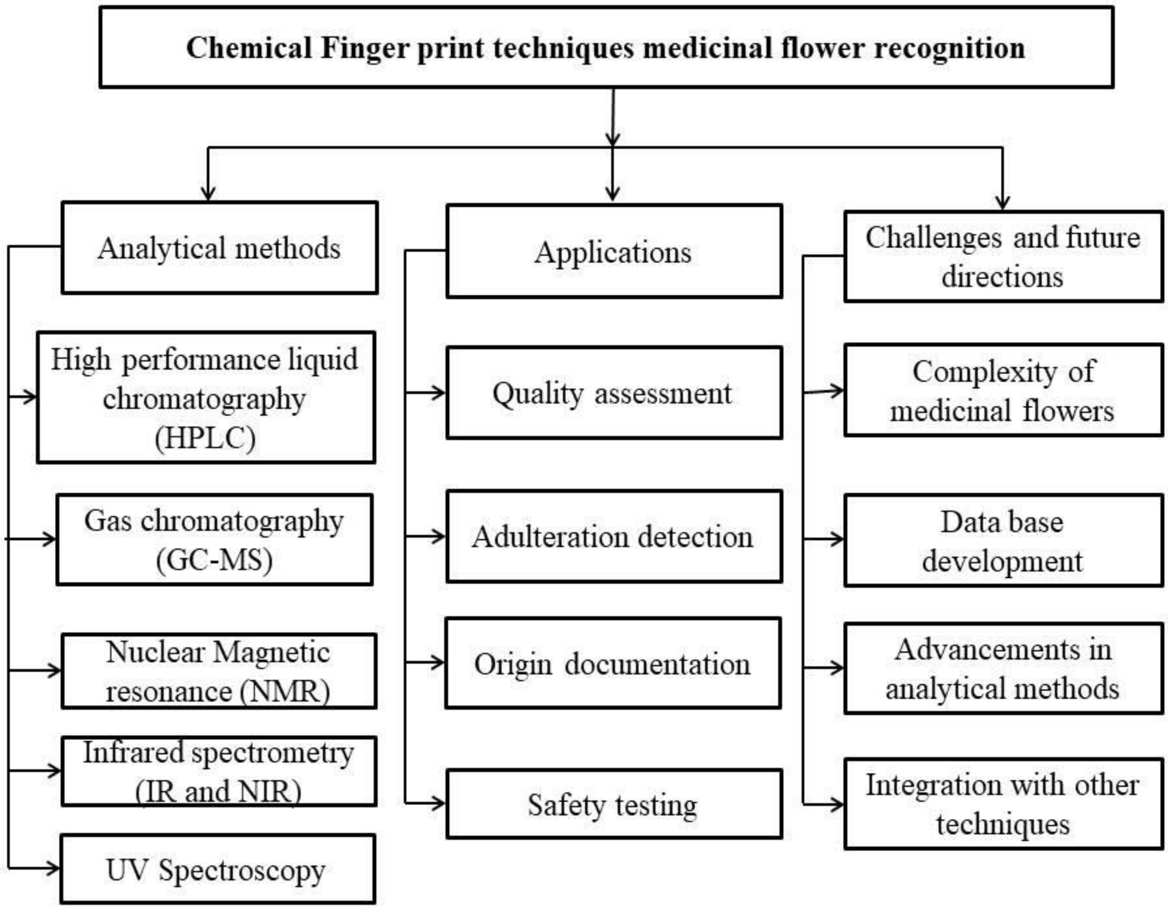

Figure 6. Chemical finger print prediction methods

Sophisticated analytical tools like HPLC, GE-MS can provide precise information about the specific chemical molecule present in a particular flower. Initially, spectral techniques like UV-Vis, IR and NMR are used to present the type of chemicals present in medicinal flower extracts. Combining chemical fingerprinting with other technologies, such as image analysis and DNA barcoding, can provide a more comprehensive approach to medicinal flower recognition. Figure 6 illustrated various chemical analytical tools used extract molecular features of medicinal flowers.

2.6.2. Chromatography

Chromatography is a versatile isolation and purification of compounds from complex plant materials with high precision and efficiency widely used technique for herbal extraction [34]. Various chromatographic techniques are employed for the extraction of herbal medicines here used some common chromatographic techniques for herbal extraction were liquid chromatography (HPLC) [35-37] gas chromatography (GC) coupled with mass spectroscopy [38, 39] thin-layer chromatography (TLC) [40-42], and capillary electrophoresis (CE) [43]. The acquisitions of fingerprint data for herbal medicine involved the utilization of various specific tools were also reported by various authors. Among these methods [19, 44, 45], LC hyphenated techniques stand out due to their broad applicability, exceptional resolution. A major advantage of liquid chromatography (LC) lies in its capacity to select arrays of detectors tailored to the physicochemical properties of specific target compounds [44, 46]. Furthermore, in numerous studies, researchers have investigated the utilization of multi-wavelength combinations in high-performance liquid chromatography with diode array detection (HPLC–DAD) [47], as well as the integration of data from complementary detectors, to extract additional information from complex biological samples [48, 50]. The use of hyphenated techniques for analysing volatile or semi-volatile organic constituents in herbal products has gained unanimous acceptance in the field [51, 52]. A proposed approach for obtaining a comprehensive chemical profile, encompassing both volatile and also non-volatile compounds, involves the integration of LC and GC metabolomics data through a chromatographic fingerprint method [53]. TLC and HPTLC analyses traditionally canteredon peak identification and intensity comparison without employing chemometric techniques, leaving them limited in achieving the comprehensive fingerprint analysis possible through chemometric methods [54]. Despite offering a promising level of resolution, 2D chromatography continues to grapple with unresolved issues [55, 56].

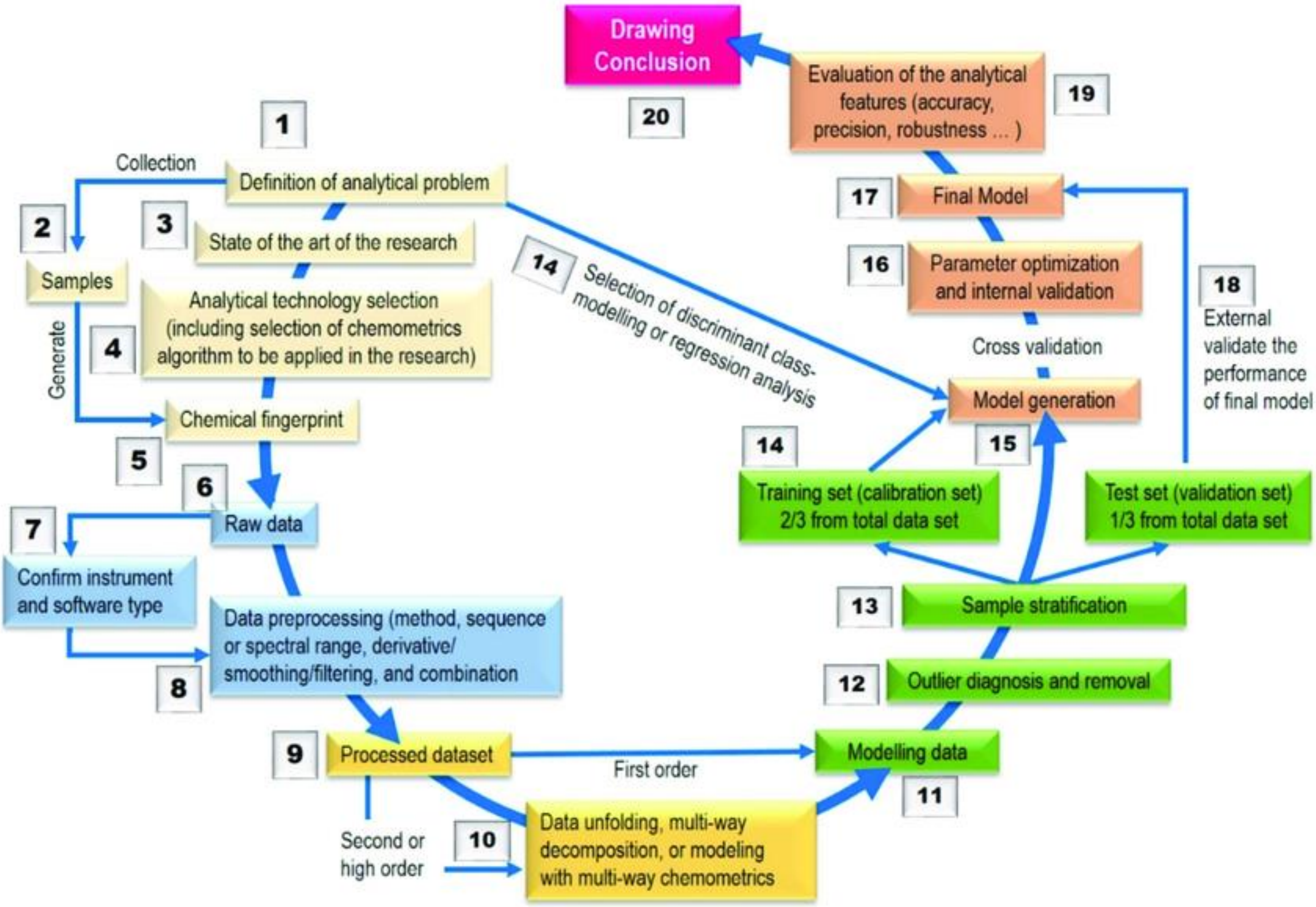

Figure 7. The typical analytical workflow of chemo metric methods [65]

In this context, chemometric techniques have evolved into mathematical approaches designed to untangle overlapping analyte peaks. Such methods, encompassing parallel factor analysis (PARAFAC) [56,57], PARAFAC2 [58] the generalized rank annihilation method (GRAM) [59] and multivariate curve resolution-alternating least squares (MCR-ALS) [55, 60] are employed to reveal concealed information and correct distorted data within second- or high-order chemical fingerprints [61, 62] The ultimate aim is to deliver precise results for both quantitative and qualitative analyses [63]. The chromatographic fingerprint can also find application in modeling the efficacy of the fingerprint, allowing for rapid screening of related active substances or quality control markers for herbal medicines [64]. The By using chemical fingerprint techniques, researchers and practitioners can gain valuable insights into the composition, quality, and authenticity of medicinal flowers, ensuring the safety and efficacy of traditional medicine practices see figure 7.

2.7. Training and Evaluation

2.7.1. Model Training

Split the pre-processed dataset into training and validation sets. Use the training data to train the AI model for the specific task, which may involve predicting chemical values or identifying medicinal properties. During this phase, the model should learn patterns and relationships within the data.

2.7.2. Model Evaluation

Evaluate the performance of the trained model using the validation set for apply its learned insights to new, unseen data, thereby confirming its accuracy and reliability of ML tool context of medicinal flower from images.

2.8 Machine Learning& Deep Learning Techniques

Jacklin *et al.* [66] aimed at identifying and categorizing plant diseases and additionally, research and comparative between the approaches of ML and DL. Pearline *et al.* [67-70] focused on plant identification, employing both DL methods and ML algorithms. They utilized conventional learning techniques to extract texture, shape, and colour features. These extracted features were then inputted into various ML algorithms, including Linear Discriminant Analysis (LDA), Logistic Regression (LR), K-Nearest Neighbour (KNN), Classification and Regression Tree (CART), and Random Forest (RF), for classification purposes. Zhu *et* *al.* [71] presented an innovative bidirectional attention model that effectively identifies plants within the Flower 102 dataset by used DL network model. This model achieved a remarkable recognition accuracy of 97.2%.Mei-Ling Huang *et al*. [72] employ a variety of machine learning and deep learning algorithms for tasks such as image segmentation and classification.

Munner and Fati *et al.* [73] recognized an automatic classification system for recognition Malaysian herbs. Through the extraction of shape and texture features from plant images and employing a DL model for classification, their system achieved remarkable performance metrics. Specifically, they attained an accuracy of 98%, precision of 93%, and sensitivity of 85%. Silky Sachar *et al.* [74] explored deep learning, a subset of Artificial Intelligence, and introduced an Ensemble learning approach for the swift identification of medicinal plants based on leaf images. The dataset comprises 30 classes of medicinal leaves. Transfer learning is employed to set the parameters in motion and pretrain three neural networks: MobileNetV2, InceptionV3, and ResNet50.

Sivaranjani.C *et al.* [75] presented a system able to recognize types of plants by relying on input leaf samples. To improve the extraction of vegetative information from the images, we employ an enhanced vegetation index known as ExedG-ExR. The classification of plant species is achieved by extracting color and texture features from individual leaves and utilizing a Logistic Regression classifier. System achieves an accuracy of 93.3% in accurately classifying the plant species.

Mohammed Brahimi *et al.* [76] proposed the adoption of a deep learning approach to construct a classifier for disease detection. The author also introduced the concept of occlusion to pinpoint disease regions and enhance disease comprehension. The datasets used by the author were published in reputable sources such as Goodfellow, Bengio, etc. Additional research is necessary to refine computational processes and minimize the dimensions of deep models, making them suitable for deployment on compact devices such as mobile phones. Akash M Bammannavar.*et al.* [77] presents medicinal plant identification using deep learning, specifically employing the Xception architecture from AI-based approach.

2.8.1 Global Average Pooling (GAP)

Azadnia, R. *et al.* [8], introduced an advanced vision-based system tailored for identifying medicinal herb plants. The system adopts an automated Convolutional Neural Network (CNN) architecture. The proposed Deep Learning model consists of two primary components: a CNN block for feature extraction from input images and a classifier block for categorizing these extracted features. The classifier block comprises several layers, including a Global Average Pooling (GAP) layer [78], a dense layer, a dropout layer, and a softmax layer.

2.8.2 Random Forest algorithm

Nayana G. Gavhaleet *et al.* [79] developed a technique to identify medicinal plants using the Random Forest algorithm, a supervised machine learning method. Their approach relies on analysing color, texture, and geometrical characteristics to accurately recognize different species of medicinal plants. Gogul I *et al.* [80] employed CNN as an attribute extractor, and when coupled with either a RF or LR classifier, it was harnessed to distinguish among different flower species. Adams Begue, Venitha Kowlessur *et al.* [81] utilized computer vision techniques to extract a diverse range of shape-based features from medicinal plant leaves. These features were then fed into machine learning algorithms to effectively categorize leaves from 24 distinct plant species. Among the classifiers tested, the random forest model demonstrated remarkable performance having an accuracy of 90.1%.

2.8.3 Support Vector Machine

Tan JW *et al.* [82] performed a classification task using the Support Vector Machine (SVM) layer positioned at the network's final stage. The study showcased that combining SVM with other techniques resulted in higher accuracy compared to using SVM alone, SVM combined with Auto-encoder, and the fusion of Convolutional Neural Network (CNN) with SVM. Consequently, they introduced an automated Identification Convolutional Neural Network (CNN) called D-Leaf.

Liu, Albert, and Yangming Huang *et al.* [83] devised a plant identification system utilizing CNN to extract bottleneck attributes known as CNN codes. Subsequently, SVM was employed for classification. However, this method is most effective for clean images featuring properly aligned Leaves set against a distinct backdrop, exhibiting limited differences in color or brightness.

Recent studies [84, 85] in radiomics have frequently relied on hand-crafted feature extraction methods, such as texture analysis, in conjunction with conventional machine learning classifiers like Random Forest (RF) and Support Vector Machines (SVMs). In contrast, various approaches are currently being utilized for the detection of plant diseases, with artificial neural networks (ANNs) and SVMs being prevalent methods according to H. Cartwright *et al.* [86] and Steinwart and Christmann, as well as Mokhtar *et al.* [87, 88]. Keyvan Asefpour Vakilian *et al.* [89] demonstrated the detection of two varieties of fungi present in the leaves of cucumber plants. An Artificial Neural Network (ANN) model with a three-layered approach was utilized to detect infections caused by Cubensis and Fuliginea.

Hiary *et al.* [90] suggested an autonomous system for detection and classification pertaining to plant disease. Pixels are grouped into a set of attributes and classified into k classes. When a leaf exhibits multiple diseases, multiple clusters are attributed to the respective diseases. An ANN is utilized for disease detection and classification. Additional research is necessary to improve the precision of disease detection.

2.8.4 Convolutional Neural Network (CNN)

Amuthalingeswaran *et al.* [91] effectively implemented a deep learning model for the recognition of medicinal plants. Researchers trained their method using a dataset consisting of 800 images representing four distinct types of medicinal plants. Remarkably, their model achieved an impressive 85% accuracy in identifying medicinal plants when deployed in real-world field conditions. Dey et al., and M. Oquab et al. [92, 93] employed diverse image processing techniques and protocols for extracting various structural features, complemented by convolutional neural networks (CNNs) for classification purposes. An illustrative example of such endeavours involves their utilization of color, texture, and shape features to effectively distinguish flowers. The prevalent trend among researchers involves the integration of image processing techniques for feature extraction, alongside CNNs for classification objectives

Schmidhuber *et al.* [94, 95] introduced a robust approach utilizing Convolutional Neural Networks (CNNs) for the recognition of distinct medicinal plants. Their methodology involves pre-processing, segmentation, hand-designed feature extraction, and classification. In a similar vein, Oppong *et al.* [96] employed Log-Gabor filters alongside advanced deep learning techniques, enabling CNNs to discern plants by analyzing their textural characteristics. Siraj *et al.* [97] discussed Neural Networks for flower classification and specifically created 'intelligent machines' capable of solving intricate tasks, including pattern recognition and classification.

Thi Thanh Nhan Nguyen *et al.* [98] utilized two primary approaches for plant recognition based on images of plant organs: hand-designed features and deep learning. For flower-based identification, several hand-crafted features, such as Kernel Descriptors (KDES), have been utilized. In the study conducted by Putri *et al.* [99], a Convolutional Neural Network approach was employed to achieve the identification of leaves derived from medicinal plants. Yamashita et al. [7] presented an overview of the fundamental concepts of CNN and explored their diverse applications in radiological tasks. Additionally, the challenges encountered were addressed and possible future avenues for CNN within the realm of radiology were outlined.

In their work [100], Reddy and colleagues presented a CNN architecture designed specifically for analyzing color images of leaves. The architecture consists of four convolutional layers, succeeded by two fully connected layers and a softmax layer. They attained impressive performance metrics, with accuracy, precision, and sensitivity reaching 97.6%, 93.4%, and 95.2%, respectively. Zhang *et al.* [101] introduced a 7-layer CNN model specifically designed for classifying 32 distinct plant species. By leveraging data augmentation (DA) techniques to enhance the dataset images, they achieved a noteworthy accuracy rate of 94.7% in plant identification.

2.8.5. Computer Vision Technology

Gittaly Dhingra *et al.* [102] investigate the utilization of computer vision technology in agriculture for the identification and classification of diseases that impact plant leaves.

3. Comparative Analysis of Existing Research

Table 1 provides a concise overview of research endeavours in the domains of Machine Learning, Deep Learning, Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Computer Vision Techniques (CV), Random Forest (RF) Classifier, and Global Average Pooling (GAP). It serves to consolidate and compare the significance of existing research pertaining to CNNs, particularly in the context of identifying plant species. CNNs represent a subset of deep learning models specifically tailored for processing grid-like data, such as images and videos.

3.1. Advantages of CNNs

1 Robust Feature Learning: CNNs autonomously learn relevant features from raw input data.

2 Spatial Hierarchy: capturing spatial hierarchies of features on multiple scales and resolutions

3 Efficient computation: CNNs have demonstrated outcomes across range of computer vision tasks, reduces the number of parameters.

3.2 Disadvantages of CNNs

1 Training requirements: CNN often requires large amounts of labeled data and computational resources.

2 Overfitting: Deep CNNs may exhibit a susceptibility to over fitting, particularly when trained on a limited dataset. Employing

regularization techniques is frequently necessary to address this concern.

3 Interpretability: CNNs are complex models, and understanding why they make certain decisions can be challenging, which can be a drawback in applications where interpretability is crucial.

According to the researcher, Table 1 points out to the importance of ML and DL. Researchers recommended finding out such kind of decision trees, SVMs, RF, KNN, and more. Deep learning models have the capability to autonomously learn data representations across layers, enabling them to capture complex patterns and hierarchical features. Common architectures in deep learning include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).

Table 1. Studies based on Convolutional Neural Network

Sl. No.	Researchers	Methods Employed	Observation and Limitations
1	Amuthalingeswaran *et al.* [91]	Deep Neural Network	Exhibited notably high classification accuracy when evaluated in real-time scenarios. Four distinct plant disease classes, limited dataset size, and lack of external validation.
2	Dey *et al.*, M. Oquab *et al.* [92, 93]	Image Processing Techniques combined with CNN	Raw images -a slight superiority over those obtained from pre-processed images. Future focus on enhancing CNN design and result fusion for better first rank accuracy. Shows significant gains in transfer learning from ImageNet, attaining state-of-the-art performance on smaller benchmarks by leveraging mid-level features, even with just a fraction of the dataset.
3	Jayalath, J. *et al*, Schmidhuber [94, 95]	Image processing and Machine Learning	Visual morphological characteristics, Leaves are categorized according to their unique feature combination. Reliance on artificial neural networks, potential dataset bias, and lack of exploration beyond CNN for rare medicinal plant identification.
4	Stephen Opoku Oppong *et al.* [96]	Log-Gabor filters, Deep Learning technique	A computer vision system employing CNNs and employing an ensemble approach incorporating Log-Gabor filters for the recognition of medicinal plants based on leaf textures. However, there is a deficiency in broader species representation, highlighting the potential for expansion into anatomical and chemo-taxonomical classification.
5	Fadzilah Siraj *et al.* [97]	Neural Network, Image processing, MATLAB	Utilize image processing to extract valuable information, low-level features thus improving Neural Network classification accuracy. Exploration in the context of evolving content-based image retrieval research.
6	Thi Thanh Nhan Nguyen *et al.* [98]	Deep Learning technique	Several hand-crafted features, such as Kernel Descriptors (KDES). Future focus on enhancing CNN design and result fusion for better first rank accuracy.
7	Yuanita A. Putri *et al.* [99]	Deep Learning, CNN	The development of a mobile-based application aimed at identifying and comprehending the diverse types and benefits of leaves derived from medicinal plants. It utilizes nearest value matching for classification purposes.

8	Rikiya Yamashita *et al.*[100]	Machine Learning, Deep Learning, CNN	The challenges faced and outlines prospective avenues for CNNs in the realm of radiology
9	Reddy *et al.* [101]	image processing and pattern recognition techniques ,machine learning	An optimized CNN model consists of four convolutional layers, succeeded by two fully connected layers and a softmax layer.
10	Zhang *et al.* [102]	data augmentation (DA) technique, ConvNet-based deep learning algorithm	Data augmentation is utilized to alleviate the degree of overfitting demonstrated by the model.
11	Meiling Huang *et al.* [6]	CNN, Bayesian optimization with ResNet-101 and SENet	The proposed ResNet101 model provides a better solution on the image classification of Chinese medical flowers with favourable accuracy.
11	Priyadarshini Pradhan *et al.* [103]	CNN, deep learning, watershed-processed dataset	Dead zone detection image processing was done effectively. This detects diseases in marigold flowers, hence assisting the marigold crop cultivation industry. It has validation accuracy of 88.03% and a testing accuracy of 91.67%.
12	Imania Ayu *Anjani et al* [104]	CNN	It was used to classify some rose verities with accuracy of 96.33%.
13	Ming Tian *et al*.[105]	Deep learning, YOLOv5	Object recognition system based on flower image classification.
14	Mastura Hanafiah *et al.* [106]	CNN and transfer learning	The reported model however couldn't resolve inter-class similarities and intra-class differences completly.
15	Asmita Shukla *et al.* [107]	Machine learning (K-nearest neighbors, neural networks, logistic regression, and support vector machines)	Neural Network and Logistic Regression both achieved 96.67% accuracy and the SVM got even higher accuracy.
16	Jong Yoon Lim *et al.* [108]	Single Shot Detector (SSD), and Faster R-CNN	Faster R-CNN NAS model achieved the maximum precision.
17	Isha Patel *et al*. [109]	pre-trained models	The 30-class dataset achieves a mAP score of 96.2%, the NAS-FPN with Faster R-CNN model, which contains transfer learning, performs inadequately on the 102-class flowers dataset, receiving a mAP score of 87.6%.
18	Rumeysa Mete *et al.* [110]	Deep CNN	Feature extraction and classification is discussed in the work
19	Isha Patel *et al.* [111]	lightweight CNN architecture, computer vision and machine learning	Multi-label classification is primarily used as the classification algorithm which achieved an accuracy of 76.92%.
20	Hazem Hiary *et al.* [112]	FCN framework, CNN	This shows a classification accuracy of 99.0% on the Zou-Nagy dataset, 98.5% on the Oxford 17 dataset, and 97.1% on the Oxford 102 dataset.

3.3 Comparative Analysis of Existing research related to Machine Learning and Deep Learning

Machine learning encompasses a wide spectrum of algorithms, incorporating traditional statistical methods, whereas deep learning specifically targets deep neural networks. Each approach has its own set of merits and drawbacks, and the selection between them is contingent upon the particular problem at hand, the data available, and the computational resources accessible. Deep learning excels in tasks involving unstructured data and has achieved ground breaking results in recent years but requires substantial data and computational power. Machine learning is more interpretable and versatile but may require more feature engineering and domain expertise. Table 2 lists the studies employed machine learning and deep learning algorithms specifically utilized to identify medicinal plants.

Table 2. Studies employed machine learning and deep learning in plant parts identification

Sl. No.	Researchers	Methods Employed	Observation and Limitations
1	C Jackulin.*et al.* [65]	NB classifier, MLP classifier ,RF classifier, SVM classifier, KNN classifier, (CNN),Inception–V4,VGG –19, VGG–16	Develop efficient strategies for the successful detection of plant diseases. The comparative analysis is conducted, focusing on a comparison between ML and DL techniques.
2	Anubha Pearline, Sunil S. Harakannanavara, K.P. Panigrahi, M.D. Zeiler *et al.* [66, 67-69]	The Random Forest (RF) algorithm is utilized alongside VGG16.	The Random Forest (RF) algorithm achieving a precision employed the VGG16 network from the realm of deep learning achieving an impressive accuracy in identifying plants.
3	Zhu *et al.* [71]	Convolutional Neural Network	Two-way attention model-recognize the plants family.
4	Mei-Ling Huang *et al.* [72]	AlexNet, InceptionV3 image segmentation and image classification	Lack of accurate visual differentiation between similar flower shapes/colors; absence of a dataset for Chinese medicinal blossoms.
5	Munner and Fati *et al.* [73]	GLCM technique, support vector machine, deep neural networks	Comparing the accuracy of DLNN and SVM algorithms, addressing limitations in mobile app development, and enhancing shape feature extraction techniques for improved accuracy.
6	Silky Sachar *et al.*[74]	MobileNetV2, InceptionV3, and ResNet50.	State-of-the-art pre-trained models and achieving high accuracy, potentially missing other useful identification features present in different plant parts.
7	Sivaranjani.C *et al*.[75]	Logistic Regression classifier	ExG-ExR vegetation index used to identifies leaves, achieving accurate plant region segmentation and classification with a Logistic Regression classifier.
8	Mohammed Brahimi *et al.*[76]	Convolutional Neural Network	Outperforming shallow models and offering practical benefits for agricultural disease protection. Potential challenges in disease region interpretation using occlusion techniques.
9	Azadnia.R.*et al*.[7]	Global Average Pooling (GAP) layer, dense layer, a dropout layer, and a softmaxlayer,CNN	The process involves extracting features and a classifier component that then categorizes these extracted features.
10	Gittaly Dhingra *et al.*[102]	computer vision technology	Identify and categorize diseases impacting plant leaves, unpredictability of manual inspection.
11	Banwaskar *et al.* [113]	ResNet 50 and AlexNet Multiclass SVM	The classification concludes with an accuracy rate of 95.3% and 92.1% on the associated datasets

3.4 Comparative Analysis of Existing Research Related to Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm employed for classification and regression tasks. SVM endeavours to maximize the margin between the categories, thereby establishing a distinct boundary between them. The SVM is a robust machine learning algorithm renowned for its capacity to manage high-dimensional data, mitigate overfitting, and accommodate non-linear patterns through the utilization of kernel functions. Table 3 lists few studies particularly employed SVM algorithm in identifying medicinal flowers.

3.5 Comparative Analysis of Existing Research Related to Random Forest

Random Forest (RF) is an ensemble learning algorithm employed for multiple other machine-learning tasks classification and regression. It includes Bagging (Bootstrap aggregating). RF is powerful and versatile ensemble learning technique known its high accuracy and handling missing value dealing with noisy data, less interpretable. Some studies dealt with identification of medicinal plants by RF algorithm are listed in Table 4.

Table 3. Studies based on Support Vector Machine (SVM)

Sl. No.	Researchers	Methods Employed	Observation and Limitations
1	Tan JW *et al.* [82]	Support Vector Machine (SVM), Artificial Neural Network (ANN), k-Nearest-Neighbor (k-NN), Naïve-Bayes (NB), and CNN.	D-Leaf CNN-based method demonstrated, outperforming traditional morphometric measurements and achieving comparative results to pre-trained and fine-tuned AlexNet models for plant species identification
2	Liu, Albert, and Yangming Huang *et al*. [83]	CNN,SVM	Handcrafted and deep ConvNets features to address the fine-grained challenges of subtle species differences and limited training data.
3	Aerts HJ, Lambin P [84, 85]	Random Forest algorithm and SVM,ANN	Detecting plant diseases effectively with reasonable accuracy.
4	Keyvan Asefpour Vakilian *et al*.[89]	Artificial Neural Network (ANN), Image processing	Detection of two types of fungus achieved.
5	H. Al-Hiary *et al.* [90]	Artificial Neural Network (ANN), Image processing	Proposed algorithm enhances automatic plant leaf disease detection and classification.

Table 4. Studies based on Random Forest algorithm in identifications of medicinal plants

Sl. No.	Researchers	Methods Employed	Observation and Limitations
1	Gogul I *et al.* [80]	Machine Learning Classifier, Deep Learning Approach (CNN),Transfer Learning approach,	CNN with Transfer Learning outperforms handcrafted features, achieving high accuracy in recognizing flower species Generalization to various environments and species could be a challenge.
2	Adams Begue, Venitha Kowlessur *et al*. [81]	Machine Learning Classifier	Extract various shape-based features.
3	Nayana G. Gavhale *et al*. [79]	Random forest algorithm supervised machine learning algorithm	Medicinal plant identification based on color, texture, and geometrical features, potential challenges in handling more diverse plant species identification.

4. Discussion

Artificial Intelligence (AI) can play a major role in finding the medicinal flowers and in analyzing their properties and chemical composition. AI has the potential to automate the process of identifying various types of flowers, even among vivid backgrounds and conditions. This technique facilitates the researchers and practitioners to recognize the medicinal plants accurately, which loads to better and enhanced botanical studies and conservation efforts. Firstly, AI gathers the data and various information from different sources, collecting images of medicinal flowers from data bases, botanical gardens and user- contributed platforms are the major steps involved. Next, taxonomic classifications and geographical allocation, is collected from botanical sources and experts in the field. In addition, traditional knowledge and ethnobotanical data, containing historical texts and native practices are also added.

From research articles, chemical sources and analytical studies, focusing the identification and measurement of bioactive molecules present in medicinal flowers. We can get the chemical compositions of different medicinal plants.AI also accumulates the clinical studies and scientific literature exploring the medicinal features and possible therapeutic uses of these flowers. By considering all the accumulated data, AI provides a wholesome knowledge base that helps the recognition of medicinal flowers, analysis of their properties and evaluation of their chemical values. This database becomes a reliable resources for researches, healthcare professionals and experts seeking valuable information on various medicinal flowers and their possible applications. Even though AI plays a very big role, it should be always remembered that it should only complement human expertise rather than replacing professional advice. The choice of classifier depends on several factors, including the complexity of the dataset, available computational resources, and the desired level of interpretability. In many cases, a combination of CNNs and traditional machine learning methods can provide the best results.

5. Conclusion and Future Work

Artificial intelligence plays an efficient role in object recognition, including flowers of plants with medicinal values. With around 369,000 known species of flowering plants are interesting subject for AI research. By leveraging advanced algorithms, especially deep learning techniques, AI systems can accurately recognize and classify various medicinal flowers based on their visual characteristics. This technology offers significant advantages over traditional methods, which often require expert botanical knowledge and can be time-consuming. AI model can learn complex patterns and features of flowers leads more accuracy, efficiency, accessibility and it helps preserving biodiversity. This field offers a plethora of possibilities in future. The image recognition algorithms may be improved which enhances the accuracy of flower recognition and can provide a more in depth understanding of medicinal flower properties. The flower date base will be enhanced with exact chemical composition of flower is use full in predicting accurate flower for particular disease. Herbal medicine can be made more accessible through real time identification mobile applications. At last, collaboration of data among the experts and organizations can improve the databases and enhance knowledge exchange. This comparative study demonstrates the effectiveness of CNNs, machine learning algorithms, and Random Forest for medicinal flower recognition. CNNs have shown superior performance in general, but traditional methods can also be effective, especially when combined with careful feature engineering. The choice of classifier should be based on the specific requirements of the application and the available resources.

References

[1] A. Altemimi, N. Lakhssassi, A. Baharlouei, D.G. Watson, D.A. Lightfoot, Phytochemicals: Extraction, isolation, and identification of bioactive compounds from plant extracts. Plants, 6(4), (2017) 42. https://doi.org/10.3390/plants6040042

[2] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, D. Stefanovic, Deep neural networks based recognition of plant diseases by leaf image classification. Computational intelligence and neuroscience, 2016(1), (2016) 3289801. https://doi.org/10.1155/2016/3289801

[3] V. Singh, A.K. Misra, Detection of plant leaf diseases using image segmentation and soft computing techniques. Information processing in Agriculture, 4(1), (2017) 41-49. https://doi.org/10.1016/j.inpa.2016.10.005

[4] J. Waldchen, P. Mader, Plant species identification using computer vision techniques: a systematic literature review. Archives of computational methods in engineering, 25, (2018) 507-543. https://doi.org/10.1007/s11831-016-9206-z

[5] U. Anand, N. Jacobo-Herrera, A. Altemimi, N. Lakhssassi, A comprehensive review on medicinal plants as antimicrobial therapeutics: potential avenues of biocompatible drug discovery. Metabolites, 9(11), (2019) 258. https://doi.org/10.3390/metabo9110258

[6] M. Huang, Y. Xu, Image classification of Chinese medicinal flowers based on convolutional neural network. Mathematical Biosciences and Engineering: MBE, 20(8), (2023) 14978-14994. https://doi.org/10.3934/mbe.2023671

[7] R. Yamashita, M. Nishio, R.K.G. Do, K. Togashi, Convolutional neural networks: an overview and application in radiology. Insights into imaging, 9, (2018) 611-629. https://doi.org/10.1007/s13244-018-0639-9

[8] R. Azadnia, M.M. Al-Amidi, H. Mohammadi, M.A. Cifci, A. Daryab, E. Cavallo, An AI based approach for medicinal plant identification using deep CNN based on global average pooling. Agronomy, 12(11), (2022) 2723. https://doi.org/10.3390/agronomy12112723

[9] R. Azadnia, A. Jahanbakhshi, S. Rashidi, P. Bazyar, Developing an automated monitoring system for fast and accurate prediction of soil texture using an image-based deep learning network and machine vision system. Measurement, 190, (2022) 110669. https://doi.org/10.1016/j.measurement.2021.110669

[10] O.E. Apolo-Apolo, M. Pérez-Ruiz, J. Martinez-Guanter, J. Valente, A cloud-based environment for generating yield estimation maps from apple orchards using UAV imagery and a deep learning technique. Frontiers in plant science, 11, (2020) 1086. https://doi.org/10.3389/fpls.2020.01086

[11] K.P. Ferentinos, Deep learning models for plant disease detection and diagnosis. Computers and electronics in agriculture, 145, (2018) 311-318. https://doi.org/10.1016/j.compag.2018.01.009

[12] P. Ziyaee, V. Farzand Ahmadi, P. Bazyar, E. Cavallo, Comparison of different image processing methods for segregation of peanut (Arachis hypogaea L.) seeds infected by aflatoxin-producing fungi. Agronomy, 11(5), (2021) 873. https://doi.org/10.3390/agronomy11050873

[13] E. Amenu, (2007) Use and management of medicinal plants by indigenous people of Ejaji area (Chelya Woreda) West Shoa, Addis Ababa, Ethiopia.

[14] R. Hu, C. Lin, W. Xu, Y. Liu, C. Long, Ethnobotanical study on medicinal plants used by Mulam people in Guangxi, China. Journal of ethnobiology and ethnomedicine, 16, (2020) 1-50. https://doi.org/10.1186/s13002-020-00387-z

[15] G. Crini, E. Lichtfouse, G. Chanet, N. Morin-Crini, Applications of hemp in textiles, paper industry, insulation and building materials, horticulture, animal nutrition, food and beverages, nutraceuticals, cosmetics and hygiene, medicine, agrochemistry, energy production and environment: A review. Environmental Chemistry Letters, 18(5), (2020) 1451-1476. https://doi.org/10.1007/s10311-020-01029-2

[16] S.F. Nabavi, A. Di Lorenzo, M. Izadi, E. Sobarzo-Sánchez, M. Daglia, S.M. Nabavi, Antibacterial effects of cinnamon: From farm to food, cosmetic and pharmaceutical industries. Nutrients, 7(9), (2015) 7729-7748. https://doi.org/10.3390/nu7095359

[17] M. Grzeszczuk, A. Stefaniak, E. Meller, G. Wysocka, Mineral composition of some edible flowers. Journal of Elementology, 23(1), (2018). https://doi.org/10.5601/jelem.2017.22.2.1352

[18] O. Rop, J. Mlcek, T. Jurikova, J. Neugebauerova, J. Vabkova, Edible flowers - a new promising source of mineral elements in human nutrition. Molecules, 17(6), (2012) 6672–6683. https://doi.org/10.3390/molecules17066672

[19] C. Tistaert, B. Dejaegher, Y.V. Heyden, Chromatographic separation techniques and data handling methods for herbal fingerprints: a review. Analytica Chimica Acta, 690(2), (2011) 148–161. https://doi.org/10.1016/j.aca.2011.02.023

[20] A.M. Gómez-Caravaca, R.M.Maggio, L. Cerretani, Chemometric applications to assess quality and critical parameters of virgin and extra-virgin olive oil. A review. Analytica Chimica Acta, 913, (2016) 1–21. https://doi.org/10.1016/j.aca.2016.01.025

[21] Y.P. Huang, Z.W. Wu, R.H. Su, G.H. Ruan, F.Y. Du, G.K. Li, Current application of chemometrics in traditional Chinese herbal medicine research. Journal of Chromatography B, 1026, (2016) 27–35. https://doi.org/10.1016/j.jchromb.2015.12.050

[22] P. Kumari, Ujala, B. Bhargava, Phytochemicals from edible flowers: opening a new arena for healthy lifestyle. Journal of Functional Foods, 78, (2021) 104375. https://doi.org/10.1016/j.jff.2021.104375

[23] R. Azadnia, K. Kheiralipour, Recognition of leaves of different medicinal plant species using a robust image processing algorithm and artificial neural networks classifier. Journal of Applied Research on Medicinal and Aromatic Plants, 25, (2021) 100327. https://doi.org/10.1016/j.jarmap.2021.100327

[24] H.J. Vala, A. Baxi, A review on Otsu image segmentation algorithm. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2(2), (2013) 387-389. https://doi.org/10.4028/www.scientific.net/AMR.989-994.1959

[25] A. Jahanbakhshi, M. Momeny, M. Mahmoudi, Y.D. Zhang, Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks. Scientia Horticulturae, 263, (2020) 109133. https://doi.org/10.1016/j.scienta.2019.109133

[26] R.C. Gonzalez, R.E. Woods, (2007) Digital image processing. Pearson Prentice-Hall Inc, New Jersey.

[27] F.S. Santana, A.H.R. Costa, F.S. Truzzi, F.L. Silva, S.L. Santos, T.M. Francoy, A.M. Saraiva, A

reference process for automating bee species identification based on wing images and digital image processing. Ecological informatics, 24, (2014) 248-260. https://doi.org/10.1016/j.ecoinf.2013.12.001

[28] A. Jumi, A. Zaenuddin, T. Mulyono, N. Hayati, Content based Image Retrieval To Identify Medicinal Plants using Shape and Color Features. International Journal of Engineering Research & Technology (IJERT), 10(12), (2021).

[29] O.A. Malik, N. Ismail, B.R. Hussein, U. Yahya, Automated real-time identification of medicinal plants species in natural environment using deep learning models—a case study from Borneo Region. Plants, 11(15), (2022)1952. https://doi.org/10.3390/plants

[30] B. Jahagirdar, D. Munot, N. Belhekar, K. Rajeswari, Identification of Indian Medicinal leaves using Convolutional Neural Networks. International Research Journal of Engineering and Technology, 8(11), (2021) 1503-1507.

[31] T.N. Quoc, V.T. Hoang, (2020) Medicinal Plant identification in the wild by using CNN. International Conference on Information and Communication Technology Convergence (ICTC), IEEE, Korea (South). https://doi.org/10.1109/ICTC49870.2020.9289480

[32] T.D. Dahigaonkar, R. Kalyane, Identification of ayurvedic medicinal plants by image processing of leaf samples. International Research Journal of Engineering and Technology (IRJET), 5(5), (2018) 351-355.

[33] G. Priyanga, A. Aravindh, K.I. Ashwin, V. Gnana Shekar, M. Manjunathan, Automated identification of medicinal plants using machine learning. International Journal of Creative Research Thoughts (IJCRT), 12(3), (2024).

[34] Y.Z. Liang, P. Xie, K. Chan, Quality control of herbal medicines. Journal of chromatography B, 812(1-2), (2004) 53-70. https://doi.org/10.1016/j.jchromb.2004.08.041

[35] D.D. Wanga, J. Liangb, W.Z. Yanga, J.J. Houa, M. Yanga, J. Daa, Y. Wang, B.H. Jianga, X. Liua, W.Y. Wua, D.A. Guoa, HPLC/qTOF-MS-oriented characteristic components data set and chemometric analysis for the holistic quality control of complex TCM preparations: NiuhuangShangqing pill as an example. Journal of Pharmaceutical and Biomedical Analysis, 89 (2014) 130–141. https://doi.org/10.1016/j.jpba.2013.10.042

[36] Y. Chen, W. Bicker, J. Wu, M.Y. Xie, W. Lindner, Ganoderma species discrimination by dual-mode chromatographic fingerprinting: A study on stationary phase effects in hydrophilic interaction chromatography and reduction of sample misclassification rate by additional use of reversed-phase chromatography. Journal of Chromatography A, 1217(8), (2010) 1255-1265. https://doi.org/10.1016/j.chroma.2009.12.024

[37] N.W. Zhang, D.I.N.G. Ming-Xing, L.I.U. Guo-Yan, S.O.N.G. Wei-Wei, C.H.A.I. Chun-Yan, Molecularly imprinted membrane-based sensor for the detection of chloramphenicol succinate residue in milk. Chinese Journal of Analytical Chemistry, 36(10), (2008) 1380-1384. https://doi.org/10.1016/S1872-2040(08)60074-2

[38] W. Liu, B. Zhang, Z. Xin, D. Ren, L. Yi, GC-MS fingerprinting combined with chemometric methods reveals key bioactive components in Acori tatarinowii rhizoma. International Journal of Molecular Sciences, 18(7), (2017) 1342. https://doi.org/10.3390/ijms18071342

[39] X.D. Liu, D.H. Yan, X.M. Deng, B. Zhao, X.Y. Xue, S.M. Wang, Y. Zhang, J. Men, Quality assessment of crude and processed LeonuriFructus by chemical and color analysis combined with chemometric method. Chinese Herbal Medicines, 10(4), (2018) 388-395. https://doi.org/10.1016/j.chmed.2018.07.006

[40] H. Sereshti, Z. Poursorkh, G. Aliakbarzadeh, S. Zarre, S. Ataolahi, An image analysis of TLC patterns for quality control of saffron based on soil salinity effect: A strategy for data (pre)-processing. Food chemistry, 239, (2018) 831-839. https://doi.org/10.1016/j.foodchem.2017.07.012

[41] T.X. Tang, W.Y. Guo, Y. Xu, S.M. Zhang, X.J. Xu, D.M. Wang, Z.M. Zhao, L.P. Zhua, D.P. Yanga, Thin-layer Chromatographic Identification of Chinese Propolis Using Chemometric Finger printing. Phytochemical Analysis, 25(3), (2014) 266-272.

[42] D. Zhu, D. Tan, Y.M. Xie, A.M. Wang, S.Y. Chen, Y.Y. Lan, Fingerprint analysis for TLC of GastrodiaeRhizoma from different habitats, Chinese Journal of Experimental Traditional Medical Formulae, 21, (2015) 75–78.

[43] X.Q. Zha, J.P. Luo, P. Wei, Identification and classification of Dendrobiumcandidum species by fingerprint technology with capillary electrophoresis. South African Journal of Botany, 75(2), (2009) 276–282. https://doi.org/10.1016/j.sajb.2009.02.002

[44] Y. Jiang, B. David, P.F. Tu, Y. Barbin, Recent analytical approaches in quality control of traditional Chinese medicines—a review. Analytica Chimica Acta, 657(1), (2010) 9–18. https://doi.org/10.1016/j.aca.2009.10.024

[45] Q.Y. Zhang, M. Ye, Chemical analysis of the Chinese herbal medicine Gan-Cao (licorice). Journal of Chromatography A, 1216(11), (2009) 1954–1969. https://doi.org/10.1016/j.chroma.2008.07.072

[46] M. Swartz, HPLC detectors: a brief review. Journal of Liquid Chromatography & Related

Technologies, 33(9-12), (2010) 1130–1150. https://doi.org/10.1080/10826076.2010.484356

[47] M. Shi, G.X. Sun, Integrated evaluation of HPLC and UV fingerprints for the quality control of Danshen tablet by systematic quantified fingerprint method combined with antioxidant activity. Journal of Separation Science, 40, (2017) 1942–1952. https://doi.org/10.1002/jssc.201601330

[48] M. Sajewicz, D. Staszek, Ł. Wojtal, T. Kowalska, M. Hajnos, M. Waksmundzka-Hajnos, Binary HPLC-diode array detector and HPLC-evaporative light-scattering detector fingerprints of methanol extracts from the selected sage (Salvia) species. Journal of AOAC International, 94, (2011) 71–76. https://doi.org/10.1093/jaoac/94.1.71

[49] A. Bajoub, S. Medina-Rodríguez, M. Gómez-Romero, E.A. Ajal, M.G. Bagur-González, A. Fernández-Gutiérrez, A. Carrasco-Pancorbo, Assessing the varietal origin of extra-virgin olive oil using liquid chromatography fingerprints of phenolic compound, data fusion and chemometrics. Food Chemistry, 215, (2017) 245–255. https://doi.org/10.1016/j.foodchem.2016.07.140

[50] K.A. Obisesan, A.M. Jiménez-Carvelo, L. Cuadros-Rodriguez, I. Ruisánchez, M.P. Callao, HPLC-UV and HPLC-CAD chromatographic data fusion for the authentication of the geographical origin of palm oil, Talanta. 170, (2017) 413–418. https://doi.org/10.1016/j.talanta.2017.04.035

[51] X.P. Chen, W. Li, X.F. Xiao, L.L. Zhang, C.X. Liu, Phytochemical and pharmacological studies on Radix Angelica sinensis. Chinese Journal of Natural Medicines, 11(6), (2013) 577–587. https://doi.org/10.1016/S1875-5364(13)60067-9

[52] J.J. Lu, Y.Y. Dang, M. Huang, W.S. Xu, X.P. Chen, Y.T. Wang, Anti-cancer properties of terpenoids isolated from RhizomaCurcumae – a review. Journal of Ethnopharmacol, 143(2), (2012) 406–411. https://doi.org/10.1016/j.jep.2012.07.009

[53] Y. Ni, M. Mei, S. Kokot. One- and two-dimensional gas chromatography–mass spectrometry and high performance liquid chromatography–diode-array detector fingerprints of complex substances: a comparison of classification performance of similar, complex RhizomaCurcumae samples with the aid of chemometrics. Analytica Chimica Acta, 712, (2012) 37–44. https://doi.org/10.1016/j.aca.2011.11.010

[54] Ł. Komsta, Chemometrics in fingerprinting by means of thin layer chromatography. Chromatography Research International, 2012, (2012), 893246. https://doi.org/10.1155/2012/893246

[55] M. Navarro-Reig, J. Jaumot, T.A. van Beek, G. Vivó-Truyols, R. Tauler, Chemometric analysis of comprehensive LC×LC-MS data: resolution of triacylglycerol structural isomers in corn oil. Talanta, 160, (2016) 624–635. https://doi.org/10.1016/j.talanta.2016.08.005

[56] R.C. Allen, S.C. Rutan, Semi-automated alignment and quantification of peaks using parallel factor analysis for comprehensive two-dimensional liquid chromatography–diode array detector data sets. Analytica Chimica Acta, 723, (2012) 7–17. https://doi.org/10.1016/j.aca.2012.02.019

[57] B. Schmidt, J.W. Jaroszewski, R. Bro, M. Witt, Combining PARAFAC analysis of HPLC-PDA profiles and structural characterization using HPLC-PDA-SPE-NMR-MS experiments: commercial preparations of St. John's wort. Analytical Chemistry, 80(6), (2008) 1978–1987. https://doi.org/10.1021/ac702064p

[58] K.D. Tian, L.J. Wu, S.G. Min, R. Bro, Geometric search: a new approach for fitting PARAFAC2 models on GC-MS data, Talanta, 185, (2018) 378–386. https://doi.org/10.1016/j.talanta.2018.03.088

[59] C.G. Fraga, B.J. Prazen, R.E. Synovec, Objective data alignment and chemometric analysis of comprehensive two-dimensional separations with run-to-run peak shifting on both dimensions. Analytical Chemistry, 73(24), (2001) 5833–5840. https://doi.org/10.1021/ac010656q

[60] H. Parastar, J.R. Radovi´c, M. Jalali-Heravi, S. Diez, J.M. Bayona, R. Tauler, Resolution and quantification of complex mixtures of polycyclic aromatic hydrocarbons in heavy fuel oil sample by means of GC× GC-TOFMS combined to multivariate curve resolution. Analytical Chemistry, 83(24), (2011) 9289–9297. https://doi.org/10.1021/ac201799r

[61] M. He, Z.Y. Yang, T.B. Yang, Y. Ye, J. Nie, Y. Hu, P. Yan, Chemometrics-enhanced one-dimensional/comprehensive two-dimensional gas chromatographic analysis for bioactive terpenoids and phthalides in ChaihuShugan San essential oils. Journal of Chromatography B, 1052, (2017) 158–168. https://doi.org/10.1016/j.jchromb.2017.03.029

[62] H.C. Goicoechea, M.J. Culzoni, M.D.G. García, M.M. Galera, Chemometric strategies for enhancing the chromatographic methodologies with second-order data analysis of compounds when peaks are overlapped. Talanta, 83(4), (2011) 1098–1107. https://doi.org/10.1016/j.talanta.2010.07.057

[63] K.M. Pierce, J.C. Hoggard, R.E. Mohler, R.E. Synovec, Recent advancements in comprehensive two-dimensional separations with chemometrics. Journal of Chromatography A, 1184(1-2), (2008) 341–352. https://doi.org/10.1016/j.chroma.2007.07.059

[64] C. Zhang, X. Zheng, H. Ni, P. Li, H.J. Li, Discovery of quality control markers from traditional Chinese medicines by fingerprint-efficacy modeling: current status and future perspectives. Journal of Pharmaceutical and Biomedical Analysis, 159, (2018) 296–304. https://doi.org/10.1016/j.jpba.2018.07.006

[65] Y. Li, Y. Shen, C.L. Yao, D.A. Guo, Quality assessment of herbal medicines based on chemical fingerprints combined with chemometrics approach: A review. Journal of Pharmaceutical and Biomedical Analysis, 185, (2020) 113215. https://doi.org/10.1016/j.jpba.2020.113215

[66] C Jackulin, S. Murugavalli, A comprehensive review on detection of plant disease using machine learning and deep learning approaches. Measurement: Sensors, 24, (2022) 100441. https://doi.org/10.1016/j.measen.2022.100441

[67] S. Anubha Pearline, V. Sathiesh Kumar, S. Harini, A study on plant recognition using conventional image processing and deep learning approaches. Journal of Intelligent & Fuzzy Systems, 36(3), (2019) 1997-2004. https://doi.org/10.3233/JIFS-169911

[68] S.S. Harakannanavar, J.M. Rudagi, V.I. Puranikmath, A. Siddiqua, R. Pramodhini, Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), (2022) 305-310. https://doi.org/10.1016/j.gltp.2022.03.016

[69] K.P. Panigrahi, H. Das, A.K. Sahoo, S.C. Moharana, (2020) Maize leaf disease detection and classification using machine learning algorithms. Progress in Computing, Analytics and Networking, Advances in Intelligent Systems and Computing, Springer, Singapore. https://doi.org/10.1007/978-981-15-2414-1_66

[70] M.D. Zeiler, R. Fergus, (2014) Visualizing and understanding convolutional networks. Computer Vision–ECCV, Springer. https://doi.org/10.1007/978-3-319-10590-1_53

[71] Y. Zhu, W. Sun, X. Cao, C. Wang, D. Wu, Y. Yang, N. Ye, TA-CNN: Two-way attention models in deep convolutional neural network for plant recognition. Neurocomputing, 365, (2019) 191-200. https://doi.org/10.1016/j.neucom.2019.07.016

[72] M.L. Huang, Y.X. Xu, Y.C. Liao, Image dataset on the Chinese medicinal blossoms for classification through convolutional neural network. Data in Brief, 39, (2021) 107655. https://doi.org/10.1016/j.dib.2021.107655

[73] A. Muneer, S.M. Fati, Efficient and automated herbs classification approach based on shape and texture features using deep learning. IEEE Access, 8, (2020) 196747-196764. https://doi.org/10.1109/ACCESS.2020.3034033

[74] S. Sachar, A. Kumar, Deep ensemble learning for automatic medicinal leaf identification. International Journal of Information Technology, 14(6), (2022) 3089-3097. https://doi.org/10.1007/s41870-022-01055-z

[75] C. Sivaranjani, L. Kalinathan, R. Amutha, R.S. Kathavarayan, K.J. Kumar, (2019) Real-time identification of medicinal plants using machine learning techniques. In 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), IEEE, India. https://doi.org/10.1109/ICCIDS.2019.8862126

[76] M. Brahimi, K. Boukhalfa, A. Moussaoui, Deep learning for tomato diseases: classification and symptoms visualization. Applied Artificial Intelligence, 31(4), (2017) 299-315. https://doi.org/10.1080/08839514.2017.1315516

[77] A.M. Bammannavar, Y. Meenakshi, M. Rashid, (2024) Medicinal Herbs Identification Using Deep Learning. Convergence of Machine Learning and IoT for Enabling the Future of Intelligent Systems, 24–35. https://doi.org/10.48001/978-81-966500-7-0-3

[78] M. Lin, Q. Chen, S. Yan, (2018) Network in network. arXiv.

[79] N.G. Gavhale, A.P. Thakare, Identification of medicinal plant using Machine learning approach. International Research Journal of Engineering and Technology (IRJET), 7(07), (2020), 1116-1119.

[80] I. Gogul, V.S. Kumar, Flower species recognition system using convolution neural networks and transfer learning. Fourth International Conference on Signal Processing, Communication and Networking (ICSCN), IEEE, India. https://doi.org/10.1109/ICSCN.2017.8085675

[81] A. Begue, V. Kowlessur, U. Singh, F. Mahomoodally, S. Pudaruth, Automatic recognition of medicinal plants using machine learning techniques. International Journal of Advanced Computer Science and Applications, 8(4), (2017) 166-175. https://doi.org/10.14569/IJACSA.2017.080424

[82] J. Wei Tan, S.W. Chang, S. Abdul-Kareem, H.J. Yap, K.T. Yong, Deep learning for plant species classification using leaf vein morphometric. IEEE/ACM transactions on computational biology and bioinformatics, 17(1), (2018) 82-90. https://doi.org/10.1109/TCBB.2018.2848653

[83] A. Liu, Y. Huang, (2016) Plant leaf recognition. In conference proceedings.

[84] H.J. Aerts, E.R. Velazquez, R.T. Leijenaar, C. Parmar, P. Grossmann, S. Carvalho, J. Bussink, R. Monshouwer, B. Haibe-Kains, D. Rietveld, F. Hoebers, M.M. Rietbergen, C.R. Leemans, A. Dekker, J. Quackenbush, R.J. Gillies, P. Lambin, Decoding tumour phenotype by noninvasive

imaging using a quantitative radiomics approach. Nature communications, 5(1), (2014) 4006. https://doi.org/10.1038/ncomms5644

[85] P. Lambin, E. Rios-Velazquez, R. Leijenaar, S. Carvalho, R.G. Van Stiphout, P. Granton, C.M.L. Zegersa,· R. Gilliesb, R. Boellard, A. Dekker, H.J. Aerts, Radiomics: extracting more information from medical images using advanced feature analysis. European journal of cancer, 48(4), (2012) 441-446. https://doi.org/10.1016/j.ejca.2011.11.036

[86] H. Cartwright, (2015) Artificial Neural Networks, Humana Press. https://doi.org/10.1007/978-1-4939-2239-0

[87] I. Steinwart, A. Christmann, (2008) Support Vector Machines, Springer Science & Business Media, New York, USA.

[88] U. Mokhtar, M. A.Ali, A.E. Hassenian, H. Hefny, (2015) Tomato leaves diseases detection approach based on support vector machines. In 2015 11th International computer engineering conference (ICENCO), IEEE, Egypt. https://doi.org/10.1109/ICENCO.2015.7416356

[89] K. Asefpour Vakilian, J. Massah, An artificial neural network approach to identify fungal diseases of cucumber (Cucumis sativus L.) plants using digital image processing. Archives of Phytopathology and Plant Protection, 46(13), (2013) 1580-1588. https://doi.org/10.1080/03235408.2013.772321

[90] H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M.Braik, Z.AlRahamneh, Fast and Accurate Detection and Classification of Plant Diseases. International Journal of Computer Applications, 17(1), (2011) 31-38. https://doi.org/10.5120/2183-2754

[91] C. Amuthalingeswaran, M. Sivakumar, P. Renuga, S. Alexpandi, J. Elamathi, S.S. Hari, (2019) Identification of Medicinal Plant's and Their Usage by Using Deep Learning. In Proceedings of the 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), IEEE, India.

[92] B. Dey, J. Ferdous, R. Ahmed, J. Hossain, Assessing deep convolutional neural network models and their comparative performance for automated medicinal plant identification from leaf images. Helion 10 (2024) 1, e23655, https://doi.org/10.1016/j.heliyon.2023.e23655

[93] M. Oquab, L. Bottou, I. Laptev, J. Sivic, Learning and transferring mid-level image representations using convolutional neural networks. In Proceedings of the 27th IEEE Conference on Computer Vision and Pattern Recognition (CVPR '14), IEEE, USA. https://doi.org/10.1109/CVPR.2014.222

[94] A.D.A.D.S. Jayalath, T.G.A.G.D. Amarawanshaline, D.P. Nawinna, P.V.D. Nadeeshan, H.P Jayasuriya, (2019) Identification of Medicinal Plants by Visual Characteristics of Leaves and Flowers. 14th Conference on Industrial and Information Systems (ICIIS), IEEE, Sri Lanka. https://doi.org/10.1109/ICIIS47346.2019.9063275

[95] J. Schmidhuber, Deep Learning in neural networks: an overview. Neural Networks, 61, (2015) 85–117. https://doi.org/10.1016/j.neunet.2014.09.003

[96] S.O. Oppong, F. Twum, J.B. Hayfron-Acquah, Y.M. Missah, A Novel Computer Vision Model for Medicinal Plant Identification Using Log-Gabor Filters and Deep Learning Algorithms. Computational Intelligence and Neuroscience, 2022(1), (2022) 1189509. https://doi.org/10.1155/2022/1189509

[97] F. Siraj, H.M. Ekhsan, A.N. Zulkifli, (2014) Flower image classification modeling using neural network. In 2014 International Conference on Computer, Control, Informatics and Its Applications (IC3INA), IEEE, Indonesia. https://doi.org/10.1109/IC3INA.2014.7042605

[98] T.T.N. Nguyen, V.T. Le, T.L. Le, V. Hai, N. Pantuwong, Y. Yagi, (2016) Flower species identification using deep convolutional neural networks. In AUN/SEED-Net Regional Conference for Computer and Information Engineering.

[99] Y.A. Putri, E.C. Djamal, R. Ilyas, Identification of medicinal plant leaves using convolutional neural network. In Journal of Physics: Conference Series, IOP Publishing, 1845(1), (2021) 012026). https://doi.org/10.1088/1742-6596/1845/1/012026

[100] S.R. Reddy, G.S. Varma, R.L. Davuluri, Optimized convolutional neural network model for plant species identification from leaf images using computer vision. International Journal of Speech Technology, 26(1), (2023) 23-50. https://doi.org/10.1007/s10772-021-09843-x

[101] C. Zhang, P. Zhou, C. Li, L. Liu, (2015) A convolutional neural network for leaves recognition using data augmentation. In 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing, IEEE, UK. https://doi.org/10.1109/CIT/IUCC/DASC/PICOM.2015.318

[102] G. Dhingra, V. Kumar, H.D. Joshi, Study of digital image processing techniques for leaf disease detection and classification. Multimedia Tools and Applications, 77, (2018) 19951-20000.

[103] T.P. Pradhan, S. Meher, T. Pradhan, N. Pandey, A. Panda, Image Derivative and K-means Clustering based Dead Zone Identification from Flower Image. Image, 10(05), (2021) 1122-1135.

[104] I.A. Anjani, Y.R. Pratiwi, S.N.B. Nurhuda, Implementation of deep learning using convolutional neural network algorithm for classification rose flower. In Journal of Physics: Conference Series IOP Publishing, 1842(1), (2021) 012002. https://doi.org/10.1088/1742-6596/1842/1/012002

[105] M. Tian, Z. Liao, (2021) Research on flower image classification method based on YOLOv5. In Journal of Physics: Conference Series, IOP Publishing, (2024) 012022. https://doi.org/10.1088/1742-6596/2024/1/012022

[106] M. Hanafiah, M.A. Adnan, S. Abdul-Rahman, S. Mutalib, A. M. Ab Malik, M.R. Shamsuddin, Flower recognition using deep convolutional neural networks. In IOP Conference Series: Earth and Environmental Science, IOP Publishing, 1019(1), (2022) 012021. https://doi.org/10.1088/1755-1315/1019/1/012021

[107] A. Shukla, A. Agarwal, H. Pant, P. Mishra, Flower classification using supervised learning. International Journal of Engineering Research & Technology (IJERT), 9(05), (2020) 757-762. https://doi.org/10.17577/IJERTV9IS050582

[108] J.Y. Lim, H.S. Ahn, M. Nejati, J. Bell, H. Williams, B.A. MacDonald, (2020) Deep neural network based real-time kiwi fruit flower detection in an orchard environment. arXiv.

[109] I. Patel, S. Patel, An optimized deep learning model for flower classification using NAS-FPN and faster R-CNN. International Journal of Scientific & Technology Research, 9(03), (2020) 5308-5318.

[110] T. Ensari, B.R. METE, (2019) Flower Classification with Deep CNN and Machine Learning Algorithms. 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), IEEE, Turkey. https://doi.org/10.1109/ISMSIT.2019.8932908

[111] I. Patel, S. Patel, Flower identification and classification using computer vision and machine learning techniques. International Journal of Engineering and Advanced Technology (IJEAT), 8(6), (2019) 277-285. https://doi.org/10.35940/ijeat.E7555.088619

[112] H. Hiary, H. Saadeh, M. Saadeh, M. Yaqub, Flower classification using deep convolutional neural networks. IET computer vision, 12(6), (2018) 855-862. https://doi.org/10.1049/iet-cvi.2017.0155

[113] M.R. Banwaskar, A.M. Rajurkar, An Efficient Flower Classification System using Feature Fusion. International Journal of Engineering Trends and Technology, 70(11), (2022) 70-80. https://doi.org/10.14445/22315381/IJETT-V70I11P207

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Manoranjitham Sivaraj: Conceptualization, Methodology, Software, Validation, Formal analysis Writing - Original Draft. Ramesh Thanapppan: Conceptualization Project administration Supervision, Writing - Review & Editing. Alok Kumar Sharma: Methodology, Software, Validation and Formal analysis.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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