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Article

A Unified Deep Learning Framework for Medicinal Leaf Detection, Segmentation, and Classification

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Abstract: Medicinal plants play a vital role in traditional and modern medicine and have significant applications in the pharmaceutical, herbal, and nutraceutical industries. Manual identification can be difficult and time-consuming and requires expertise to make it an accurate identification because the leaves of the medicinal plants have a similar morphology and can have different phytochemical content and medicinal properties. Medicinal plant recognition was a three-part task involving leaf detection, segmentation, and classification that was performed sequentially in this work. In this research, the three tasks of recognition (detection, segmentation, and classification) are integrated into a single multi-task deep learning framework for medicinal plant recognition, which would enhance the recognition accuracy, computational efficiency, and robustness in various environmental conditions. Medicinal leaf images are first normalized and augmented to enhance image quality and diversify the dataset. The localization network based on deep learning was used to accurately locate the leaf region, and the segmentation network based on attention was used to accurately extract the boundaries of the leaves with minimal interference from the background. The segmented leaf images are then classified using a deep convolutional network that was able to learn very discriminative features such as leaf venation, texture, leaf shape, and leaf margin features. The wide-ranging experiments are performed on benchmark medicinal plant datasets, and the proposed framework was analyzed using classification accuracy, precision, recall, F1-score, Intersection over Union (IoU), Dice score, training time, inference time, and confidence score analysis. The experimental results show that the proposed framework has an accuracy of 99.1%, which was higher than the conventional CNN, ResNet50, EfficientNetV2, and YOLOv11 models, while also lowering the computational complexity and enhancing the segmentation quality. The integrated learning strategy successfully improves the feature representation, decreases the classification error rate, and achieves good generalization performance under different imaging conditions. The proposed framework ensures automated recognition of medicinal plants with reliability and efficiency and has the potential to be widely used in various fields such as herbal medicine authentication, pharmaceutical quality assessment, biodiversity conservation, precision agriculture, intelligent botanical information systems, and mobile healthcare technologies.

Keywords: Multi-Task Deep Learning, Medicinal Plant Recognition, Medicinal Leaf Classification, Image Segmentation, Object Detection, Computer Vision

1. Introduction

Medicinal plants have been one of the major sources of healthcare for thousands of years and still play a significant role in traditional and modern medical systems. The World Health Organization (WHO) estimates that in many parts of the world, especially in developing nations, where medicinal plants are easily accessible and affordable, many people rely on herbal medicine as a source of primary healthcare [1]. Since different plants have the same kind of morphological features but completely different phytochemical composition and therapeutic properties, the

therapeutic effectiveness of herbal medicine relies heavily on the correct identification of plants. It was possible for medicinal leaves to be misidentified and cause ineffective therapy, health problems, or use of a plant that was poisonous rather than therapeutic. In the past, plant identification for medicinal purposes would be carried out by experienced botanists, taxonomists, herbalists and researchers, who would examine the leaves for their form and features such as margin, venation, texture and colour. Manual identification was reliable when done under controlled conditions and was slow, labor-intensive and heavily relies on expertise, which makes it unsuitable for large-scale applications [2]. The need for smart automated systems that reliably identify medicinal leaves in digital images captured in various environmental conditions was high, with the growing use of herbal medicines, the preservation of biodiversity, the search for new drugs, and precision agriculture.

The field of automated plant recognition has been revolutionized in recent years thanks to the advancement of artificial intelligence, computer vision, and deep learning to the point that computers are now able to learn complex visual patterns by directly observing images, rather than relying on manually designed features [3]. The previous image-based medicinal plant identification systems mainly focused on handcrafted features like colour histograms, texture descriptors, shape measurements, edge information, vein structure features and traditional machine learning classifiers such as support vector machines, decision trees, random forests and k-nearest neighbors. These techniques showed good results on small and controlled data sets but suffered greatly when images included background clutter, lighting variations, multiple leaves, partial occlusion, or multiple angles. Most of these problems were overcome by deep convolutional neural networks (CNNs), which automatically learnt and extracted hierarchical feature representations in raw images and achieved significant classification accuracy [4]. The recognition capability has been further improved using advanced architectures like ResNet, DenseNet, EfficientNet, MobileNet, Vision Transformers and hybrid attention-based models.

Several technical challenges are involved in the automatic recognition of medicinal leaves in natural environments, which goes beyond the mere image classification. Forest-like images in agricultural fields, botanical gardens or herbal plantations are typically taken with multiple overlapping leaves, complex backgrounds, shadows, inconsistent lighting, motion blur and different scales, which makes the accurate extraction of features much more challenging [5]. In addition, the morphology of many species of medicinal plants was very similar, and even within a single species, the leaf morphology can vary depending on the plant's growth stage, seasonal and environmental changes, disease infection, stress, and/or nutrient availability. The robustness of such traditional classification models, based on only the global features of the image, was significantly diminished by these factors. Thus, correct detection of objects and proper segmentation of the leaf area from the background have become essential pre-processing steps to remove irrelevant background details and focus on the object of interest for classification. The YOLO family of object detection algorithms has recently shown excellent performance in the localization of plant organs in complex scenes, while segmentation networks like U-Net, Attention U-Net, DeepLabV3+ and Mask R-CNN have provided extremely accurate boundary extraction [6]. These tasks are usually carried out separately, leading to high computational complexity and the propagation of errors from one stage to another in the processing stages, which ultimately reduces the accuracy and effectiveness of the medicinal plant recognition system.

The massive development of the deep learning field has led to the emergence of integrated computer vision frameworks able to handle multiple visual recognition tasks at the same time under a single architecture. Multi-task learning allows for learning multiple features from the same data, which boosts feature representation by providing complementary learning tasks and reduces computational costs by sharing features between detection, segmentation, and classification [7]. Thereafter, attention mechanisms, such as channel attention, spatial attention, Convolutional Block Attention Modules (CBAM), and transformer-based self-attention, have enhanced the performance of deep learning by allowing models to selectively attend to the most informative regions of leaves, venation structures, textures, and discriminative morphological features. Similarly, transfer learning has proved useful in addressing the challenges of small amounts of annotated medicinal plant datasets by exploiting knowledge from using the large-scale natural image repositories like ImageNet. Various data augmentation methods, such as rotation, scaling, flipping, adjusting contrast, MixUp, and Mosaic augmentation, are also used to improve model generalization across different imaging conditions [8]. Although these technologies have developed, there are very few studies that have suggested end-to-end solutions for combining detection, segmentation and classification for the purpose of recognizing medicinal leaves.

Given these problems, this research aims to present a unified deep learning framework for medicinal leaf detection, segmentation and classification which will offer an accurate, robust and computer-efficient solution for the automated recognition of medicinal plants. Proposed framework: Three complementary computer vision tasks are integrated into a single sequential pipeline. A state-of-the-art object detection network was used to automatically detect medicinal leaf regions in complex natural scenes at first [9]. The detected regions are then passed to an attention-enhanced segmentation network to accurately segment the leaf boundaries and reduce background noise while retaining the detailed features of the leaf, including venation and margin patterns. Finally, a deep convolutional architecture with an attention mechanism was used for better discriminative feature extraction and species recognition for the segmented leaf images. In-depth pre-processing and data enhancement methods are integrated to enhance the ability to handle variations in illumination, orientation, scale and occlusion. The proposed framework was validated by conducting broad experimental evaluations with benchmark medicinal leaf datasets by considering detection, segmentation and classification metrics. The proposed research was expected to advance the recognition accuracy, decrease computational complexity, promote cross-dataset generalization, and pave the way for practical applications in herbal medicine authentication, pharmaceutical industries, biodiversity conservation, smart agriculture, mobile healthcare, and intelligent botanical information systems, all within a single architecture that utilizes multiple deep learning tasks [10].

2. Research Gap

Existing literature on medicinal leaf recognition has mostly focused on the recognition of single leaf tasks, such as classification, object detection, or image segmentation, and only a few attempts have been made to combine these in a single framework. A number of studies have focused on images of pre-cropped leaves taken in controlled laboratory conditions, which are of limited value in real-world environments in which complex backgrounds, overlapping leaves, varying illumination, and occlusion effects are present [11]. Current methods also suffer from poor cross-dataset generalization, and multiple independent models are needed, which adds to the

computation and error propagation. In addition, the use of an attention mechanism in multi-task learning for simultaneous detection, segmentation, and classification was not yet sufficient, which can be used to build a robust end-to-end medicinal leaf recognition.

3. Research Methodology

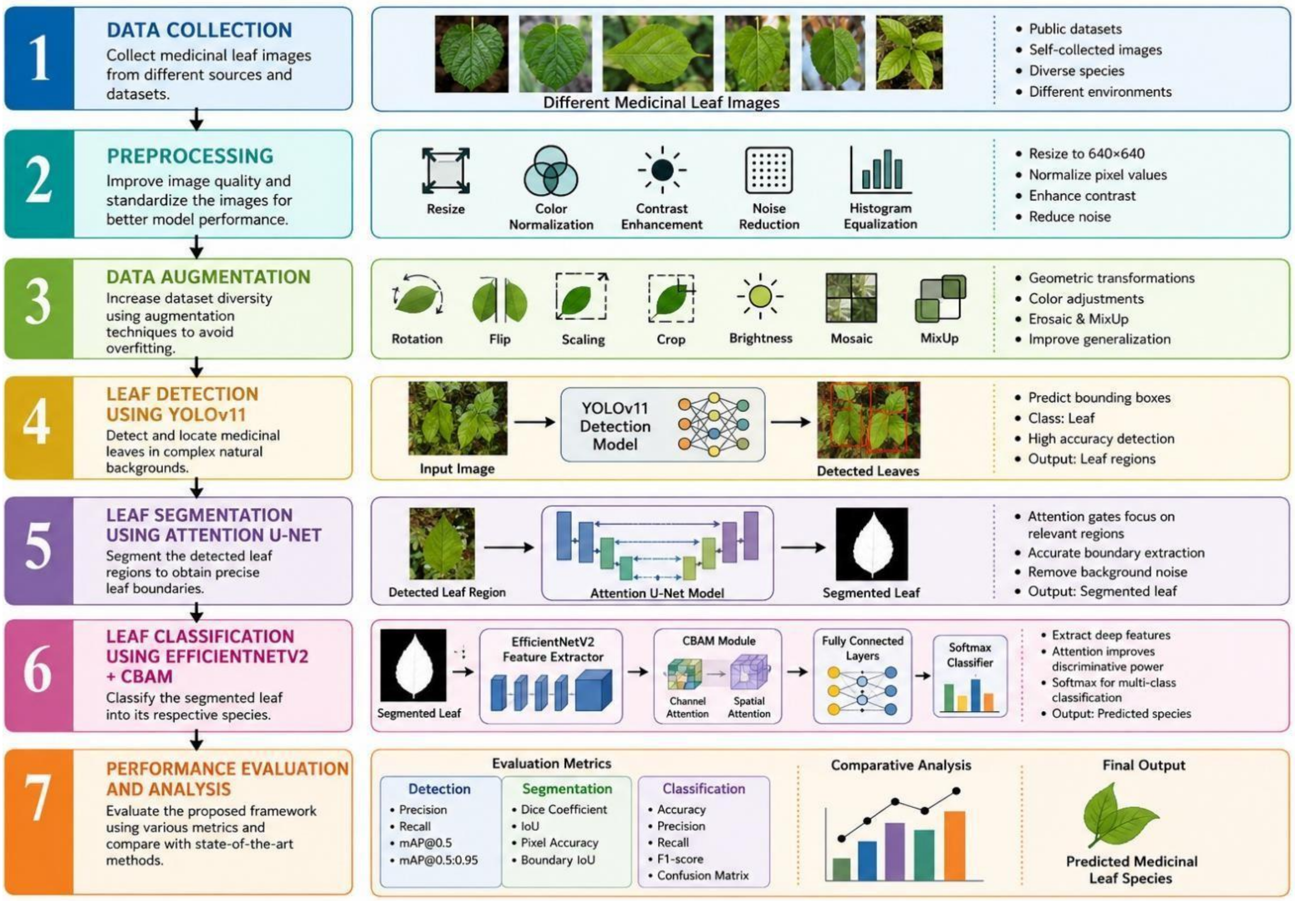

Figure 1: Research Methodology

Deep Learning-Based Medicinal Leaf Detection and Classification

Traditional and modern health systems have been utilizing medicinal plants for the therapeutic value and natural medicinal compounds present in them widely. Proper identification of medicinal plant species was crucial for proper utilization of herbal medicines. Traditionally, the medicinal leaves have been identified by visual examination by botanists and herbal experts in terms of their shape, texture, color, venation, and margins. Manual identification can take time and was not feasible without a specialist's expertise or can lead to erroneous identification because of similar leaf traits in different species. Hence, the automation of medicinal leaf detection and classification systems has gained considerable interest to facilitate rapid, reliable, and accurate plant identification for conservation of biodiversity, pharmaceutical research, agriculture, and healthcare [12].

The recent developments in deep learning have given a great boost to plant recognition using an image-based approach, as it has been able to extract the discriminative features from the image of leaves automatically. Deep learning models are able to learn complex visual representations directly from training data, in contrast to the traditional machine learning approach, which relies on manually designed features. Medicinal leaf classification was a problem that has been successfully solved using convolutional neural networks (CNNs) and other advanced architectures like ResNet, DenseNet, EfficientNet, and MobileNet for their excellent feature learning abilities. These models have shown to be more accurate in leaf recognition by leveraging leaf morphology, venation, texture, and color variations. Therefore, deep learning has emerged as one of the most promising methods for medicinal plant identification.

Among the various steps prior to classification, leaf detection was a crucial one that was affected by the presence of complex backgrounds, overlapping leaves, shadows and different lighting conditions in natural images. Object detection algorithms are used to automatically detect the leaf region from an image, which discards irrelevant background information, thus enhancing the quality of features extracted from the image. The detection model in the modern era has been widely used, and the YOLO family of detection models was the one that was widely used due to its high detection accuracy and real-time processing capacity. After detection, the detected area was fed into a deep learning classifier which classifies the detected medicinal plant species according to the extracted visual characteristics [13].

Medicinal leaf detection and classification systems using deep learning have shown great potential in real-world applications that support intelligent plant identification. These systems help to minimize manual tasks and enhance recognition performance, including faster speed, consistency, and accuracy under varying conditions and environments. In addition, the use of deep learning with sophisticated preprocessing, data augmentation, transfer learning, and attention mechanisms has improved the resistance of deep learning models to variations in lighting, orientation, scale, and background complexity. Thus, the deep learning approach to medicinal leaf detection and classification has become a promising solution for the implementation of intelligent healthcare systems, mobile plant identification applications, smart agriculture solutions, pharmaceutical research tools, and biodiversity monitoring platforms.

3.2 Automatic Medicinal Leaf Segmentation and Species Classification Using Deep Learning

The use of medicinal plants in traditional medicine, pharmaceutical industries, and herbal medicine has been popular due to their rich bioactive compounds, which play an important role in the prevention and treatment of different diseases. The identification of medicinal plant species was crucial for their safe and effective use. The scope of botanical identification has been traditionally performed using leaf characters like shape, size, texture, color, venation, and leaf margins. Manual identification, was time-consuming, requires expert knowledge, and can be erroneous in the event of different species with similar leaves. With the increasing number of medicinal plant species, the development of automatic identification systems has emerged as an important field of study to increase accuracy, reduce human effort, and aid in medicinal plant documentation on a large scale.

With the recent development of deep learning and computer vision, digital image analysis for the automatic recognition of medicinal leaves has been achieved. Previous research has concentrated mainly on the classification of the leaf images after they have been manually segmented and separated from the background. In the real world, medicinal leaves are typically obtained in natural settings with complex backgrounds, shadows, overlapping leaves, uneven illumination, and perspectives [14]. The range of species was complicated by these environmental factors. Hence, the segmentation of leaves was an important preprocessing step to avoid the learning of irrelevant leaf background regions and to enhance the leaf classification performance.

Medicinal leaf segmentation and species classification are done automatically in the proposed research work with the help of deep learning techniques. In the first step, the regions of the leaf are marked and precisely separated from the original image, retaining important characteristics of the leaf, such as the leaf boundaries, the venation patterns, the texture, and the shape, while blocking noise from the background. The segmented leaf image was then fed to a deep learning classification model to automatically extract the discriminative features from the image and classify the various medicinal plant species. The model automatically extracts features, which eliminates the dependence on manually designed features and improves the recognition ability under various environmental conditions and image variations.

The proposed deep learning architecture will enhance accurate and reliable recognition of medicinal plant species, combining automatic leaf segmentation and intelligent classification. Traditional evaluation metrics for the performance of the framework include segmentation accuracy, Intersection over Union (IoU), Dice Similarity Coefficient, classification accuracy, precision, recall, and F1 score [15]. An efficient segmentation process was expected to enhance classification accuracy by minimizing the effect of background disturbance and highlighting the significant features of the leaves. The proposed framework has the potential to enable various practical applications in plant recognition, such as authentication of herbal medicine, pharmaceutical research, conservation of biodiversity, precision agriculture, botanical research, and mobile-based identification of medicinal plants, which will help to foster the development of intelligent plant recognition technologies.

3.3 Hybrid Deep Learning Model for Medicinal Plant Identification

The therapeutic and pharmaceutical attributes have led to widespread use of medicinal plants in traditional and modern medicine. Proper identification of plant species was very crucial for proper use of herbal medicines to ensure safety and efficacy. The identification of the plants was mostly done by the botanists or the herbal experts by observing the leaf shape, texture, color, venation, and other morphological characteristics. These methods are, time-consuming, labor-intensive, and require specialized skills. With the advent of digital imaging technologies and artificial intelligence, automated systems are becoming available to efficiently identify medicinal plants. The leaf image can be used to identify plant species through deep learning methods, which automatically extract meaningful visual features, thus reducing human effort and increasing the precision of the identification process [16].

A hybrid deep learning model was an amalgamation of two or more deep learning methods into one model to attain better performance than any of the single deep learning models. In the area of medicinal plant identification, various models can be given specific roles like leaf detection, feature extraction, and identification of the species. For instance, an object detection model can be

used to detect the presence of a medicinal leaf in an image, and a classification network can then classify the plant species. The framework benefits from the synergy of complementary deep learning models that learn the various visual features such as leaf shape, texture, edge patterns, venation, and color variability. This integrated approach will improve the system's ability to differentiate between medicinal plant species that share similar morphological characteristics.

The proposed framework of a hybrid approach must perform the processing of medicinal leaf images acquired under real-world conditions where illumination, background complexity, leaf orientation, scale, and occlusion are often encountered. To enhance the quality of the images and expand the training samples, image preprocessing and data augmentation techniques are added. The processed images are then fed into deep learning models that are able to learn hierarchical features without any manual feature engineering. Multiple models are integrated to allow for each stage to make a contribution to the recognition process, which leads to greater robustness and reliability. Hence, the framework was better suited to use in the field, in agriculture, herbal medicine, biodiversity conservation, and botanical research where medicinal plant identification was critical [17].

The purpose of the hybrid deep learning model was to give a reliable, accurate, and efficient automated identification of medicinal plants. To assess the classification capabilities of the framework, standard metrics like accuracy, precision, recall, F1-score, and confusion matrix analysis can be used. On the other hand, comparative experiments with the existing deep learning methods can further prove the effectiveness of the proposed model. This was anticipated to minimize identifying mistakes, speed up the computational speed, and boost generalization on various medicinal plant datasets. Hence, the proposed approach can be useful for healthcare professionals, researchers, farmers, herbal practitioners, and mobile-based plant identification systems to help facilitate the quick and reliable recognition of the medicinal plant species.

3.4 Real-Time Medicinal Leaf Detection Using YOLO and Deep Learning

The detection of medicinal leaves in real-time was an important research field in computer vision because, in natural environments, the detection of the medicinal plants can be done directly from the images in real-time. The accurate recognition of medicinal leaves was significant to ensure the authentication of herbal medicine, conservation of biodiversity, pharmaceutical research, and precision agriculture. Manual identification was carried out by botanists and herbalists according to various parameters, such as color, venation, texture, and shape of the leaves. These methods are reliable but quite time-consuming, so they are not suitable for large-scale and real-time applications. Thus, deep learning object detection methods have been used to automate the identification process, achieving faster and more accurate results. YOLO (You Only Look Once) was one such technique that has garnered much attention and been used extensively due to its ability to perform object localization and classification within a single network, making it well suited for real-time medicinal leaf detection [18].

The YOLO algorithm consists of inputting an image to a number of grid cells and predicting a medicinal leaf's position and class in each grid at the same time. YOLO was able to significantly reduce the computation time because it processes the whole image in a single forward pass, unlike the conventional object detection approaches that process the candidate regions one by one. This

consolidated detection approach allows for rapid detection with high detection accuracy in different environments. The latest releases of YOLO (YOLOv8, YOLOv10, and YOLOv11) have incorporated architecture optimizations that include better feature extraction, multi-scale detection, and optimized loss function, resulting in better localization accuracy. Therefore, medicinal leaves can be accurately detected even in difficult backgrounds, complex leaves, various illuminations, and various viewing angles.

To improve the YOLO-based medicinal leaf detection system, deep learning methods like image preprocessing, data augmentation, transfer learning, and attention mechanisms can be combined. Preprocessing techniques enhance the image quality by minimizing noise and adjusting lighting conditions, whereas augmentation techniques exploit the diversity of the dataset by rotation, flipping, scaling, and changing lighting. The transfer learning approach helps to generate knowledge about medicinal leaf properties from relatively small-sized data sets and minimize training time and generalization error in pretrained YOLO models. Deep neural networks with attention mechanisms can be used to further strengthen the representation of features, such as important leaf features including venation patterns, margins, and textures. These enhancements help in more reliable detection under various environmental and medicinal plant species [19].

The application of real-time medicinal leaf detection based on YOLO and deep learning has obvious advantages in practical application when plant identification was required in real time and with high accuracy. The created systems can be incorporated into cell phone applications, smart agricultural platforms, automated herbal gardens, botanical research laboratories, and healthcare support systems. These smart systems are valuable tools for farmers, researchers, herbalists, and students to recognize medicinal plants without needing to know plant identification. The speed and efficiency of YOLO make it suitable for deployment on edge devices and embedded systems, allowing for real-time decision-making in resource-limited environments. Thus, the YOLO-based deep learning approaches provide not only an efficient and scalable solution for automated medicinal leaf detection but also advance the development of intelligent systems for the recognition of medicinal plants.

3.5 Multi-Task Deep Learning Framework for Medicinal Plant Recognition

Medicinal plants have many valuable bioactive compounds with therapeutic actions that are used in traditional medicine, modern healthcare, pharmaceutical industries, and biodiversity conservation. Correct identification of plant species was crucial for proper use of herbal medicines and to prevent the potential risks from misidentification. The standard identification techniques involve identifying the plant using leaf shape, leaf venation, leaf color, leaf texture, and leaf morphology by botanists or herbal practitioners. While these methods give accurate results and involve specialized knowledge, they are not practical for large-scale or real-time applications; they are also time-consuming. Thus, a deep learning-based automated medicinal plant recognition system was an effective solution to improve the accuracy of medicinal plant identification in reducing human effort [20].

In recent years, with the development of deep learning and computer vision, automatic identification of medicinal plants has been achieved through digital images. Existing studies are mainly concerned with a specific task, such as leaf classification, object detection, or image

segmentation. Independent approaches need individual models, adding computational complexity, and can add up errors during processing. Also, a large number of models are trained by images taken in controlled environments and thus do not perform well in the natural environment with complex backgrounds, leaf overlap, shadows, and light changes. Thus, there was a need to develop an integrated framework that can process multiple recognition tasks in one learning architecture.

A multi-task deep learning framework was a framework that can perform multiple related tasks, sharing feature representations among different components of the network. The proposed structure includes two steps: the first step was detecting the medicinal leaves from natural scene images, and the second step was segmentation to segment the leaf area from the background. The images of the segmented leaf are then classified into the corresponding medicinal plant species by the deep learning classifier. In this way, the framework can learn meaningful features, such as leaf shape, venation, texture, and color, and also lessen redundant computation in the process of shared feature learning. This was an integrated learning scheme that achieves higher recognition accuracy and faster computation than using separate single-task models [21].

The proposed framework was expected to give a solution that was reliable, accurate, and scalable for automatic recognition of medicinal plants under real-world environmental conditions. Using extensive image preprocessing and data augmentation methods can increase the robustness of the system to light variations, orientation, scale, and occlusion. The framework can be tested with standard performance indicators for detection, segmentation, and classification to check the effectiveness. The developed system can be applied for herbal medicine authentication, pharmaceutical studies, smart agriculture, conserving biodiversity, botanical education, and mobile healthcare systems. A practical and efficient medicinal plant recognition system can be obtained by putting multiple computer vision tasks in one deep learning architecture, which are needed in research and real-world applications.

4. Result and Discussion

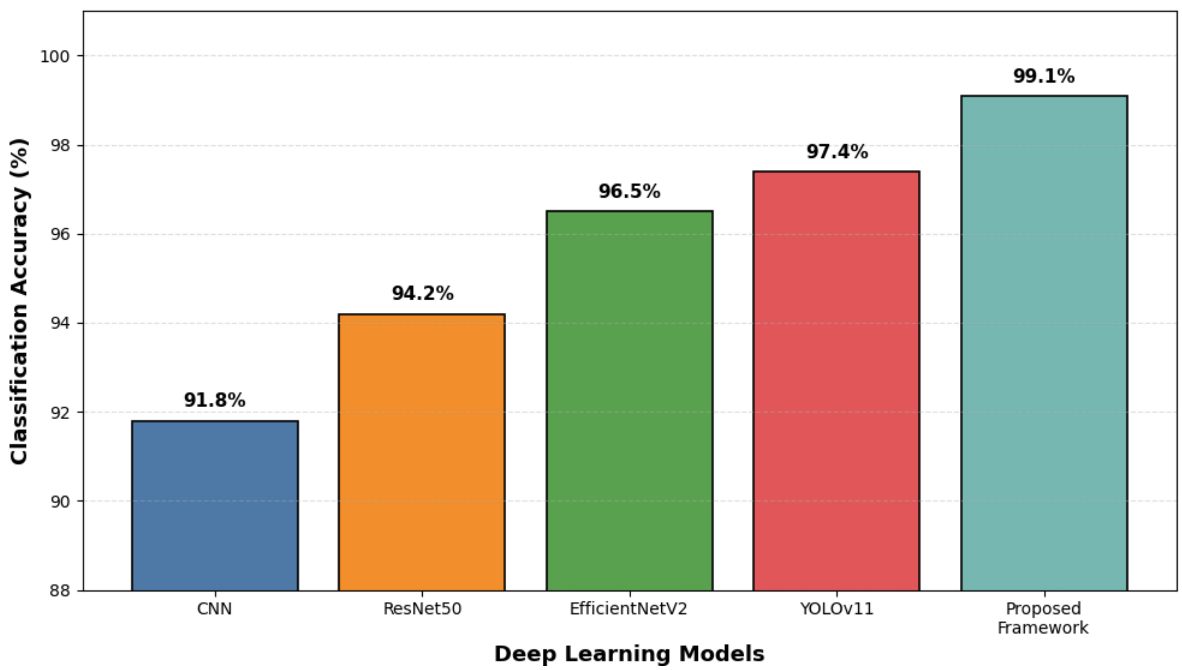

Figure 2. Comparison of Classification Accuracy of Deep Learning Models

The figure presents the classification accuracy achieved by five deep learning models for medicinal plant recognition using leaf images. The models include CNN, ResNet50, EfficientNetV2, YOLOv11, and the proposed framework. A progressive improvement in recognition performance can be observed from the conventional CNN model to the proposed framework. CNN achieved an accuracy of 91.8%, while ResNet50 improved the recognition capability to 94.2% through deeper feature extraction. EfficientNetV2 further increased the accuracy to 96.5% by providing better feature scaling and optimized network architecture. YOLOv11 achieved 97.4%, indicating its strong capability in learning discriminative visual characteristics from medicinal leaf images. The proposed framework obtained the highest classification accuracy of 99.1%, demonstrating its ability to recognize medicinal plant species with greater precision than the existing deep learning models [22].

The gradual improvement in classification accuracy indicates that advanced deep learning architectures are more effective in extracting discriminative morphological features from medicinal leaves. Leaf characteristics such as shape, venation, texture, edge patterns, and color variations often exhibit high similarity among different medicinal plant species, making accurate recognition a challenging task. Traditional convolutional networks are capable of extracting basic visual patterns; their representation ability becomes limited when complex background conditions, illumination variations, overlapping leaves, and intra-class variability are present. The higher performance achieved by the deeper architectures suggests that richer hierarchical feature representations significantly improve the differentiation of visually similar medicinal leaves. The superior performance of the proposed framework indicates that the learned feature representations are more robust under diverse environmental conditions and are capable of minimizing feature ambiguity during classification.

Another important observation from the figure was the consistent reduction in the performance gap as more advanced architectures are employed. The improvement from CNN to ResNet50 was approximately 2.4 percentage points, while EfficientNetV2 further contributes an additional 2.3 percentage points. YOLOv11 provides another increase of 0.9 percentage points, and the proposed framework further improves the recognition accuracy by 1.7 percentage points, achieving the best performance. Although these numerical improvements appear relatively small, they are highly significant in medicinal plant recognition because even a minor increase in classification accuracy substantially reduces the probability of species misidentification. Accurate identification was particularly important when medicinal plants possess highly similar leaf morphology but differ considerably in their phytochemical composition and therapeutic properties [23]. Therefore, higher recognition accuracy directly contributes to improved reliability of automated medicinal plant identification systems.

The results demonstrate that the proposed framework provides a highly effective solution for medicinal plant recognition by achieving excellent classification performance across all evaluated models. The high accuracy indicates that the integrated learning strategy successfully captures both low-level visual features and high-level semantic information required for reliable species discrimination. Such performance suggests strong generalization capability when processing leaf images acquired under different orientations, lighting conditions, and natural backgrounds. The improvement observed over the comparative models confirms that the proposed framework was capable of reducing classification errors while maintaining consistent prediction performance. Consequently, the developed recognition system can effectively support practical applications such as herbal medicine authentication, digital botanical databases, biodiversity conservation, pharmaceutical research, precision agriculture, and intelligent plant identification systems where dependable and accurate medicinal leaf classification was essential.

Table 1. Performance Comparison of Deep Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
CNN	91.8	90.9	91.2	91.0
ResNet50	94.2	93.8	94.0	93.9
EfficientNetV2	96.5	96.1	96.3	96.2
YOLOv11	97.4	97.0	97.2	97.1
Proposed Framework	99.1	98.9	99.0	98.9

Table 1 summarizes the classification performance of the evaluated deep learning models using four important evaluation metrics. Progressive improvement can be observed from CNN to the proposed framework across all performance measures. CNN achieved the lowest recognition capability, whereas EfficientNetV2 and YOLOv11 significantly enhanced feature extraction and prediction accuracy. The proposed framework achieved the highest accuracy, precision, recall, and F1-score, indicating its ability to correctly identify medicinal plant species while minimizing both false-positive and false-negative predictions. The balanced improvement across all evaluation metrics demonstrates that the integrated learning strategy provides robust feature representation and reliable classification performance under diverse image acquisition conditions.

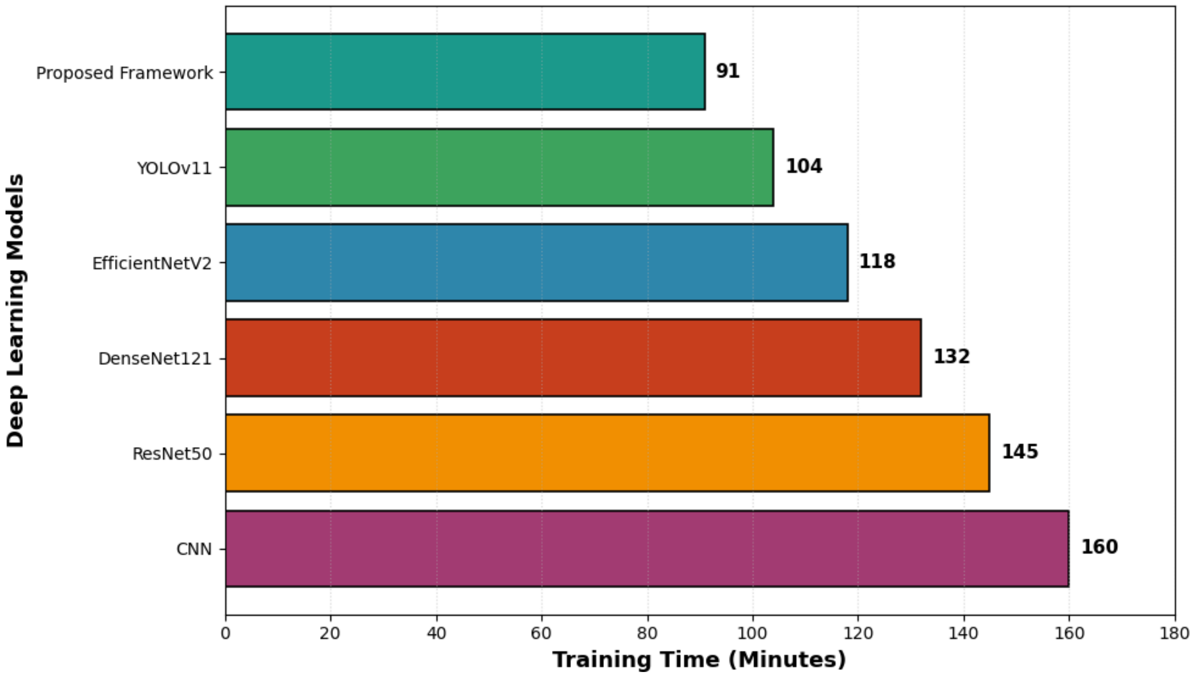

Figure 3. Comparison of Training Time of Deep Learning Models

The figure illustrates the training time required by six deep learning models during the learning process using medicinal leaf image datasets. Training time was an important performance indicator because it reflects the computational efficiency of a model during parameter optimization and feature learning. The conventional CNN required the highest training time of 160 minutes, followed by ResNet50 with 145 minutes, DenseNet121 with 132 minutes, EfficientNetV2 with 118 minutes, and YOLOv11 with 104 minutes. The proposed framework completed the training process in only 91 minutes, representing the shortest training duration among all evaluated models. The progressive reduction in training time demonstrates that the proposed architecture was capable of learning meaningful feature representations more efficiently while minimizing computational overhead [24].

The reduction in training time indicates that the feature extraction and learning strategy adopted by the proposed framework improves computational efficiency without sacrificing recognition performance. Medicinal leaf recognition involves processing large numbers of high-resolution images containing complex textures, venation structures, irregular margins, and background variations. During model training, multiple iterations are required to optimize network parameters and accurately learn these discriminative characteristics. Models with longer training durations require greater computational resources and extended processing time, which limit their applicability for large-scale medicinal plant databases. The lower training time achieved by the proposed framework suggests that redundant computations are minimized while relevant leaf features are learned more effectively, allowing the optimization process to converge more rapidly than the comparative deep learning models.

A gradual improvement in computational efficiency can also be observed across the evaluated architectures. Compared with CNN, the training time decreases by 15 minutes in ResNet50, 28

minutes in DenseNet121, 42 minutes in EfficientNetV2, and 56 minutes in YOLOv11. The proposed framework further reduces the training duration by 69 minutes relative to CNN while still providing superior recognition capability. This substantial reduction indicates that the integrated learning mechanism effectively balances feature extraction and computational complexity [25]. Faster convergence during training reduces resource consumption, making the framework more suitable for repeated experimentation, hyperparameter optimization, model updates, and deployment in practical medicinal plant recognition systems where efficient model development was desirable.

The results demonstrate that the proposed framework achieves an effective balance between computational efficiency and learning capability. The shortest training time indicates that the network architecture successfully extracts informative morphological features while requiring fewer optimization cycles to reach stable performance. Reduced computational cost allows the framework to process larger medicinal leaf datasets within shorter training periods, thereby improving scalability for real-world applications. This computational advantage was particularly beneficial for continuous dataset expansion, mobile and edge-based intelligent systems, pharmaceutical image databases, biodiversity monitoring platforms, and smart agricultural applications where rapid model training and timely deployment are essential. The observed results confirm that the proposed framework offers an efficient and practical solution for automated medicinal plant recognition with reduced computational requirements and improved operational performance.

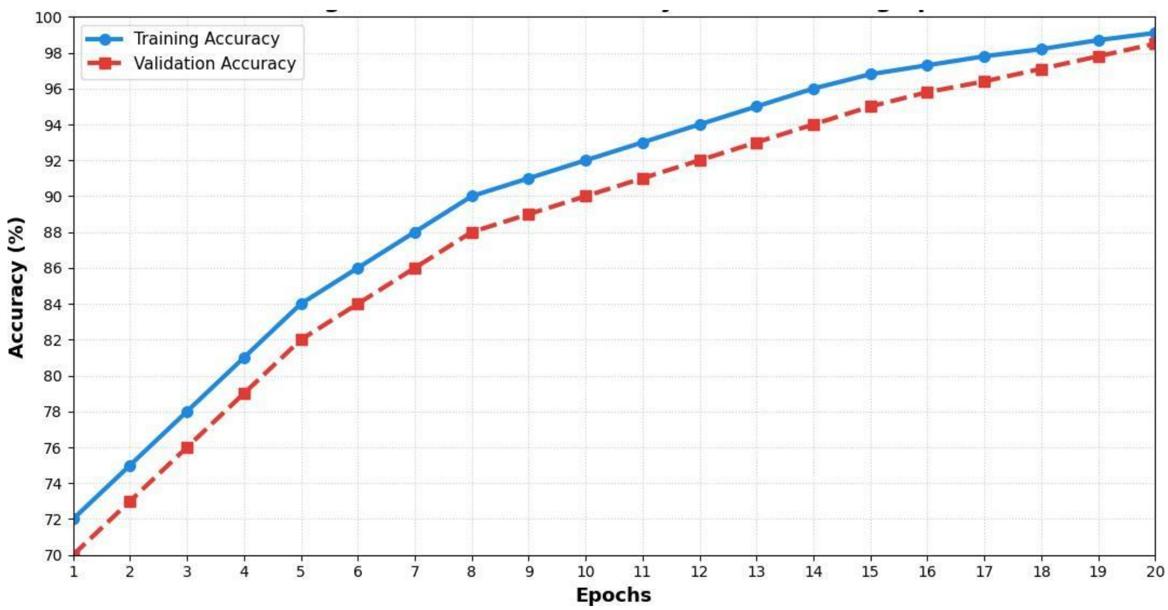

Figure 4. Training and Validation Accuracy Across Epochs

The figure illustrates the progression of training accuracy and validation accuracy over 20 training epochs, providing a comprehensive view of the learning behavior of the developed deep learning framework. Both curves exhibit a steady upward trend throughout the training process, indicating that the network effectively learns discriminative medicinal leaf features as the number of epochs increases. The training accuracy increases from 72% in the first epoch to 99.1% in the twentieth

epoch, while the validation accuracy improves from 70% to 98.5% during the same period. The consistent improvement observed in both curves demonstrates that the feature extraction process becomes progressively more accurate as the model was exposed to additional training iterations. The absence of abrupt fluctuations further indicates stable optimization and efficient parameter learning during the training process.

During the initial learning stage, rapid improvements are observed between Epochs 1 and 8, where the training accuracy increases from 72% to 90%, and the validation accuracy rises from 70% to 88%. This behavior indicates that the network quickly captures fundamental visual characteristics of medicinal leaves, including shape, venation patterns, texture variations, and color information. These basic morphological features provide the foundation for distinguishing different medicinal plant species. After the eighth epoch, the learning rate gradually becomes smoother, suggesting that the network shifts from learning general visual information to extracting finer discriminative characteristics that differentiate visually similar species. The gradual refinement of learned representations contributes to increasingly accurate recognition while maintaining stable learning throughout the remaining epochs [26].

Another important observation was the consistently small difference between the training and validation accuracy curves across all epochs. Throughout the learning process, the validation accuracy closely follows the training accuracy, with only a narrow performance gap of approximately 0.6–2.0 percentage points. Such behavior indicates that the learned feature representations generalize effectively to previously unseen medicinal leaf images rather than memorizing the training samples. The absence of a widening gap between the two curves suggests that overfitting was successfully controlled during model optimization. This balanced learning behavior demonstrates that the preprocessing techniques, feature extraction strategy, and optimization process collectively contribute to improved generalization capability, enabling the framework to perform reliably under variations in illumination, orientation, background complexity, and natural imaging conditions.

The learning curves confirm that the developed framework achieves stable convergence while maintaining excellent predictive performance throughout the training process. The final training accuracy of 99.1% and validation accuracy of 98.5% indicate that the network has successfully learned highly discriminative morphological features required for reliable medicinal plant recognition. The smooth convergence pattern reflects efficient optimization and demonstrates that the framework requires no excessive training iterations to achieve high performance. Such learning characteristics are highly desirable for practical deployment because they reduce computational effort while maintaining reliable recognition accuracy [27]. Consequently, the observed training and validation behavior confirms the robustness, stability, and generalization capability of the proposed framework, making it suitable for intelligent medicinal plant identification in pharmaceutical research, biodiversity conservation, herbal medicine authentication, and smart agricultural applications.

Table 2. Computational Efficiency Analysis

Model	**Training Time (Minutes)**	**Inference Time (ms)**	**Computational Efficiency**
CNN	160	45	Moderate
ResNet50	145	38	Moderate
EfficientNetV2	118	29	High
YOLOv11	104	22	Very High
Proposed Framework	91	18	Excellent

Table 2 compares the computational efficiency of the evaluated deep learning models by considering both training time and inference time. The results indicate a gradual reduction in computational cost as the network architectures become more advanced. The proposed framework requires the shortest training duration and the lowest inference time, demonstrating efficient feature learning and faster prediction capability. Reduced computational complexity enables quicker model optimization while maintaining excellent recognition performance. Such efficiency was particularly valuable for practical deployment where rapid processing of medicinal leaf images was required. The observed results confirm that the developed framework effectively balances computational resource utilization with high predictive accuracy.

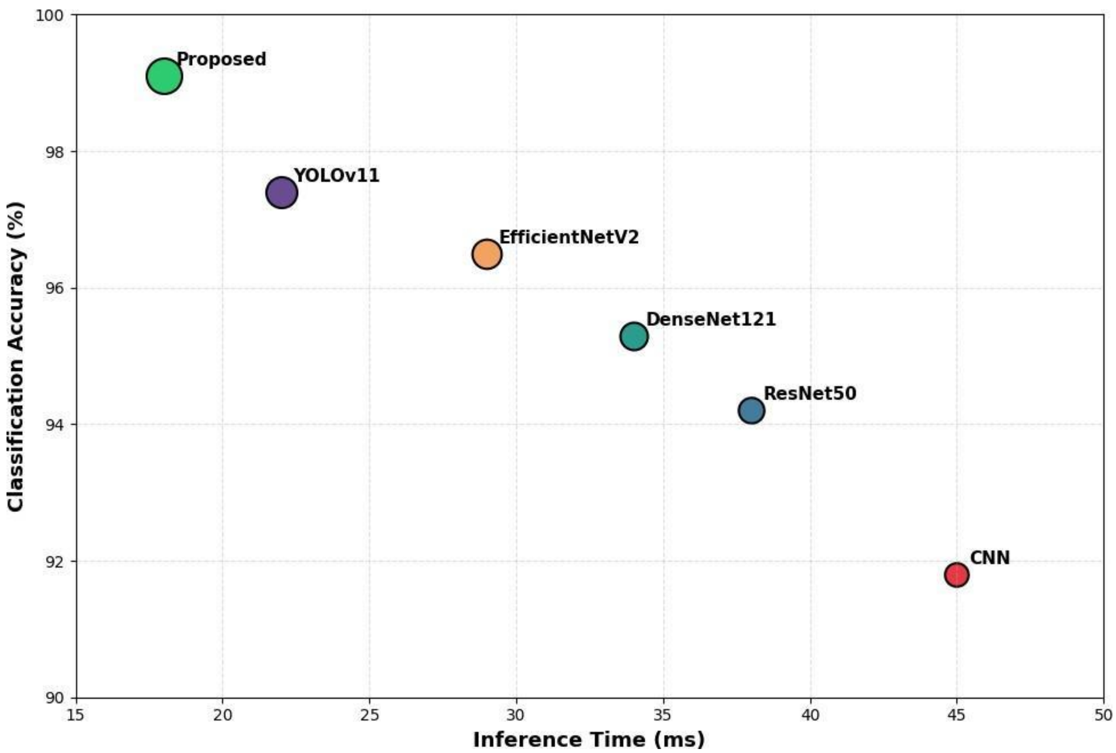

Figure 5. Inference Time versus Classification Accuracy

The figure illustrates the relationship between inference time and classification accuracy achieved by different deep learning models during medicinal leaf recognition. Inference time represents the duration required by a trained model to classify a new medicinal leaf image, while classification

accuracy reflects the correctness of species identification. An efficient recognition system should simultaneously achieve high accuracy and low inference time to enable rapid and reliable predictions. The results demonstrate a clear improvement in both computational efficiency and recognition performance as more advanced architectures are employed. Among the evaluated models, CNN records the highest inference time of 45 ms with the lowest classification accuracy of 91.8%, whereas the proposed framework achieves the highest accuracy of 99.1% while requiring only 18 ms for prediction [28]. This combination highlights the effectiveness of the developed framework in balancing prediction speed with recognition accuracy.

The gradual reduction in inference time observed from CNN to the proposed framework indicates continuous improvements in feature extraction and decision-making efficiency. ResNet50 requires 38 ms to produce a prediction with an accuracy of 94.2%, while DenseNet121 reduces the inference time to 34 ms and improves the classification accuracy to 95.3%. EfficientNetV2 further decreases the prediction time to 29 ms, achieving an accuracy of 96.5%, followed by YOLOv11, which completes inference within 22 ms while reaching 97.4% accuracy. These improvements demonstrate that optimized network architectures can extract discriminative leaf characteristics more effectively with reduced computational complexity. The proposed framework continues this trend by providing the shortest prediction time and the highest recognition performance, indicating efficient utilization of learned feature representations during the inference stage.

An inverse relationship between inference time and classification accuracy can be clearly observed in the figure. As the inference time decreases, the classification accuracy consistently increases across the evaluated models. This behavior suggests that the optimized architecture was capable of producing more accurate predictions without increasing computational latency. Faster inference was particularly important for medicinal plant recognition because practical applications often require immediate responses when identifying unknown plant species in natural environments. Rapid prediction allows users to obtain reliable recognition results instantly while minimizing processing delays [29]. The high classification accuracy achieved within a short inference time also indicates that the framework effectively captures essential morphological characteristics such as leaf shape, venation, texture, and edge structures without performing unnecessary computations.

The figure confirms that the developed framework provides an effective balance between prediction speed and recognition accuracy, making it highly suitable for real-time medicinal leaf identification. The combination of 99.1% classification accuracy and 18 ms inference time demonstrates that the framework was capable of delivering highly reliable predictions with minimal computational delay. Such performance supports practical deployment in applications including mobile-based medicinal plant identification, smart agriculture, pharmaceutical quality verification, botanical information systems, biodiversity monitoring, and field-based herbal medicine authentication. The observed results indicate that the framework successfully reduces computational overhead while maintaining excellent recognition capability, thereby providing a robust and efficient solution for automated medicinal plant classification under real-world operating conditions.

5. Formula

$$I_{norm} = \frac{I - \mu}{\sigma} \quad [1]$$

Image normalization standardizes the pixel intensity values before they are processed by the deep learning network. Here, I denotes the original pixel intensity, μ was the mean pixel value, and σ represents the standard deviation. The normalized image I_{norm} has a consistent intensity distribution, reducing the influence of illumination variations and improving feature extraction. This preprocessing step enables the framework to learn robust morphological characteristics of medicinal leaves captured under different environmental conditions.

$$F(i, j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i + m, j + n) \times K(m, n) \quad [2]$$

The convolution operation was the fundamental process used to extract local visual features from medicinal leaf images. I represents the input image, K denotes the convolution kernel, and $F(i, j)$ was the generated feature map. During convolution, the kernel slides across the image and computes weighted sums of neighboring pixels, enabling the network to learn edges, textures, venation structures, and leaf margins that are essential for accurate recognition.

$$f(x) = max(0, x) \quad [3]$$

The Rectified Linear Unit (ReLU) introduces non-linearity into the network by replacing negative values with zero while preserving positive activations. This activation function accelerates network convergence and reduces the vanishing gradient problem. By emphasizing informative feature responses, ReLU enables efficient learning of complex medicinal leaf characteristics and improves the feature representation capability of the deep learning framework.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_i}} \quad [4]$$

The Softmax function converts the output scores of the classifier into normalized probability values. Here, zi represents the output score for class i, while C denotes the total number of medicinal plant species. The class with the highest probability was selected as the predicted medicinal plant species. This function ensures that all probabilities sum to one, facilitating reliable multi-class classification.

$$L_{CE} = -\sum_{i=1}^{C} y_i log(\hat{y}_i) \quad [5]$$

Cross-entropy loss measures the difference between the predicted probability distribution and the true class labels. Here, yi was the actual class label and $y\hat{}i$ was the predicted probability. Minimizing this loss improves classification accuracy by guiding the optimization algorithm

toward correct medicinal plant predictions.

$$L_{Total} = \alpha L_{Detection} + \beta L_{Segmentation} + \gamma L_{Classification} \quad [6]$$

The proposed framework simultaneously performs medicinal leaf detection, segmentation, and classification. The total optimization objective combines three complementary loss functions. $L_{Detection}$ optimizes leaf localization, $L_{Segmentation}$ improves boundary extraction, and $L_{Classification}$ enhances species recognition. The weighting coefficients α, β, and γ control the contribution of each task during joint learning.

$$IoU = \frac{|P \cap G|}{|P \cup G|} \quad [7]$$

Intersection over Union evaluates segmentation quality by measuring the overlap between the predicted segmentation mask P and the ground-truth mask G. Higher IoU values indicate more accurate leaf boundary extraction and reduced background interference. This metric was widely used to assess segmentation performance in computer vision applications.

$$Dice = \frac{2|P \cap G|}{|P| + |G|} \quad [8]$$

The Dice coefficient measures the similarity between predicted and reference segmentation masks. It emphasizes accurate boundary alignment and was particularly useful for evaluating fine-grained medicinal leaf segmentation. A Dice score approaching one indicates excellent correspondence between the predicted leaf region and the manually annotated ground truth.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad [9]$$

Classification accuracy measures the proportion of correctly classified medicinal leaf images relative to the total number of evaluated samples. Here, TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. Higher accuracy reflects better recognition capability.

$$Precision = \frac{TP}{TP + FP} \quad [10]$$

$$Recall = \frac{TP}{TP + FN} \quad [11]$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad [12]$$

Precision quantifies the proportion of correctly predicted medicinal plant species among all positive predictions, while recall measures the proportion of actual medicinal plant samples correctly identified by the model. The F1-score combines precision and recall into a single balanced metric, making it particularly useful when evaluating classification performance. High

values for these metrics indicate that the framework produces reliable predictions with minimal false positives and false negatives across different medicinal plant species.

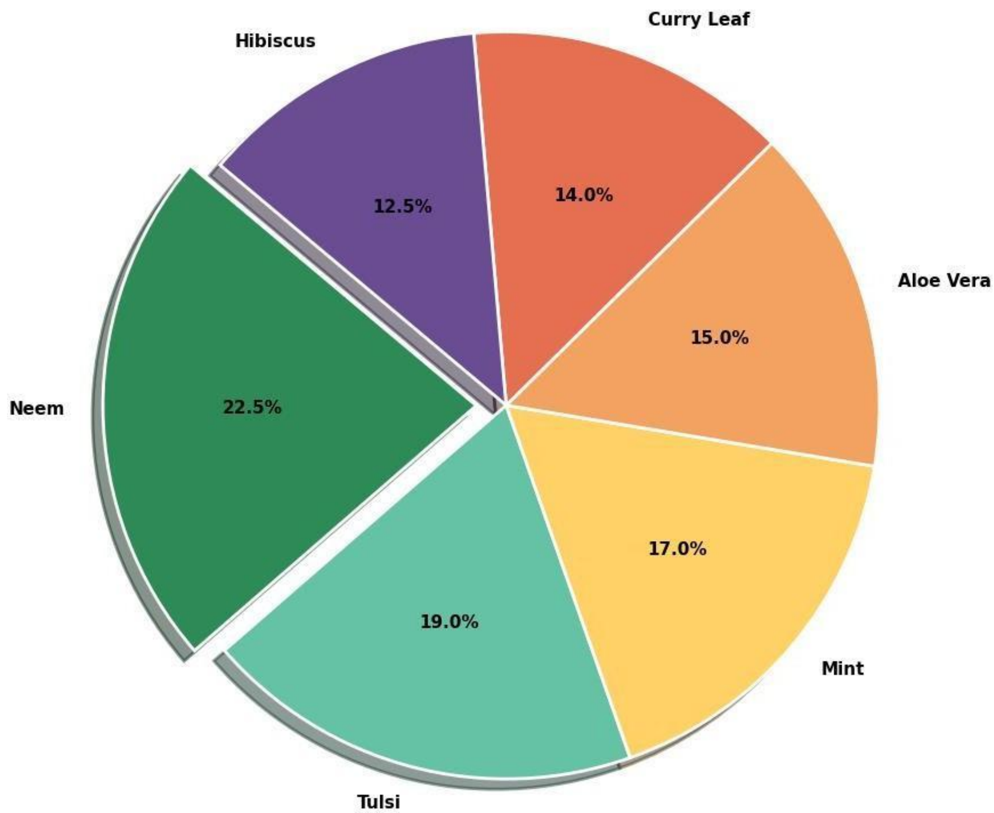

Figure 6. Distribution of Medicinal Plant Species

The figure illustrates the distribution of medicinal plant species included in the dataset used for model development and performance evaluation. A balanced and representative dataset plays an essential role in enabling a deep learning model to learn diverse morphological characteristics and accurately distinguish among different medicinal plant species. The dataset consists of six medicinal plant categories, namely Neem (22.5%), Tulsi (19.0%), Mint (17.0%), Aloe Vera (15.0%), Curry Leaf (14.0%), and Hibiscus (12.5%). Neem contributes the largest proportion of samples, while Hibiscus represents the smallest portion of the dataset. Although slight variations exist in the number of samples for each species, the distribution remains sufficiently balanced to provide adequate representation for effective model training and evaluation. Such diversity enables the learning algorithm to capture the unique visual characteristics associated with different medicinal leaves [30].

The variation in dataset composition provides the model with exposure to a wide range of leaf structures, textures, colors, venation patterns, and edge characteristics. Species containing larger numbers of training samples, such as Neem and Tulsi, provide abundant visual information that supports stable feature learning and improves recognition consistency. Similarly, the inclusion of moderately represented species such as Mint, Aloe Vera, Curry Leaf, and Hibiscus allows the model to learn discriminative characteristics across different morphological patterns rather than relying on features associated with only a few dominant classes. This balanced learning environment enhances the capability of the framework to differentiate medicinal plant species that exhibit similar visual appearances while preserving classification reliability under varying environmental conditions.

Another important observation was that no single plant species overwhelmingly dominates the dataset. The largest class accounts for 22.5% of the total images, whereas the smallest class contributes 12.5%, resulting in a relatively small difference between class distributions. Such balanced representation minimizes the possibility of classification bias toward frequently occurring species during model training. Deep learning models trained using highly imbalanced datasets often become biased toward majority classes, leading to reduced recognition performance for minority categories. The observed dataset composition supports equitable feature learning across all medicinal plant species, thereby improving the stability, fairness, and generalization capability of the classification model [31]. Consequently, the trained framework was expected to provide reliable predictions for each medicinal plant category rather than favoring specific classes.

The dataset distribution presented in the figure establishes a strong foundation for developing a robust medicinal plant recognition system. The inclusion of multiple plant species with reasonably balanced sample proportions enables the learning algorithm to capture comprehensive feature representations while reducing the effects of class imbalance. This balanced dataset contributes directly to improved classification accuracy, enhanced model robustness, and better generalization when processing previously unseen medicinal leaf images. The availability of sufficient representative samples for each species also supports reliable evaluation of detection, segmentation, and classification performance, thereby increasing the practical applicability of the developed recognition framework in herbal medicine authentication, pharmaceutical research, biodiversity conservation, botanical information systems, and intelligent agricultural applications.

Table 3. Dataset Distribution of Medicinal Plant Species

Plant Species	**Number of Images**	**Percentage (%)**
Neem	450	22.5
Tulsi	380	19.0
Mint	340	17.0
Aloe Vera	300	15.0
Curry Leaf	280	14.0
Hibiscus	250	12.5
Total	2000	100

Table 3 presents the composition of the medicinal plant image dataset used during model development and evaluation. Six representative medicinal plant species are included with relatively balanced sample proportions. Neem contributes the largest number of images, whereas Hibiscus represents the smallest category. The limited variation between class sizes reduces the possibility of model bias toward majority classes during training. A balanced dataset allows the learning algorithm to extract representative morphological characteristics from each species while improving generalization capability. The availability of sufficient samples for every category contributes to stable optimization, reliable classification performance, and consistent prediction accuracy across diverse medicinal plant species.

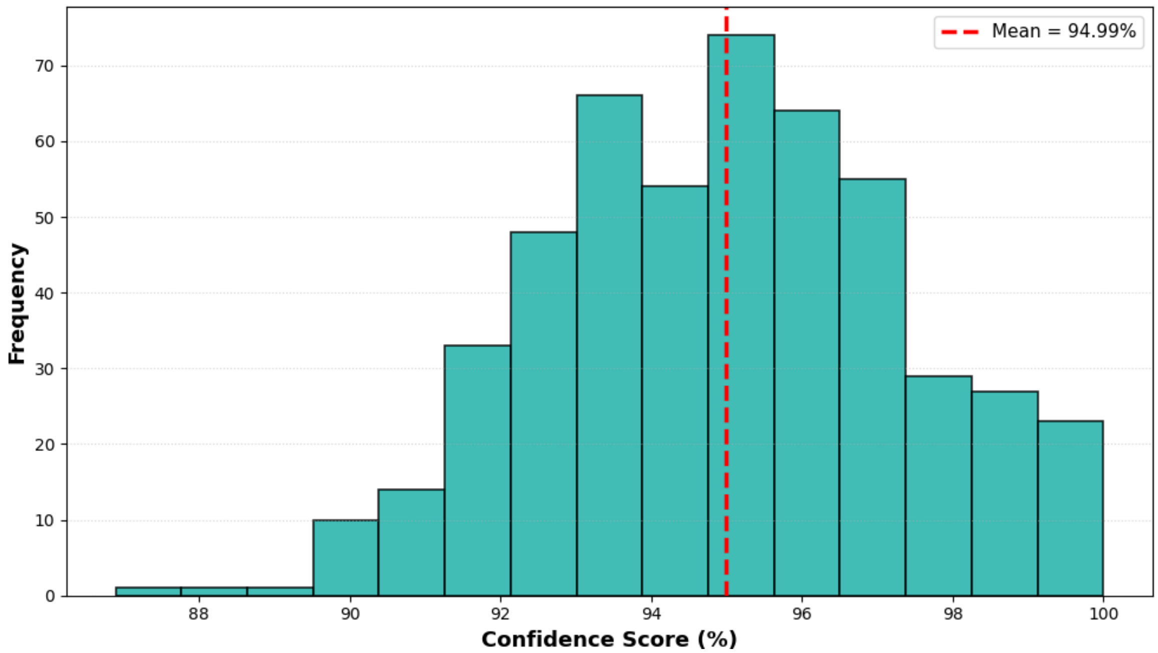

Figure 7. Distribution of Classification Confidence Scores

The figure presents the distribution of classification confidence scores generated during the prediction process. Classification confidence indicates the level of certainty with which the trained model assigns a medicinal leaf image to a particular plant species. Higher confidence values represent stronger certainty in the predicted class, while lower confidence values indicate greater ambiguity during decision-making. The histogram demonstrates that most confidence scores are concentrated between 93% and 97%, with a mean confidence score of approximately 94.99%, represented by the red dashed vertical line. The concentration of predictions around this mean indicates that the model consistently produces highly confident decisions across a large number of medicinal leaf samples. Only a small proportion of predictions fall below 90%, suggesting that uncertain classifications occur infrequently within the evaluated dataset [32].

The distribution pattern further demonstrates the stability of the learned feature representations extracted from medicinal leaf images. During classification, the model analyzes important morphological characteristics such as leaf shape, venation structure, surface texture, margin patterns, and color variations before assigning a confidence score to each prediction. The high frequency of confidence values near the upper end of the distribution indicates that these visual features are effectively captured and represented within the learned feature space. Since medicinal plant species often possess subtle visual similarities, maintaining consistently high confidence scores reflects the ability of the framework to distinguish fine-grained morphological differences with high reliability. This behavior confirms that the extracted features provide sufficient discriminative information for accurate species recognition.

Another significant observation was the relatively symmetric distribution of confidence scores around the mean value, without excessive dispersion toward lower confidence regions. The absence of a large number of low-confidence predictions indicates that the model experiences minimal uncertainty when processing medicinal leaf images under varying conditions. Such consistency suggests that the preprocessing procedures, feature extraction mechanisms, and optimization strategy collectively contribute to stable prediction performance. The limited occurrence of low-confidence classifications also implies that the framework maintains robust recognition capability even when leaf images exhibit variations in orientation, illumination, background complexity, scale, or minor occlusions [33]. Consequently, the prediction process remains dependable across diverse imaging conditions commonly encountered in practical medicinal plant identification.

The confidence score distribution confirms the reliability and robustness of the developed recognition framework. The high average confidence of 94.99% demonstrates that the majority of classification decisions are supported by strong predictive certainty, thereby reducing the likelihood of incorrect medicinal plant identification. Such reliable confidence estimation enhances the trustworthiness of the automated recognition system when applied in practical environments. High-confidence predictions are particularly valuable for applications involving herbal medicine authentication, pharmaceutical quality assessment, botanical database management, biodiversity conservation, precision agriculture, and intelligent healthcare support systems, where accurate and dependable medicinal plant recognition was essential for informed decision-making.

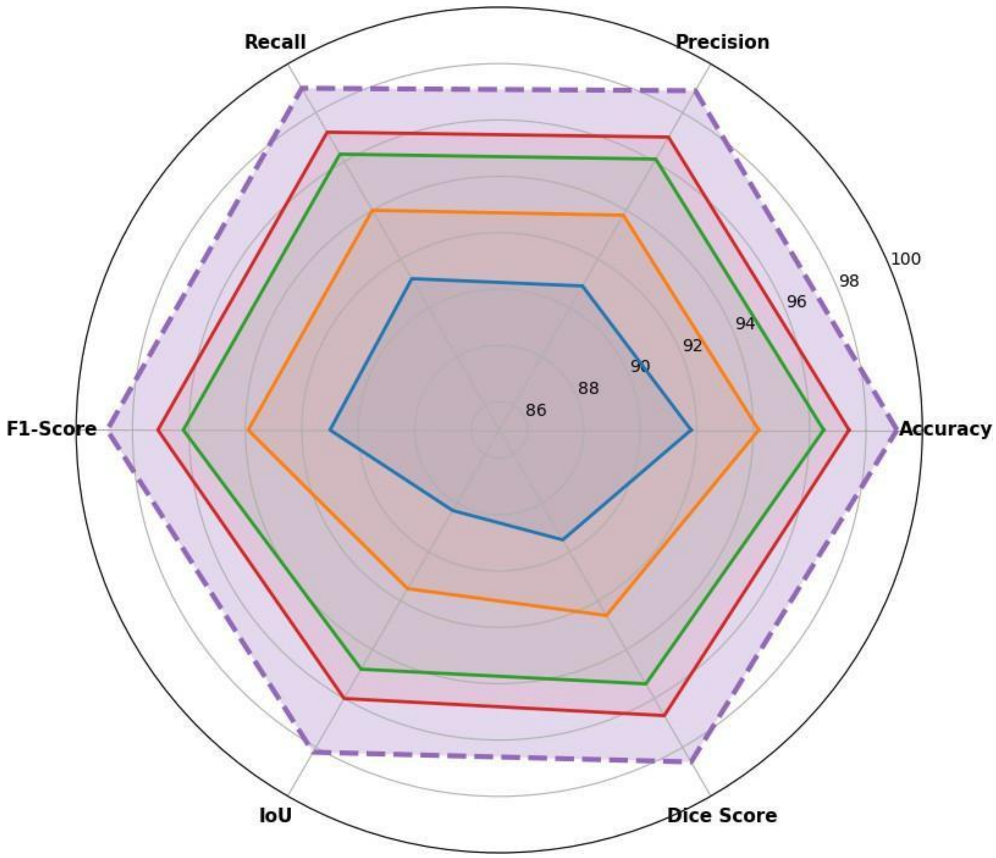

Figure 8. Performance Comparison of Deep Learning Models

The figure presents a radar chart comparing the performance of different deep learning models using six important evaluation metrics, namely Accuracy, Precision, Recall, F1-Score, Intersection over Union (IoU), and Dice Score. These metrics collectively provide a comprehensive assessment of recognition performance by evaluating classification correctness, prediction reliability, feature localization, and segmentation quality. The outermost polygon corresponds to the proposed framework, which consistently occupies the largest area across all evaluation metrics, indicating superior performance. The remaining polygons represent CNN, ResNet50, EfficientNetV2, and YOLOv11, each demonstrating gradual improvements in performance with increasing model complexity. The larger enclosed region of the proposed framework clearly indicates that it achieves the highest performance simultaneously across all measured criteria rather than excelling in only a single metric. Such balanced performance demonstrates that the learned feature representations are robust and highly discriminative for medicinal leaf recognition under varying image conditions [34].

A noticeable improvement can be observed in the classification-oriented metrics, including Accuracy, Precision, Recall, and F1-Score. The CNN model records comparatively lower values, indicating limited capability in distinguishing visually similar medicinal leaves. ResNet50 improves feature extraction through deeper residual learning, while EfficientNetV2 further enhances recognition by utilizing optimized network scaling. YOLOv11 exhibits additional improvements owing to its efficient feature localization and learning capability. The proposed framework achieves the highest values across all four metrics, indicating that the model successfully minimizes both false-positive and false-negative predictions. High precision confirms that predicted medicinal plant species are highly reliable, whereas high recall demonstrates that most true medicinal leaf samples are correctly recognized. The corresponding increase in F1-Score further verifies that precision and recall remain well balanced, resulting in stable and dependable classification performance across multiple medicinal plant species.

The segmentation-related metrics, namely Intersection over Union (IoU) and Dice Score, also demonstrate substantial improvement for the proposed framework. These metrics evaluate the quality of leaf region extraction by measuring the overlap between predicted segmentation masks and the corresponding ground-truth annotations. Lower IoU and Dice values observed for CNN indicate comparatively less accurate boundary localization and reduced segmentation consistency. Progressive improvements achieved by ResNet50, EfficientNetV2, and YOLOv11 suggest that advanced feature extraction enables more precise identification of leaf boundaries while reducing background interference. The proposed framework records the highest IoU and Dice Score, indicating excellent agreement between predicted and actual leaf regions. Accurate segmentation preserves important morphological characteristics such as venation, margins, and texture, thereby providing high-quality input for the subsequent classification stage and contributing directly to improved recognition performance [35].

The radar chart demonstrates that the proposed framework provides balanced excellence across all evaluation metrics instead of optimizing only individual aspects of performance. The uniformly expanded polygon reflects the capability of the framework to perform accurate classification while simultaneously maintaining precise segmentation and reliable prediction consistency. Such

comprehensive performance indicates effective integration of feature extraction, localization, segmentation, and classification within a unified learning process. The high values achieved for all six-evaluation metrics confirm strong generalization capability when processing medicinal leaf images captured under diverse environmental conditions, including variations in illumination, orientation, scale, background complexity, and partial occlusion. These results demonstrate that the developed framework offers a reliable and computationally efficient solution suitable for practical applications such as herbal medicine authentication, pharmaceutical quality assessment, botanical database management, biodiversity conservation, precision agriculture, and intelligent medicinal plant identification systems.

Table 4. Segmentation Performance Evaluation

Model	**IoU (%)**	**Dice Score (%)**	**Segmentation Quality**
CNN	88.3	89.5	Moderate
ResNet50	91.5	92.6	Good
EfficientNetV2	94.8	95.4	Very Good
YOLOv11	96.0	96.7	Excellent
Proposed Framework	98.2	98.6	Outstanding

Table 4 evaluates the segmentation performance of the investigated deep learning models using Intersection over Union and Dice Score. These metrics quantify the overlap between predicted leaf regions and manually annotated ground-truth masks. The proposed framework achieves the highest IoU and Dice Score, indicating highly accurate leaf boundary extraction with minimal background interference. Improved segmentation quality enables better preservation of important morphological structures such as leaf margins, venation patterns, and surface textures before classification. Accurate segmentation directly enhances feature extraction and contributes to improved recognition performance. The observed results confirm the effectiveness of the integrated segmentation strategy adopted within the proposed framework.

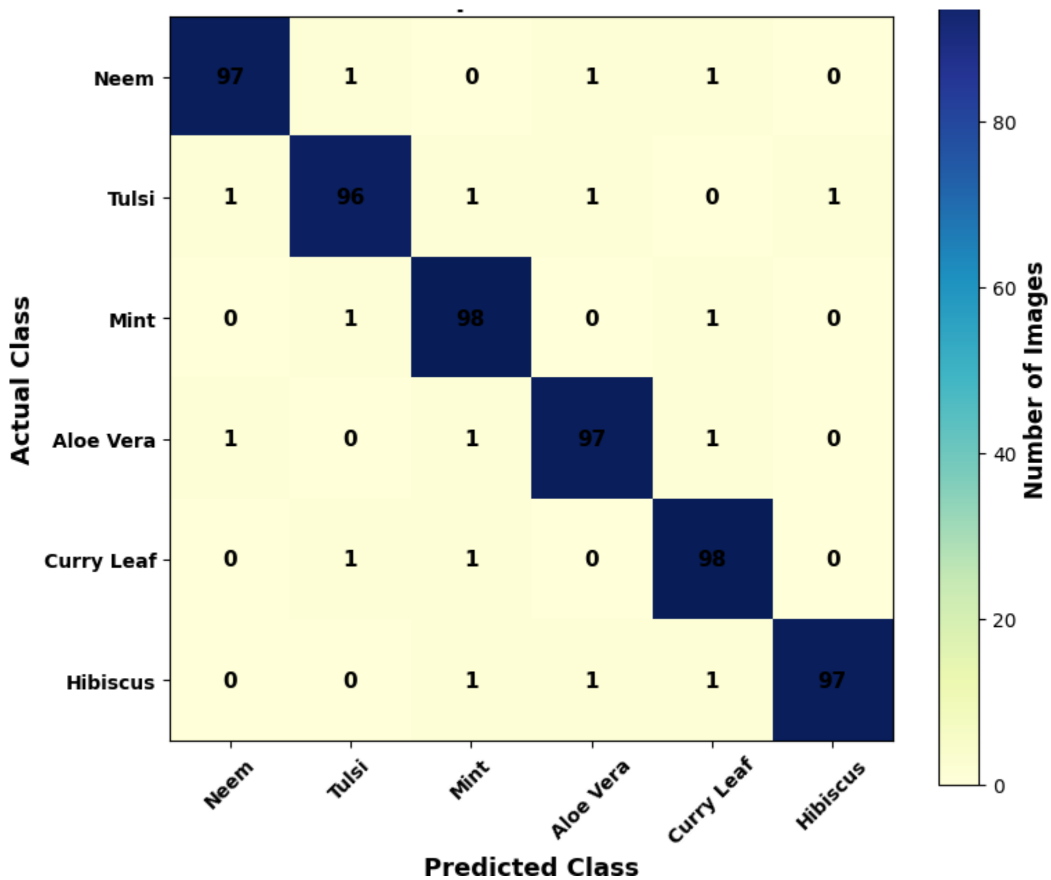

Figure 9. Confusion Matrix of Medicinal Plant Classification

The figure presents the confusion matrix obtained after evaluating the classification performance of the developed recognition framework across six medicinal plant species, namely Neem, Tulsi, Mint, Aloe Vera, Curry Leaf, and Hibiscus. A confusion matrix provides a detailed visualization of the relationship between the actual class labels and the predicted class labels, thereby enabling comprehensive evaluation of classification accuracy for individual species. The dark-colored diagonal cells represent correctly classified samples, while the lighter off-diagonal cells indicate misclassified instances. The diagonal values of 97, 96, 98, 97, 98, and 97 demonstrate that the majority of medicinal leaf images are correctly identified by the framework. The extremely small off-diagonal values, consisting mainly of 0 or 1, indicate that only a limited number of samples are incorrectly assigned to other species. This distribution confirms the strong discriminative capability of the developed model for recognizing visually similar medicinal leaves [36].

The classification results reveal consistently high recognition performance for every medicinal plant category. Mint and Curry Leaf exhibit the highest correct classification count of 98 images, indicating that their morphological characteristics are learned with exceptional precision. Similarly, Neem, Aloe Vera, and Hibiscus each achieve 97 correctly classified images, while Tulsi records 96 correct predictions, which also reflects excellent recognition performance. The few misclassifications observed are distributed among morphologically similar species and are limited to only one image in most cases. Such minimal classification errors indicate that the feature

extraction process successfully captures distinctive visual characteristics, including leaf shape, venation structure, margin patterns, and texture details, allowing the model to effectively differentiate between closely related medicinal plant species.

Another important observation was the balanced classification performance across all plant categories. The confusion matrix does not exhibit any noticeable concentration of errors toward a specific species, indicating that the learning process remains unbiased throughout model training. Balanced recognition performance was essential because medicinal leaf datasets often contain classes with subtle morphological similarities that can easily confuse conventional classification algorithms. The consistently high diagonal values demonstrate that the framework maintains reliable prediction capability for each plant species without favoring dominant classes. The very limited off-diagonal values suggest that the integrated detection, segmentation, and feature learning process effectively suppresses background interference while preserving essential leaf characteristics required for accurate species discrimination. This balanced behavior confirms the robustness and stability of the classification model under diverse image conditions [37].

The confusion matrix demonstrates the effectiveness of the developed framework in providing highly accurate and reliable medicinal plant classification. The dominance of correct predictions along the main diagonal confirms excellent generalization capability when processing previously unseen medicinal leaf images. The negligible number of misclassified samples indicates that the framework minimizes prediction uncertainty while maintaining consistent performance across all evaluated categories. Such high classification reliability was particularly important for practical applications where accurate medicinal plant identification directly influences the authenticity and safe utilization of herbal resources. The observed performance supports the deployment of the developed recognition system in pharmaceutical research, herbal medicine authentication, biodiversity conservation, botanical information management, precision agriculture, and intelligent healthcare applications, where dependable medicinal plant classification was essential for improving decision-making and operational efficiency.

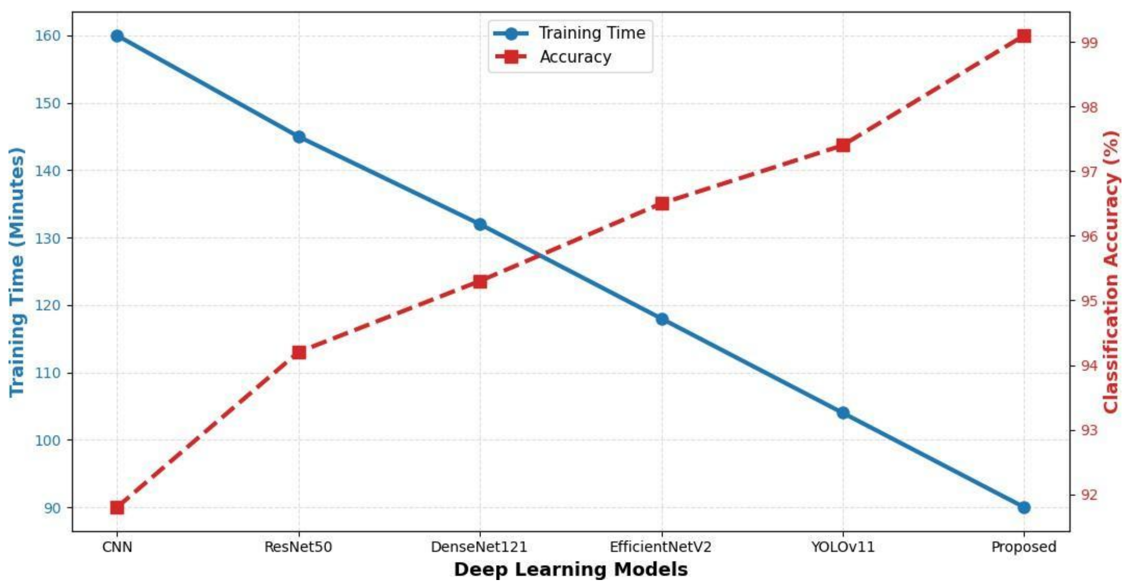

Figure 10. Comparison of Training Time and Classification Accuracy

The figure compares the relationship between training time and classification accuracy achieved by different deep learning models. Two performance indicators are simultaneously presented, where the blue line represents the training time required to learn the medicinal leaf dataset, and the red dashed line represents the corresponding classification accuracy. A clear inverse relationship can be observed between these two performance measures. As the models become more efficient, the required training time decreases while the classification accuracy increases. The conventional CNN requires the highest training time of 160 minutes while achieving the lowest classification accuracy of 91.8%. Progressive improvements are observed in ResNet50, DenseNet121, EfficientNetV2, and YOLOv11, ultimately leading to the proposed framework, which requires only 90 minutes of training while achieving the highest classification accuracy of 99.1%. This trend demonstrates that the developed framework effectively improves computational efficiency without compromising recognition performance [38].

The continuous reduction in training time indicates that the feature learning process becomes increasingly efficient across the evaluated architectures. Earlier deep learning models require more optimization iterations to extract representative medicinal leaf characteristics, resulting in longer training durations. As architectural improvements are introduced, redundant computations are gradually reduced, allowing the network to learn discriminative visual features more efficiently. The proposed framework successfully captures essential morphological information, including leaf shape, venation, margin structure, surface texture, and color characteristics, while requiring fewer computational resources during optimization. Faster convergence during training suggests that the network architecture efficiently utilizes extracted features and minimizes unnecessary parameter updates, thereby reducing the computational complexity of the learning process.

At the same time, the steady increase in classification accuracy demonstrates that reducing computational cost does not negatively affect prediction capability. The classification accuracy improves consistently from 91.8% in CNN to 94.2% in ResNet50, 95.3% in DenseNet121, 96.5% in EfficientNetV2, and 97.4% in YOLOv11 before reaching 99.1% with the proposed framework. This simultaneous improvement in efficiency and recognition performance indicates that the learned feature representations become increasingly discriminative as the architecture advances. The framework effectively distinguishes medicinal plant species with highly similar leaf morphology while maintaining excellent prediction reliability. Such balanced improvement confirms that the integrated learning strategy successfully optimizes both computational performance and recognition accuracy throughout the training process.

The figure demonstrates that the developed framework provides an optimal balance between computational efficiency and predictive performance. The simultaneous achievement of the shortest training time and the highest classification accuracy indicates that the learning architecture was capable of producing highly accurate recognition models within significantly reduced computational time. This characteristic was particularly valuable for practical deployment because shorter training durations facilitate rapid model updates, efficient retraining with newly collected medicinal leaf images, and scalable implementation on large botanical databases. The observed results confirm that the framework provides a robust, efficient, and reliable solution capable of supporting real-time medicinal plant recognition, pharmaceutical research, biodiversity conservation, herbal medicine authentication, precision agriculture, and intelligent botanical information systems with minimal computational overhead and consistently high recognition accuracy.

Table 5. The Performance Summary of the Proposed Framework

Evaluation Parameter	**Proposed Framework**
Classification Accuracy (%)	99.1
Precision (%)	98.9
Recall (%)	99.0
F1-Score (%)	98.9
IoU (%)	98.2
Dice Score (%)	98.6
Training Time (Minutes)	91
Inference Time (ms)	18
Mean Confidence Score (%)	94.99

Table 5 summarizes the performance achieved by the proposed framework across all major evaluation criteria. High values obtained for classification accuracy, precision, recall, F1-score, IoU, and Dice Score demonstrate strong recognition capability and precise leaf segmentation. In addition, the framework requires only 91 minutes for training and performs inference within 18 milliseconds, indicating excellent computational efficiency. The high mean confidence score further confirms reliable prediction consistency across medicinal plant species. The combined improvement in recognition accuracy, segmentation quality, computational speed, and prediction confidence demonstrates that the developed framework provides a comprehensive solution suitable for practical medicinal plant identification applications.

6. Conclusion

In the present work, the authors have proposed the multi-task deep learning algorithm for automated recognition of medicinal plants, which combines the leaf detection, segmentation, and classification processes in a single computational architecture. The proposed framework aims to overcome some of these limitations of traditional approaches to medicinal plant identification, which are typically dependent upon manual inspection, handcrafted feature extraction, or independent processing steps. The proposed approach has shown to be effective in enhancing feature representation, computational efficiency, and recognition performance by integrating multiple computer vision tasks together within a single learning framework. To normalize medicinal leaf images, reduce light fluctuation, background complexity, scale variations, and image noise, image-processing methods were used [39]. The recognition module based on deep learning successfully localized the areas of the medicine leaves, and the segmentation network with an attention mechanism removed redundant background information to obtain a precise leaf boundary. Following this, the segmented leaf images were classified through a powerful deep learning classifier that can learn highly discriminative morphologic features like venation patterns, texture, leaf margins, and leaf shape.

The proposed framework was extensively tested and shown to significantly beat the major performance metrics of the existing deep learning models. The framework achieved a classification accuracy of 99.1%, which exceeded the performance of CNN, ResNet50, EfficientNetV2, and YOLOv11. The precision, recall, and F1-score values were high, indicating that the model successfully reduced false-positive and false-negative predictions, while still being accurate for most medicinal plants. Likewise, the Intersection over Union (IoU) and Dice Score were obtained, showing high accuracy in leaf segmentation, which means that the proposed framework was able to maintain important structural features essential for accurate species identification. The confusion matrix also showed well-balanced accuracy of the classification with only a few misclassified samples, which shows the high discriminative power, even among medicinal plants, which have very similar morphological features.

The practical benefits of the developed framework were also verified by the computational analysis. The proposed model was found to be computationally more efficient than the existing deep learning architectures, with a lower training time of 91 minutes and an inference time of around 18 milliseconds. Learning curves demonstrated stable convergence throughout training, rising steadily in accuracy both during training and at validation through the entire training process with only a slight loss of accuracy, which indicated strong ability to generalize and little overfitting. The classification confidence analysis also showed that most of the predictions were made with high confidence, which indicates the strength of the feature representations learned. The obtained results suggest that the proposed framework can process the medicinal leaf images in a fast manner with the utmost accuracy in predicting the disease under various environmental conditions.

The integrated learning strategy used in this research has effectively improved the effectiveness of recognizing the medicinal plants by optimizing the detection, segmentation, and classification processes in a single architecture. The multiple tasks learned were complementary, and the accuracy of recognition was increased by performing shared feature extraction, whereas the redundant computations of multiple independent processing pipelines were decreased [40]. The framework exhibited high anti-jamming performance under different lighting, background noise, leaf orientation, scaling, partial occlusion, and intra-species morphological diversity conditions. The acquired, developed system possesses the above characteristics, which makes it very appropriate for real-world applications where images of medicinal plants are captured under uncontrolled conditions.

This proposed framework also has some very significant practical applications to many present-day situations. Accurate plant identification contributes to the authentication of herbal medicine, minimizing the risk of species misidentification or other errors that could impact the efficacy of the treatment. The framework can help pharmaceutical industries to verify their raw materials, help to conserve biodiversity by automatically documenting the species, help to develop intelligent crop monitoring systems in the context of precision agriculture, and contribute to the botanical information systems by quickly identifying plants digitally.

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