RESEARCH ARTICLE

DOI: 10.54392/irjmt2548

Asian Research Association

INTERNATIONAL RESEARCH JOURNAL OF MULTIDISCIPLINARY TECHNOVATION

A Novel Multistage Approach for Medicinal Plant Classification with Deep Learning Techniques

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DOI: https://doi.org/10.54392/irjmt2548

Received: 12-12-2024; Revised: 09-06-2025; Accepted: 06-07-2025; Published: 14-07-2025

Abstract: Accurate classification of medicinal plant images into high-level categories and specific sub-groups is essential for various applications, including agriculture, plant research, and conservation. This paper proposes a multi-stage deep learning approach to enhance the precision of medicinal plant image classification. In the first stage, known as Broad Classification, CNN and pre-trained models such as VGG16, ResNet50 and EfficientNetB0 are utilized to categorize images into high-level groups, including "Medicinal Plants," "Fruit-Related Plants," and "Flower-Related Plants." The model is fine-tuned using data augmentation techniques to ensure robust learning and generalization. In the second stage, referred to as Detailed Classification, separate models are trained for each high-level group to classify images into specific sub-groups within that category. The architecture of these models is adjusted to accommodate the unique number of classes in each sub-group. Each model undergoes training with optimized hyperparameters and is evaluated based on precision, recall, F1-score, and accuracy. The proposed multi-stage method demonstrates the ability to handle both broad and fine-grained medicinal plant classifications effectively, showcasing an improvement in classification performance over traditional single-stage models. This approach highlights the potential for deep learning to contribute to more precise and practical medicinal plant image classification solutions.

Keywords: Intrusion Detection, Ranking Algorithms, Machine Learning, Ensemble Learning

1. Introduction

The classification of medicinal plants is a crucial endeavor that supports a variety of fields, including traditional medicine, pharmacology, conservation, and biodiversity studies. Medicinal plants have been used for centuries to treat ailments and are the foundation for many modern pharmaceutical compounds. Identifying and classifying these plants accurately is vital for preserving their use in traditional practices and for scientific research that aims to discover new medicinal properties. However, the task of plant classification can be challenging due to the vast diversity within the plant kingdom, subtle differences between species, and the often-ambiguous characteristics that distinguish closely related plants.

Traditional approaches to plant classification have heavily leaned on specialist botanists and physical verification procedures that are time-consuming and prone to human error. Recent progresses in computer vision and DL technologies have offered novel advantages to automating this process. Machine learning models that leverage large datasets and advanced algorithms had already started identifying patterns and extracting features undetectable to the human eye. It also has enabled big gains in image classification problems, such as plant-related ones, with deep learning models like CNNs, along with its derivatives yielding good results [1].

Pre-trained CNNs such as VGG16, ResNet50, MobileNetV2 and EfficientNet have been widely used and have video achieved significant results in many image recognition tasks due to their powerful feature extraction capabilities and hierarchical feature detailed structure. These models may be adapted to use in specialization classification issues for raising accuracy as well as productivity. Transfer learning, the concept of fine-tuning a model that has been pre-trained on a different but similar task [2], has proven quite useful in low-data scenarios. The introduction of attention-based methods has seen major progress in the accuracy and interpretability of plant classification models and allows for adequate handling of contextual information and spatial dependencies within images [3]. Moreover, some hybrid models that merge CNN models with GCNs contribute more superiorly to evaluating relational instances in datasets that increase the accuracy of fine-grained plant species classification [4].

Deep learning methods have proven to be effective for plant recognition [5] and the literature already mentions the capability of these algorithms to reduce the work that experts need to do, as well as scaling up their solutions. Similarly, more recent studies highlight the effectiveness of few-shot learning methods coupled with semi-supervised learning for plant classification tasks, for use cases where labeled datasets are scarce, allowing for the construction of more robust and generalizable classification systems [6]. More recently, a number lightweight deep learning models specifically designed for mobile and edge computing devices have been developed, allowing for real-time identification of plants deployed in-field, and dramatically increasing potential for practical applications [7].

Despite these advancements, few studies have directly compared the performance of plant identification techniques, especially concerning evolutionary effects on chosen species types [8]. Moreover, multistage classification methodologies specifically tailored for medicinal plant classification have received relatively limited exploration [9]. Hierarchical and layered models for combined broad and detailed classification have received relatively little attention but have the potential to improve classification system efficacy. Recent studies highlighted the importance of hierarchical approaches by demonstrating improved accuracy and robustness in classifying plants with subtle inter-class variations, suggesting that hierarchical methods effectively address class imbalance and enhance overall model generalization [10]. Additionally, recent integration of advanced data augmentation methods and adaptive training strategies has further boosted performance by mitigating overfitting and adapting models to complex datasets reflecting real-world scenarios [11].

This paper proposes using a new multistage approach combining deep techniques to more accurately and robustly classify medicinal plants at various levels. The images are grouped in two stages according to high-level classes (medicinal plants, fruits, or flowers) and the second stage identifies the subtype of each high-level group (medicinal plants, fruits, or flowers). By using the cumulative approach, the model can build on what it already knows to improve classification as task difficulty increases. The proposed model has more accuracy, and the tier model structure allows it to adept with complicated image classification problems. Our step-wise approach focuses on stages, where setups evolve from simple image-based checks (Stage 1) to more sophisticated processes capable of processing larger plant datasets and adapted environmental conditions (Stage 3) adaptable through a consistent design protocol, establishing a reliable system for plant research and automated medicinal plant identification.

2. Related Works

The classification of plant images using ML and DL has garnered significant research attention due to its potential to enhance plant identification accuracy and promote botanical research. Kant, 2024 [12] used transfer learning to classify species like maize, cashew, cassava and tomato based on leaf morphology using VGG16. They compiled datasets and standardized the scale and input of the images so that the model could actually extract traits specific to the leaf. Evaluation metrics, such as precision and F1-score, demonstrated that the model could improve precision agriculture and conserve biodiversity. Mufeeda *et al.,* 2024 [13] developed a CNN-assisted system for plant leaf classification that distinguished morphologically similar leaves, such as coriander and parsley. They used some preprocessing steps such as converting the images to gray scale and applying histogram equalization, obtaining an accuracy of classification of 90%. Their 15-layer network suggested that it has prospects far beyond automated agriculture. Kala *et al.,* 2024 [14] performed the comparison study of InceptionV3, VGG16 and EfficientNetBO on PlantVillage dataset. They reported EfficientNetBO the best performer, with good classification accuracy. To reduce extra data collection, it used augmented datasets, which made it a more efficient model for field use.

Palanivel *et al.,* 2024 [15] employed CNN based model on VNP200 data for multi-class plant species classification yielding 96.42 evaluation accuracy. The method leveraged pre-trained weights and specialized training schemes tailor fit to numerous plant species, highlighting its relevance to biodiversity monitoring. "Deep Flower," a ViT-based model for flower species classification (Soundarya *et al.*, 2024 [16]). Their model outperformed conventional CNNs in capturing subtle morphological variations, which led to improved generalization and interpretability in ecological monitoring and horticultural applications. For instance, Zhao *et al.,* 2024 introduced the few-shot learning model

MAFDE-DN4, which is based on the bidirectional weighted feature fusion and episodic attention modules [17]. Summary: This model achieves 81.41% accuracy while addresses the issues of inter-class similarity and background noise under limited data perspectives. For plant disease detection, Hanif *et al.,* 2024 compared their results against ResNet, Inception-v3, and SVM models, and they achieved good accuracy, noting ResNet was the most robust overall [18]. Their open-source work showed how resilient ResNet is to hyperparameter variation and environmental noise, enabling the potential for scale across general agricultural use cases.

Renukaradhya *et al.,* 2024 [19] proposed DeepHybrid-OptNet, a hybrid DL approach integrating CNN, RNN architectures for medicinal plant classification. The model outperformed all the traditional metrics (accuracy, precision, and recall) when it's tested on the Mendley and Folio datasets. The high-level method can be beneficial for fast learning and often successful species-level classification, as it helps learn better features from plants. Custodio *et al.,* 2024 [20] explored a model averaging ensemble comprising ResNet50, ResNet101, ResNet152, VGG16, and VGG19 architectures to classify medicinal plant leaves. Transfer learning was employed to reduce training time, and data augmentation added variance to enhance accuracy. For medicinal plants classification, Vidya *et al.,* 2024 [21] have proposed a CNN-based DL model with the integration of InceptionV3 and ResNet50. Using InceptionV3, their method reached an accuracy of 100% and outperformed all other models in recognizing three plant classes which include neem, peepal and tulsi. This study showcases the capabilities of pre-trained networks for medicinal taxonomy. Our literature survey also compared five CNNs: MobileNet, VGG16, and DenseNet121 for medicinal plant classification of 3500 images (Salsabila *et al.,* 2024 [22]). Indonesian Herb Leaf Dataset, the other models were attaining 98.86% accuracy in MobileNet. These results were only made possible through critical components of data augmentation and transfer learning. Lakshmanarao *et al.,* 2024 [23] used DL features from VGG16 and combined them with traditional feature extraction methods (shape, texture and color) to classify medicinal plants. Out of many regular machine learning classifiers we tested with, Random Forest classifier scored the best accuracy. This method indicates the strength of combining conventional with DL approaches.

A light weight DL model using inception tiers with residual connections for plant disease classification is present by Caluyo *et al.,* 2024 [24]. This model gives rise to an accuracy of 97.2%, 98.4% and 96.3% for the PlantVillage dataset, rice disease dataset and cassava disease dataset respectively which minimizes both parameters and space complexity as compared to the existing techniques. Rao *et al.,* 2024 [25], proposed a new CNN-GCN hybrid model combining the feature extraction capabilities of convolutional neural networks (CNN) with those of graph convolutional networks (GCN). The integrated model was compared against standalone models on a variety of metrics, and it outperformed all standalone models by realizing the strength of combined visual and relational information, tested on Kaggle dataset with 31 plant disease classes they described ML, DL approaches to plant disease detection, to compare with CNNs, RNNs, SVMs, and decision trees. Sharma & Bansal, 2024 [26] reviewed recent advances in plant disease detection using ML and DL techniques, comparing CNNs, RNNs, SVMs, and decision trees. It highlighted CNNs' superiority in multi-class plant disease classification accuracy, particularly for crop datasets, and challenges to real-time monitoring, and the need for multi-modal approaches.

Ullah *et al.,* 2023 [27] proposed a lightweight DL architecture for plant disease classification, which was inspired by the limitations of traditional plant disease classification methods such as low accuracy and high cost. It contained 28 layers and advanced features provider such as leaky ReLU, batch normalization, and fire module and classifies the plants disease in 10 group includes Apple Black Rot and Maize Common Rust. Saad *et al*., 2023 [28] proposed one-shot learning (OSL) method based on Siamese Neural Networks (SNN) for the classification of plant diseases when there is limited data. They classified diseases over five crops, grape, wheat, cotton, cucumber, and corn using 875 leaf images in 25 classes. To solve the small-size problem, they augmented the dataset and developed an advanced region-based image segmentation method to improve localization. Wang *et al.,* 2023 [29] present a detailed process for plant disease recognition, proficient in traditional and DL features. They proposed an OSTU based algorithm with Naive Bayes model for leaf localization, multivariate feature model to understand the interpretable features of leaves, as well as MobileNet V2 network with two attention mechanism for channel and spatial level analysis.

Verma *et al.,* 2022 developed an automatic plant disease detection system to classify diseases based on symptoms on leaf surfaces into three categories: fungal, bacterial, and viral [30]. They utilized a convolutional neural network (CNN) trained on a dataset of 64,963 samples, with 80% used for training and 20% for validation. Based on a single-layer feed-forward neural network known as Extreme Learning Machine (ELM), Xian *et al*., 2021 [31] used the proposed model to classify plant diseases from leaf images. The original images were pre-processed from HSV color space, and features were extracted with the help of Haralick textures and afterwards fitted with the ELM classifier during training and testing. The experiment, which was carried out with a subset of the PlantVillage dataset that was concerned with tomato leaves from which tomato leaf images were taken, showed an accuracy of 84.94% compared to other models SVM and Decision Tree. A.L.

Rao *et al.,* of used transfer learning approaches for predicting plant diseases on the PlantVillage dataset containing images of 15 types of leaves of tomato, potato, and bell pepper plants [32]. A comprehensive review on plant diseases, their types, identification and disease detection methods has been summarized in Uppal *et al.,* 2022, where the authors highlighted the challenges of manually detecting and identifying plant diseases which justifies the transition towards automated systems [33]. They explored several artificial intelligence and machine learning models for classifying diseases, emphasizing their ability to detect diseases in early stages so that crops can be saved.

3. Method

Figure 1 illustrates the proposed methodology for medicinal plant images classification.

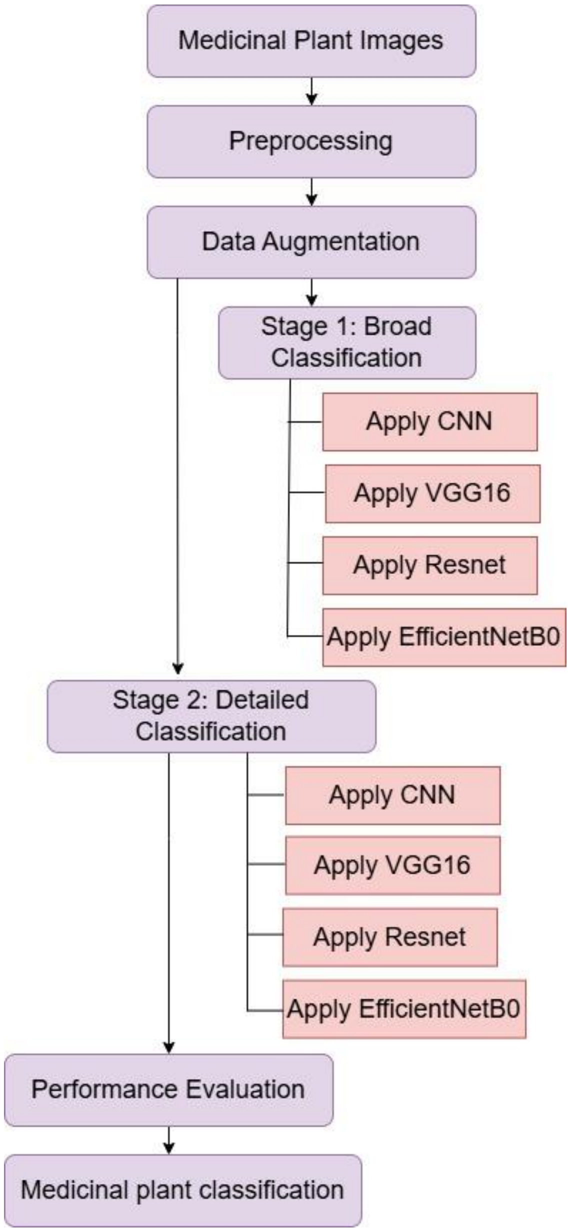

Figure 1. Proposed Method.

The proposed methodology employs a multi-stage deep learning approach for the classification of medicinal plant images. The work is divided into two stages to address both broad and fine-grained classification tasks effectively. Stage 1 focuses on broad classification, categorizing images into high-level groups such as "Medicinal Plants," "Fruits," and "Flowers." Stage 2 further refines this classification by identifying specific sub-groups or species within each high-level category. This was achieved by applying CNNs with transfer learning on VGG16, ResNet50, and EfficientNetB0. All images were resized, normalized, and augmented to ensure quality, and enhance model generalization. At each stage, they improved model architectures and fine-tuned hyperparameters specifically for the characteristics of the classification problem. This allows for adapting both model architectures and learning strategies depending on stage of classification complexity. The class imbalance was also reduced, and different classes were able to be classified by training separate models on the sub-groups to better performance. This hierarchical approach guarantees a scalable format to handle heterogeneous and complex-structured datasets..

3.1 Medicinal plant image collection

In the proposed work a dataset of medicinal plant image taken from Kaggle [34]. The selection of plant species is representative of a diverse number of plants so the dataset is suitable for classification tasks. It contains images from 30 plant types (medicinal plants or sub-groups, groups) by providing a wide range of examples, the model can learn and distinguish between different species of plants. The dataset that they released also has images, taken under different lighting conditions, angles and backgrounds to mimic the real world. This diversity in the dataset will enable the development of a more generalizable classification model that performs well under different conditions and variations present in practical applications.

3.2. Preprocessing

Pre-processing is one of the key steps that confirms the image data to be ready for feeding into the DL model [20]. The Following pre-processing steps were performed to transform the dataset to be fir it for the model training for this study. The first step was to resize the images to a standard size of 224x224 pixels, compatible with most of the models available pre-trained in this work. If everything were to happen at the same time, no balance would exist; therefore, uniform resizing serves to create a balance and make the processing pipeline easier.

Data normalization is an important step in image data [35]. The data were normalized by scaling the pixel values to the range [0, 1]. To do that, we need to convert our image pixel values from 0-255 to a range of 0-1, this can be achieved by dividing the image pixel values by 255. Image centering was also applied by subtractig the mean pixel value of the whole dataset from each pixel, which has been shown to center the data distribution around zero and helps stabilize training and improve model performance. In cases where the model required specific formats for input (RGB channels, etc.), proper conversion between color spaces was performed.

3.3 Data Augmentation

In the case of medicinal plant classification, data augmentation is an important factor that enhances the robustness and generalization of DL models. We utilized techniques including random rotations, horizontal and vertical flipping, and random cropping to mirror potential real-world scenarios of image orientation and visibility. Zooming the image to 20% helped the model adjust to different scales and color jittering changed the brightness and saturation to handle lighting differences. Random shearing induced slight distortions to simulate other photographing angles [36].

These data augmentation techniques helped to enhance the training data therefore helping the model to learn more generalised features but preventing overfitting. Such interplay of private and public data resulted in impressive performance of the model being able to give accurate results by interacting with unseen and variety of data. This approach ensured that the model will be able to accurately classify plant images in different conditions and real-world environments.

3.4 Transfer Learning Approach

Transfer learning contributed greatly to getting the classification model accuracy up. Using pre-trained models, the study used DL architectures capable of powerful feature representations learned on massive image datasets. This is especially important for settings for which sufficient training data is not available and saves us from needing large amounts of data to fit complicated models.

Recent studies have demonstrated the potential of transfer learning for fine-grained classification tasks, particularly in domains with limited datasets. For instance, Wang *et al.* (2023) effectively employed MobileNet V2 with attention mechanisms for plant disease classification, achieving high accuracy even with small datasets [29]. Similarly, Saad *et al.* (2023) utilized one-shot learning techniques with Siamese Neural Networks for limited data, achieving robust classification [28].

In this work, pre-trained and transfer learned CNN models like ResNet50 [37], VGG16 [38] and EfficientNetB0 [39] were chosen as base models for the coarse-grained and fine-grained classification (These models were selected as they have proven to be competent in image classification tasks). VGG16 for its simplicity but also deep architecture and will be used not for final selection, but as baseline of others model while ResNet50 handle for residual learning to reduce the drawback of vanishing gradient problem. Conversely, we harnessed EfficientNetB0 for its advantageous trade-off between accuracy and computational efficiency, thus, providing a promising option for tackling large-scale image data across a range of resolutions.

The transfer learning step consists of employing these models trained on ImageNet to fine-tune the target task: classifying medicinal plants. The models were initially initialized with weight values from the ImageNet training process, which enabled them to start off with an effective feature extraction framework. Models were modified by replacing the top layers with custom dense layers that matched the number of classes in the dataset. By freezing all model layers except the 2 custom layers when first training, we preserved the result of training on ImageNet and only enabled fine-tuning of the custom layers. This strategy decreased training time and computational cost, but maintained the models' ability to extract relevant features.

After adding the new layers, the whole model was fine-tuned with a lower learning rate. This phase gave the pre-trained weights more specificity to the plant image data without overfitting. The choice of fine-tuning such models in an incremental manner allowed them to generalize well both to the coarse as well as the detailed classification tasks.

By employing these techniques, a very solid transfer learning method was utilized for developing a potential model to classify medicinal plants in all levels of application. Significantly, this step greatly enhanced model accuracy, while shortening the training time by fine-tuning pre-trained models, which eventually led to reliable and efficient plant classification.

3.5 Stage 1- Broad Classification

The broad classification stage serves as the initial layer of the proposed multistage approach, where images are categorized into general groups such as medicinal plants, fruits, and flowers. This step sets the foundation for more detailed classification and facilitates better model training. To achieve this, CNNs and pre-trained models, specifically VGG16, ResNet50, and EfficientNetB0, were utilized. These models were selected for their exceptional performance in image recognition tasks due to their deep architecture and pre-learned representations, enabling them to capture intricate features from images effectively. The dataset was organized into three primary categories: Common Medicinal Plants, Fruit-Related Plants, and Flower-Related Plants. Table 1 shows plant categories and types in broad classification.

Table 1. Plant Categories and Types Used in Broad Classification

Category	Plant Types
Common Medicinal Plants	Amaranthus Viridis (Arive-Dantu), Basella Alba (Basale), Mentha (Mint), Azadirachta Indica (Neem), Ocimum Tenuiflorum (Tulsi), Moringa Oleifera (Drumstick), Ficus Religiosa (Peepal Tree), Nerium Oleander (Oleander), Pongamia Pinnata (Indian Beech), Murraya Koenigii (Curry), Santalum Album (Sandalwood), Plectranthus Amboinicus (Mexican Mint), Alpinia Galanga (Rasna), Ficus Auriculata (Roxburgh fig), Piper Betle (Betel), Trigonella Foenum-graecum (Fenugreek), Brassica Juncea (Indian Mustard), Hibiscus Rosa-sinensis, Carissa Carandas (Karanda), Citrus Limon (Lemon), Mangifera Indica (Mango), Syzygium Jambos (Rose Apple), Syzygium Cumini (Jamun), Punica Granatum (Pomegranate), Tabernaemontana Divaricata (Crape Jasmine)
Fruit-Related Plants	Mangifera Indica (Mango), Citrus Limon (Lemon), Artocarpus Heterophyllus (Jackfruit), Psidium Guajava (Guava), Muntingia Calabura (Jamaica Cherry-Gasagase), Syzygium Jambos (Rose Apple), Syzygium Cumini (Jamun), Pongamia Pinnata (Indian Beech)
Flower-Related Plants	Hibiscus Rosa-sinensis, Jasminum (Jasmine), Tabernaemontana Divaricata (Crape Jasmine), Nyctanthes Arbor-tristis (Parijata)

The dataset for broad classification is composed of three major categories of various plants namely, Common Medicinal plants, Plants Related to Fruits, and Plants Related to Flowers There is the maximum category available for the Common Medicinal Plants which consists of many medicinal and therapeutic plants. Plants That Are Fruits category: plants used as if they are fruits; Plants That Are Flowers category: plants used as if they are flowers the training set is relatively balanced; there are two of each plant type per 15 total for a balanced sample, which will also allow the machine learning algorithms to generalise well when classifying images.

Table 2 shows the distribution of images within each category, indicating the number of images allocated to medicinal plants, fruits, and flowers. This distribution highlights the dataset's composition, essential for evaluating the model's performance in each category.

Table 2. Distribution of Images in Broad Classification

Category	Number of Images
Common Medicinal Plants	1500
Fruit-Related Plants	1200
Flower-Related Plants	800

3.6 Stage 2- Detailed Classification

The detailed classification stage follows the broad classification and aims to accurately identify specific plant types within each general group identified in Stage 1, such as medicinal plants, fruits, and flowers. This stage enhances the granularity of the classification process, enabling precise recognition of individual species. Detailed classification requires precise feature extraction and adaptability to inter-class variations. Zhao *et al.* (2024) addressed this challenge by integrating bidirectional weighted feature fusion with episodic attention modules, achieving 81.41% accuracy in plant disease classification under constrained data conditions [17].

To do this, the stage 1 architecture is repurposed, or new variants are introduced to perform the more fine-grained classification task properly. They use pre-trained networks such as VGG16, ResNet50 develop, and EfficientNetB0 then use custom layers and/or specialized activation functions to improve the models' ability to distinguish between plant species that are similar. This phase of fine tuning is also expanded on to maximize performance across each individual plant category. During this process, data augmentation strategies may be more extreme and learning rates may be greater both to achieve faster convergence and to escape from the local minima. Pre-trained feature extraction followed by specially designed customizations dx-provides models with abilities to perform high-accuracy classification facilitating complete multistage system.

Table 3 Detailed Breakdown of Images in Stage 2 Classification presents the distribution of images for specific plant types within each general category. This breakdown provides insight into the dataset's composition, illustrating the variety and focus of images used for training in the detailed classification stage. The distribution highlights the emphasis on both commonly recognized and less represented plant types to support nuanced model training.

3.7 Training Strategy

The training strategy is crucial for optimizing model performance.

Table 3. Detailed Breakdown of Images in Stage 2 Classification

Category	Specific Plant Type	Number of Images
Medicinal Plants	Amaranthus Viridis (Arive-Dantu)	100
	Azadirachta Indica (Neem)	120
	Mentha (Mint)	90
	Other Medicinal Plants	1190
Fruit-Related Plants	Mangifera Indica (Mango)	300
	Citrus Limon (Lemon)	200
	Psidium Guajava (Guava)	250
	Other Fruits	450
Flower-Related Plants	Hibiscus Rosa-sinensis	200
	Jasminum (Jasmine)	150
	Crape Jasmine	100
	Other Flowers	350

The dataset is split into training, validation and test dataset for training and metrics report. Model learning on the data is typically conducted on a l train set while hyperparameter tuning is done on a validation set followed by the Use of the test set for a final generalizability evaluation. We choose a batch size that strikes a balance between computational efficiency and model stability. This is done over several epochs where we adjust based on convergence and available resources. Due to its adaptive learning rate, the Adam optimizer is used to help the model converge more efficiently. To prevent overfitting and encourage generalization the mainstream regularization techniques (like dropout, L2 regularization, etc.) are used in my training. This method of adding random cropping, rotation, and flipping of the training data increases the training examples while making the model robust to variable real benefits. This strategy builds the foundation for a sound and robust classification system.

3.8 Evaluation Metrics

Accuracy and loss graphs were mainly used for the assessment of the proposed multistage model to visualize how the model performed at various stages. Test accuracy graph shows our models how well our model (training on images) is dividing the images into their respective categories. The loss graph is a plot of the loss function over the course of training and describes the learning of the model. Apart from this, these visualizations give us an understanding of the convergence of the model, also to know whether the model is underfitting/overfitting, more specifically, to adjust the training strategy to get the best results.

4. Experimental Results and Analysis

The experimental results highlight the effectiveness of the proposed multistage model for plant classification. Stage 1 (General Class) shown the strong performance with regards to assigning image inputs to general groups of plants, and Stage 2 (Specific Class) accurately identified particular types of plant forms. Performance comparisons reveal superior efficacy over baseline models, confirming the viability of the proposed method for accurate, efficient medicinal plant identification and classification. In the results section, challenges faced are also mentioned and how the solution was formed, to highlight strengths and limitations of methodology.

4.1 Performance of Stage 1 (Broad Classification)

Stage 1 of the proposed approach focused on classifying images into general categories such as medicinal plants, fruits, and flowers.

Figure 2 shows CNN model's performance over 20 epochs, with training and validation accuracy. Both accuracies increase over time, indicating the model's learning progress. However, training accuracy remains higher than validation accuracy throughout, suggesting overfitting.

Figure 3 illustrates the loss over 20 epochs for the CNN model, with separate curves for training and validation loss. Both show a general downward trend, signifying reduced model error as training progresses. Training loss starts high and drops quickly in the initial epochs, slowing down and plateauing around epoch 10, reaching about 0.15.

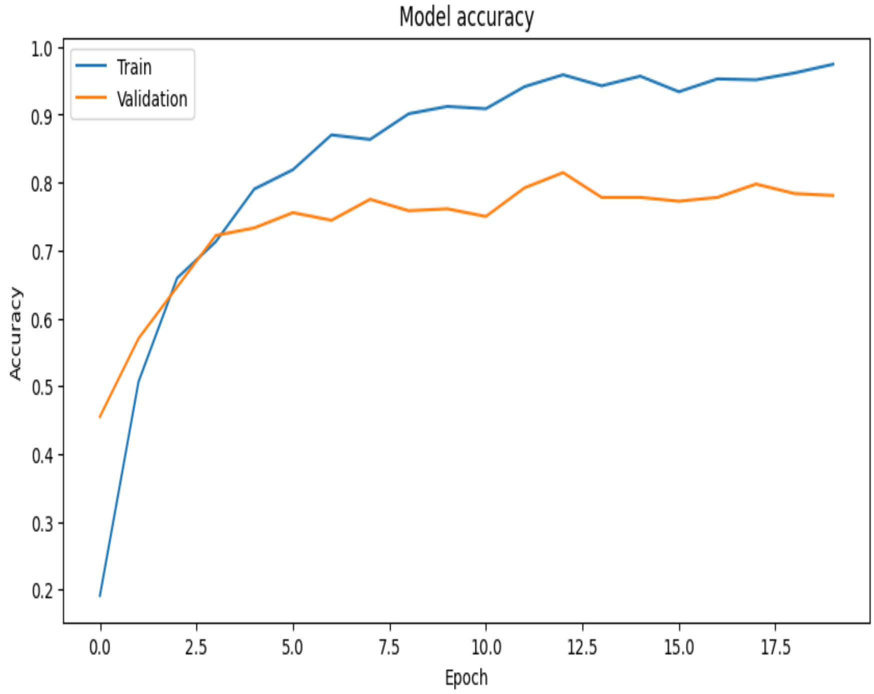

Figure 2. Epoch wise accuracy with CNN model

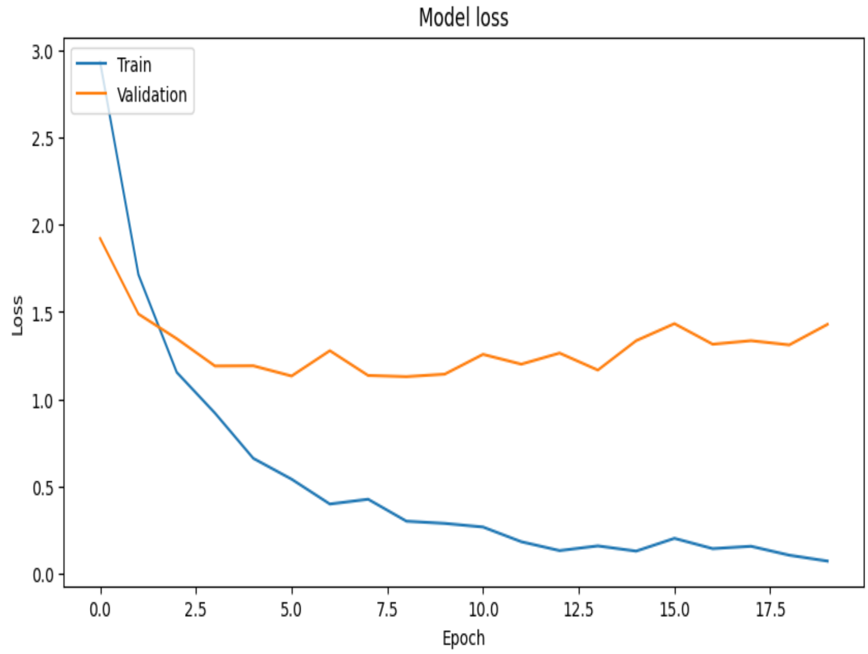

Figure 3. Epoch wise loss with CNN model

In contrast, validation loss starts high and decreases steadily but remains consistently higher than the training loss, stabilizing around 1.3 by the end.

The transfer learning methods were applied using VGG16, ResNet50, and EfficientNetB0, with the models achieving accuracies of 82%, 87%, and 87.4%, respectively. Figure 4 shows epoch wise accuracy with VGG16. These results highlight the effectiveness of pre-trained models in leveraging learned features from large datasets, although the performance is still below optimal. The slight improvement observed with ResNet50 and EfficientNetB0 over VGG16 suggests that deeper and more advanced architectures could potentially yield better results. Further fine-tuning of hyperparameters or more sophisticated techniques may be required to enhance model performance for this specific task.

The use of EfficientNetB0 aligns with findings from Kala *et al.* (2024), who reported its superior performance on the PlantVillage dataset due to its scalability and efficient architecture [14]. Such pre-trained models significantly reduce the computational cost while ensuring high accuracy.

4.2. Performance of Stage 2 (Detailed Classification)

To increase the classification granularity, stage 2 of the approach involved categorizing images into specific plant types. Transfer learning has already been shown to work well on fine-grained classification from recent studies. For instance, Custodio *et al.*, 2024 (identifying other medicinal plants) used ResNet and VGG architectures in ensembles for medicinal plant classification, noting their power of feature extraction and improvement by transfer learning [20]. Similarly, Zhao *et al.,* 2024 The episode attention modules were merged with pre-trained networks for plant disease classification under constrained data conditions, reaching the highest accuracy rate [17]. These results reinforce the fact that transfer learning can be effective for complex classification problems as employed in this work.

Figure 5 shows the performance of the CNN model over 20 epochs shows that both training and validation accuracy exhibit a general upward trend, indicating that the model improved as training progressed. The training accuracy starts at a lower value and increases rapidly at first before slowing down and plateauing. Throughout the training process, training accuracy consistently remains higher than validation accuracy, suggesting overfitting. The validation accuracy follows a similar pattern, it begins low and steadily rises, aligning with the training accuracy's trend. Despite this, the validation accuracy remains lower throughout, stabilizing at around 0.88 (88%) by the end of the training period. This difference points to overfitting, where the model performs well on training data but struggles to generalize to unseen validation data. Figure 6 shows the epoch wise loss values with CNN.

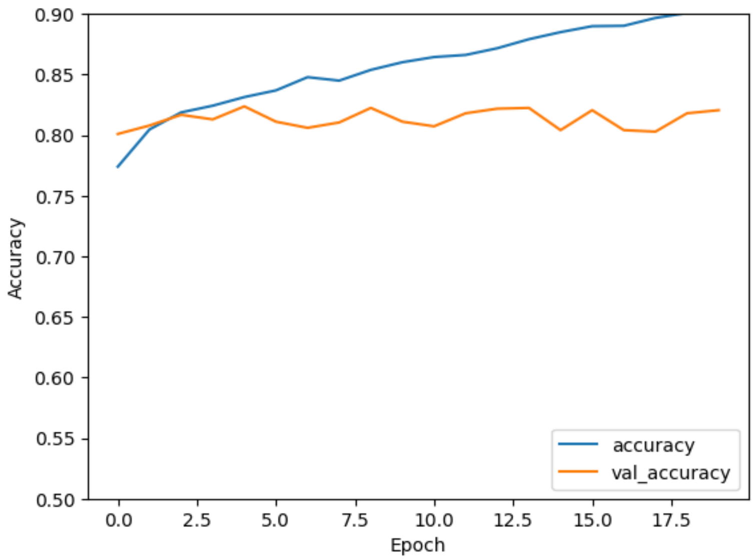

Figure 4. Epoch wise accuracy with VGG16 model

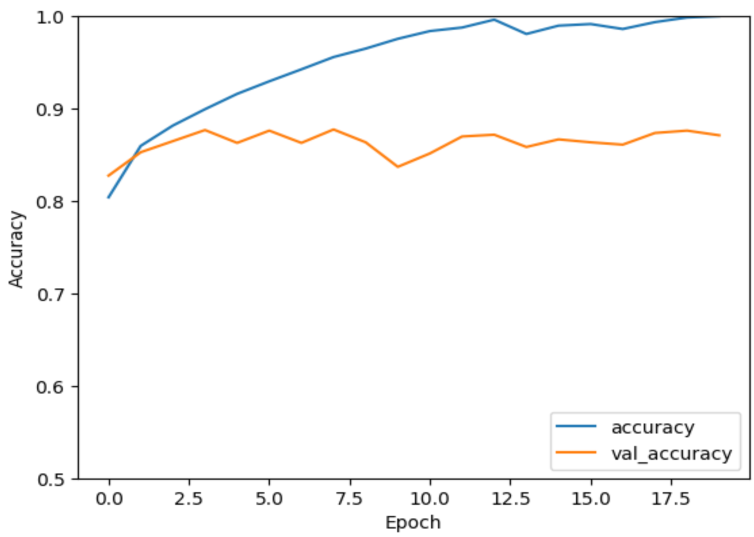

Figure 5. Epoch wise accuracy with CNN model

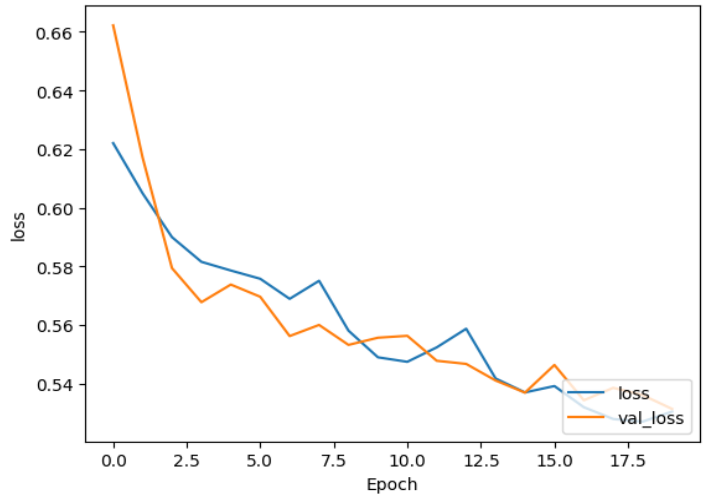

Figure 6. Epoch wise loss with CNN model

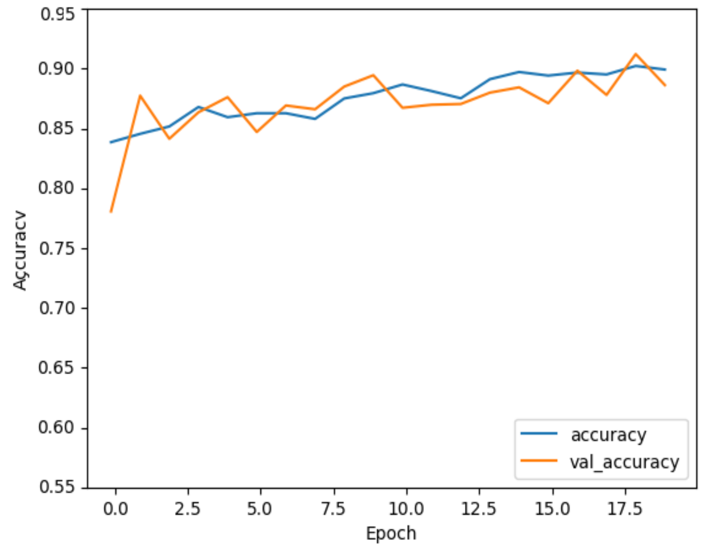

Figure 7. Epoch wise accuracy with Efficient model

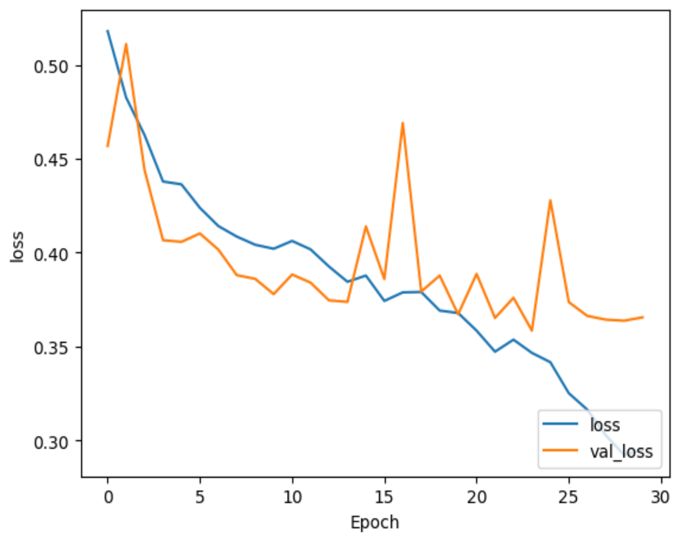

Figure 8. Epoch wise loss with efficient model

Next the transfer learning models VGG16 and ResNet50 applied and achieved accuracies of 89% and 90%, respectively. These results indicate strong performance in the classification task, with ResNet50 slightly outperforming VGG16. While the models demonstrated effective feature extraction and learning, further tuning and more advanced methods may be needed for optimal performance..

Later, Efficientnet applied in stage-2. Figure 7 showing the performance of the EfficientNetB0 model over 20 epochs shows that both training and validation accuracy improve as training progresses. The training accuracy begins at a relatively low value and rises quickly during the initial epochs. It continues to increase with some fluctuations and reaches a plateau around epoch 15. The final training accuracy is around 0.92 (92%). The final validation accuracy stabilizes at approximately 0.92 (92%), suggesting the model's good performance. Figure 8 shows epochwise loss with efficientnet model.

5. Discussion of Results

The multi-stage deep learning approach demonstrated its effectiveness in tackling the hierarchical classification of medicinal plant images. Table 4 and Figure 9 shows accuracy compariso in stage-1 and stage-2.

Table 4. Accuracy comparison of applied models

Model	Stage 1 Accuracy	Stage 2 Accuracy
CNN	78%	88%
VGG16	82%	89%
ResNet50	87%	90%
EfficientNetB0	87.4%	92%

In Stage 1, which involved broad classification into categories such as medicinal plants, fruits, and flowers, ResNet50 and EfficientNetB0 achieved accuracies of 87% and 87.4%, respectively. These results highlight the effectiveness of transfer learning in leveraging pre-trained features for generalized tasks. EfficientNetB0's slightly superior performance stems from its balanced architecture, which optimally scales depth, width, and resolution to maximize efficiency and accuracy.

In Stage 2, focusing on detailed classification of individual species, EfficientNetB0 outperformed other models with an accuracy of 92%, followed by ResNet50 at 90%. This improvement underscores EfficientNetB0's ability to extract nuanced features required for fine-grained classification tasks. However, a consistent gap between training and validation accuracies across all models suggests slight overfitting, emphasizing the need for techniques like dropout, L2 regularization, and enhanced data augmentation.

Table 5 presents the average loss values for Stage 1 and Stage 2 classification tasks across the applied models. Figure 10 shows loss comparison of Stage-1 classifciers. Figure 11 shows loss comparison of Stage-2 classifiers.

Table 5. Loss comparison of applied models

Model	Stage 1 Average Loss	Stage 2 Average Loss
CNN	0.77375	0.455
VGG16	0.719	0.549
ResNet50	0.6465	0.482
EfficientNetB0	0.5895	0.3485

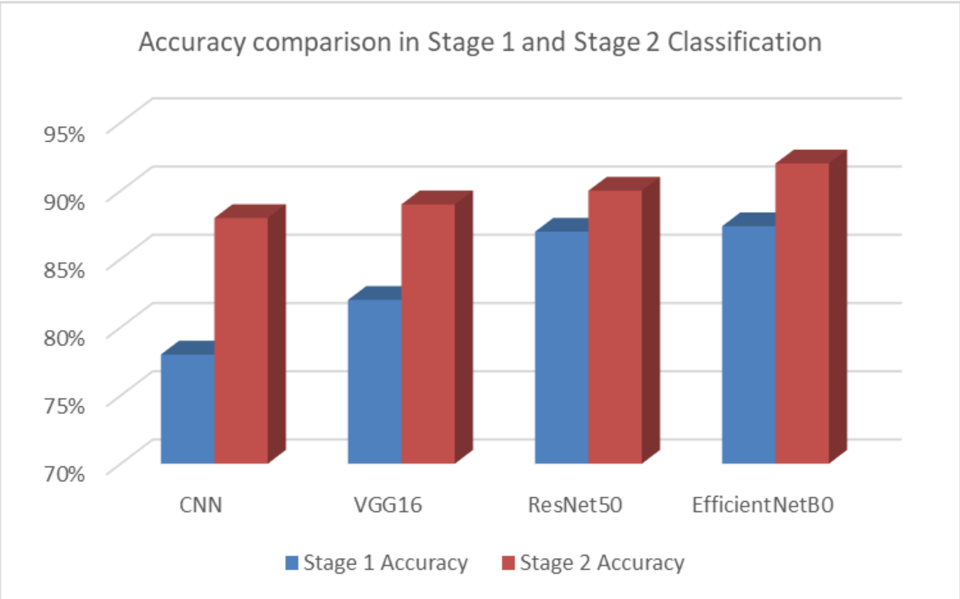

Figure 9. Accuracy of Models in Stage 1 and Stage 2 Classification

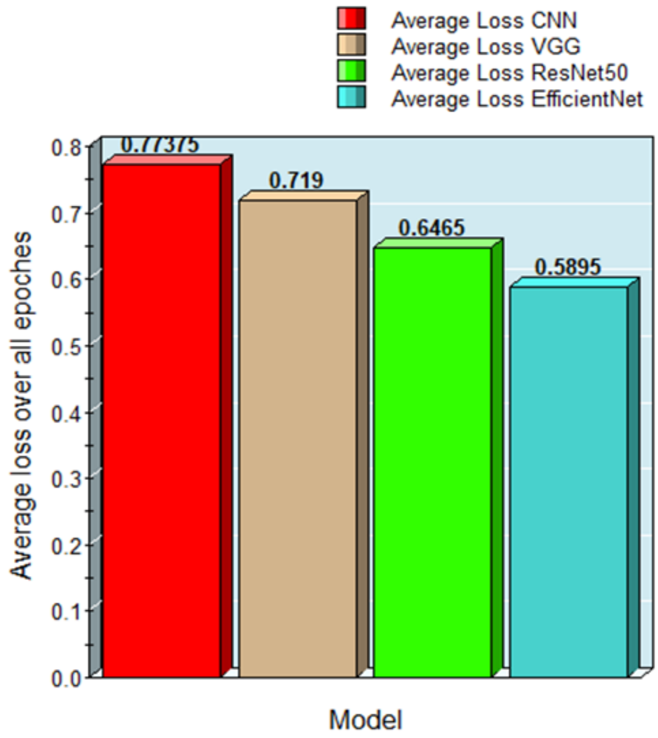

Figure 10. Loss values comparison of Models in Stage 1 Classification

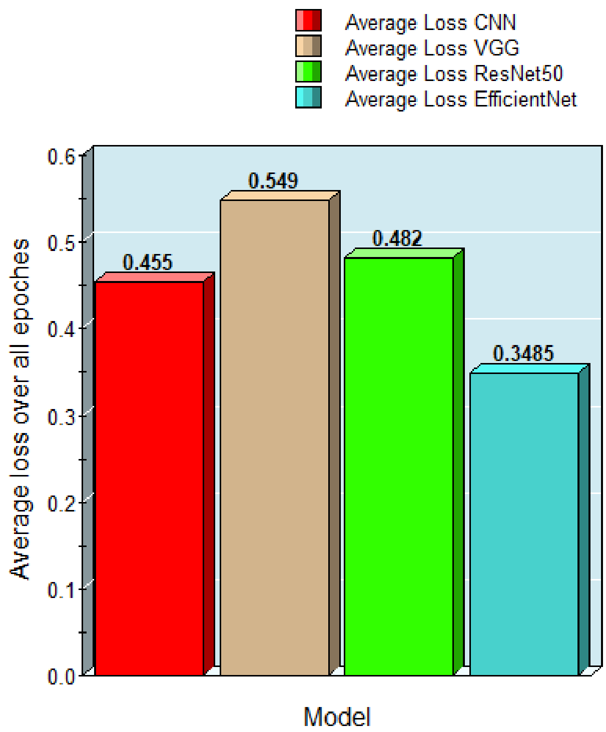

Figure 11. Loss values comparison of Models in Stage 2 Classification

In Stage 1, which involved broader classification, EfficientNetB0 achieved the lowest average loss (0.5895), closely followed by ResNet50 (0.6465). These results align with their higher accuracy metrics and highlight their ability to capture generalized features effectively. By contrast, CNN and VGG16 exhibited slightly higher loss values, indicating a less precise feature extraction process during Stage 1.

In Stage 2, the focus shifted to fine-grained classification, and the loss values across all models decreased further, reflecting improved model refinement. EfficientNetB0 again demonstrated superior performance with the lowest average loss of 0.3485, emphasizing its ability to adapt and learn intricate distinctions between classes. Meanwhile, VGG16 and ResNet50 maintained competitive loss values but showed slightly less efficiency in capturing the finer details required for detailed classification.The merged loss charts (Figure 11) provide a comprehensive visual overview of loss behavior across the epochs for both stages. These charts clearly depict the steady reduction in loss as the training progresses, with EfficientNetB0 consistently achieving lower loss values in both stages. The ability to merge and analyze these loss curves aids in understanding the learning dynamics of the models, offering insights into their optimization efficiency and convergence behavior.

The results from Table 5, Figure 10 and Figure 11 collectively validate the robustness of the proposed approach. The consistent improvement in loss values from Stage 1 to Stage 2 demonstrates the effectiveness of the hierarchical classification strategy and the significant contribution of transfer learning-based models like ResNet50 and EfficientNetB0 in enhancing classification precision.

The proposed methodology has significant practical implications. Therefore, accurate classification of the medicinal plants can have important implications for the pharmacological research, conservation of biodiversity, and agricultural practice. The hierarchical structure allows for greater flexibility, as the model can effectively address high-dimensional and class-imbalanced datasets. The precise identification of species at different environmental conditions can also aid in biodiversity studies, such as through detailed classification of medicinal plants.

Despite these achievements, certain challenges remain. While pre-trained models like EfficientNetB0 are beneficial, they introduce computational overhead during fine-tuning. Additionally, the reliance on high-quality, diverse datasets is critical for ensuring generalizability to real-world scenarios.

In summary, the proposed multi-stage framework increased classification accuracy by breaking down more information into smaller steps. This scalable and independently adaptable solution opens pathways for progress in medicinal plant classification among other domains and serves as a powerful tool for addressing complex datasets.

5.1 Comparison with existing approaches

Table 6 and figure 12 shows comparison of proposed model with eisting appraoches. This comparison highlights the improvements achieved by integrating hierarchical classification with advanced transfer learning techniques.

Table 6. Comparsion with existing work

Reference	Technique	Accuracy
Tejaswini *et al*. [1]	CNN based model	86.2%
Mufeeda *et al*. [13]	CNN model	90%
Maheswara Rao *et al*. [25]	GCN model	91%
A.L.Rao *et al*. [32]	Transfer Learning	90%
Proposed Approach	Multistage DL Approach	92%

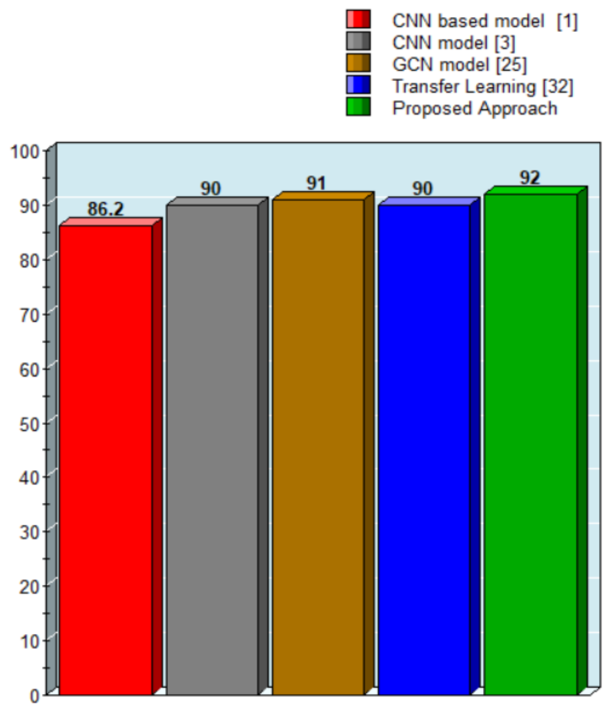

Figure 12. Comparison of proposed model with existing approaches

The CNN-based model introduced by Tejaswini *et al.* [1] saying that primitive CNN architectures can efficiently classify medicinal plants, achieving an accuracy with 86.2%. But due to a lack of powerful feature extraction and hierarchical segmentation it was not able to perform well. Similarly, Mufeeda et al. [13] improved the accuracy to 90% by using a deeper CNN architecture specific to morphologically similar plant leaves. Although successful, their method did not attempt to scale or multi-stage classification.

Maheswara Rao *et al.* [25] applied a Graph Convolutional Network (GCN) model and reached 91% accuracy. It is effective at learning relationships from data dimensions, depending on the data type, and it works nicely for certain datasets. But it is resource-demanding and not well-suited for hierarchical tasks.

Transfer Learning, as used by A.L. Rao et al. [32], reported 90% accuracy, using pre-trained models for rapid feature extraction. While this method decreased computational expense, it lacked the organized segmentation provided by a multi-stage framework.

However, the proposed model achieved an accuracy of 92%, surpassing the performance of such approaches of single-stage architecture and also, due to the use of EfficientNetB0. Leveraging hierarchical segmentation and transfer learning, this model performed well in both broad- and fine-grained classification tasks. The adaptability to class imbalance and real-world conditions of the proposed SRN is another driver of its scalability and robustness.

6. Conclusion

The proposed multi-stage deep learning approach effectively addressed the challenge of medicinal plant image classification by structuring the task into two stages: broad and detailed classification. This hierarchical framework offered distinct advantages, including improved focus and accuracy at each stage. Stage 1 achieved accuracies of 87% with ResNet50 and 87.4% with EfficientNetB0 for general classification, leveraging pre-trained models for robust feature extraction. Stage 2 refined the granularity of classification, with EfficientNetB0 achieving 92%, demonstrating strong performance in fine-grained classification tasks. This multi-stage technique enables adaptation in model architectures and hyperparameters to the specific properties of every stage, increasing flexibility and precision. After stage 2, by isolating specific sub-groups by role in that stage the researchers solved a class imbalance and complexity which resulted in improved generalization. The approach not only enhanced the precision of classification but also offered a scalable methodology for intricate datasets possessing hierarchical formations. This work demonstrates the benefits of using transfer learning with multi-stage architectures to create better solutions for agriculture.

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Authors Contribution Statement

K. Narayana Rao: Data Curation, Formal analysis. Srinivas Kalime: Data Curation, Formal analysis. P. Sujatha: Methodology, Investigation, Validation. Vunnava Dinesh Babu: Methodology, Investigation, Validation. S. Sushma: Writing - Original Draft, Writing - Review & Editing, Conceptualization, Methodology, Visualization. Sajja Tulasi Krishna: Writing - Original Draft, Writing - Review & Editing, Visualization. All authors have read and approved the final manuscript.

Funding

The authors declare that no funds, grants or any other support were received during the preparation of this manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

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

Has this article screened for similarity?

Yes