Multiattribute Deep CNN-Based Approach for Detecting Medicinal Plants and Their Use for Skin Diseases

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***Abstract*—Skin health is a critical concern for humans, especially in geographical areas where environmental conditions and lifestyle factors adversely affect their condition, leading to a prevalence of skin diseases. This issue is exacerbated in rural regions, like parts of India, where a notable dermatologist shortage exists, leading to overlooked skin diseases. In response, the use of medicinal plants for dermatological purposes has been a longstanding tradition. However, traditional plant identification often relies on a single attribute, such as leaves or flowers, which can be unreliable due to seasonal variations. This article introduces a novel approach for accurately identifying medicinal plants using a multiattribute deep convolutional neural network. This approach aims to bridge the gap in healthcare access by empowering individuals to recognize and utilize these plants effectively. Our objective is to develop a robust deep CNN model trained on a diverse dataset of images encompassing leaves, trunks, and seeds of medicinal plants associated with skin health. Our findings demonstrate that the model achieves high accuracy in plant identification, effectively addressing the limitations of single-attribute methods. This research not only contributes to the field of medicinal plant classification but also empowers individuals to make informed decisions about their skin health while preserving valuable traditional knowledge.**

***Impact Statement*—Multiattribute deep CNN model can significantly aid the healthcare and botanical sciences by offering an accurate yet accessible solution for normal users to help them identify plants and their medicinal properties, especially in regions with limited healthcare resources. In rural India, where dermatologist shortages are prevalent, our model facilitates accurate identification of trees such as Karanj, Neem, and Peepal from any attribute leaves, trunks, or seeds with 97.91% precision. Leveraging the widespread availability of mobile phones, this technological advancement empowers individuals to utilize local medicinal plants for easy identification of plants with medicinal properties and use them to treat skin conditions, bridging a critical healthcare gap. By integrating this model into mobile phones and digital platforms, we enhance health education and promote sustainable healthcare practices. This innovation not only democratizes botanical knowledge but also supports primary healthcare in underserved areas, reducing dependency on scarce medical professionals and promoting self-sufficient health management.**

***Index Terms*—Convolutional neural network (CNN), feature extraction, ML, plant recognition.**

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I. Introduction

THE human skin is for shielding and sensation, defends against environmental threats but is vulnerable due to constant exposure. Climate changes, dietary shifts, and crowded living conditions exacerbate this vulnerability, leading to increased susceptibility to skin ailments such as fungal infections. In rural areas such as parts of India, where there is a significant shortage of dermatologists, skin diseases often go unnoticed. In resource-constrained settings, particularly rural regions, traditional herbal remedies are the primary form of healthcare, which includes skin conditions. Identifying trees solely by a single attribute such as leaves, flowers, or seeds can be challenging, especially considering the seasonal variations they undergo. Trees may shed their leaves, become leafless for a period, or bloom flowers only during certain times of the year, leaving them without flowers for the rest of the time. Additionally, some trees may shed their bark at specific times. For laypersons with limited knowledge about trees, relying on just one characteristic for identification becomes even more difficult under these circumstances. To provide a complete solution for plant identification and skin health education, our research proposes a multiattribute deep convolutional neural network-based system. This system overcomes the limitations of traditional methods by enabling the identification of trees not only through singular attributes such as leaves, trunk, seeds, or flowers but also through any part of the tree. Moreover, our novel model integrates information on the primary medicinal uses of identified trees for addressing common skin diseases. Our research endeavors involved training our model on a robust dataset consisting of 22 500 images showcasing diverse attributes of Karanj (botanical name: Pongamia pinnata), Neem (botanical name: Azadirachta indica), and

Peepal (botanical name: Ficus religiosa) trees, encompassing leaves, trunks, flowers, and seeds. Through rigorous training and optimization, our model has achieved high accuracy in tree identification when provided with any attribute of the tree. This achievement highlights the effectiveness and reliability of our multiattribute deep convolutional neural network-based system. Its ability to accurately identify trees based on any attribute not only enhances accessibility and usability but also highlights its potential to contribute significantly to botanical knowledge dissemination and healthcare education, particularly in regions with limited access to specialized resources.

The research addresses the limitations of traditional plant identification methods that rely solely on single attributes, such as leaves or flowers, particularly given their susceptibility to seasonal variations. The research proposes a novel deep convolutional neural network model trained on a diverse dataset of medicinal plant images, encompassing leaves, trunks, and seeds. By focusing specifically on medicinal plants used in treating skin diseases, the research aims to improve dermatological care. Ultimately, this multiattribute deep CNN model has the potential to contribute to the preservation of traditional knowledge about medicinal plants while offering a valuable tool for healthcare practitioners.

II. Related Studies and Findings

Chen et al. [1] in their research paper studied the potential of AutoML technology in the field of Chinese herbal medicine image recognition. The model trained on the database contains 31 460 images of various parts of plant representing 315 categories of frequently used CHMs. They utilize the Huawei model arts platform and the Baidu EasyDL platform to automatically develop and evaluate the image recognition models. During model evaluation, ModelArts and EasyDL achieved high accuracy of 99.2% and 98.4%, respectively. In held-out tests, the accuracies were 91.2% for ModelArts and 91.85% for EasyDL.

Kadiwal et al. [2] in their research article described a method for identifying plant species based on single-leaf images using convolutional neural networks (CNNs). The dataset consists of 7000 images from seven plant species, with 1000 images per species. The dataset is split into training (80%) and testing (20%) sets. The model achieves high accuracy (99.09%) and low loss (0.00086) after 20 epochs of training. The study demonstrates the effectiveness of CNNs in plant identification based on leaf images.

Begum et al. [3] focused on addressing the taxonomic gap by utilizing advancements in machine learning to improve the accuracy of identifying and cataloging medicinal plants. The researchers investigated various machine learning algorithms by using deep learning classifiers for plant identification through leaf images based on botanical features such as shape, ridges, and textures. The research explains the use of image processing and deep learning, with CNN and transfer learning, for plant recognition, pattern separation, and disease diagnosis using leaf image databases.

Kumar et al. [4] in their research paper evaluated the performance of various deep learning optimizers for classification of plants based on leaf images using pretrained CNNs such as Dense121, InceptionV3, VGG16, Xception, VGG19, and MobileNet. The dataset consists of 16 000 images of eight classes of medicinal plants. Transfer learning technique is applied for classification of medicinal plants by replacing the final layer. The Xception model with SGD achieved the highest validation accuracy (0.9750) and the lowest validation loss (0.0896). The MobileNet model with SGD demonstrated a high validation accuracy (0.9625) and lower validation loss (0.4996) with faster training times, making it the most efficient model for this task. The InceptionV3 and Dense121 models also performed well, while VGG16 and VGG19 showed comparatively lower performance.

Priya et al. [5] in their research paper demonstrated the mobile application MedPlant. It is devoted to identifying medicinal plants by analyzing leaf photos. The researcher used 1440 pictures including 30 varieties of medicinal plants. There are 48 optical pictures of each species. MedPlant achieves a 56.33% accuracy rate in plant classification based solely on leaf texture by classifying plants using local binary patterns that capture leaf texture, using visual processing technologies, computer vision, and intelligent information systems. Widians et al. [6] in their research paper recognized the importance of plant identification. This study leverages the trunk for species identification, employing a deep learning approach using the VGG16 architecture. The proposed method involves a two-stage transfer learning strategy: initially fine-tuning the pretrained VGG16 by modifying only the classification layer while keeping the feature layers frozen, followed by unfreezing the last three convolutional layers. A dataset of 681 images from various Dipterocarp species was used, achieving a 97.09% accuracy, surpassing traditional transfer learning methods.

Carpentier et al. [7] in their research paper introduced the BarkNet 1.0 dataset, comprising over 23 000 high-resolution bark images from 23 tree species. Employing deep learning techniques, particularly ResNets, the research demonstrates the efficacy of bark image-based species recognition, achieving an accuracy of 93.88% with single crop and 97.81% via majority voting on all tree images. The study suggests further research directions, including exploring multitask approaches leveraging diameter at breast height (DBH), investigating optimal scales for bark image classification, and adapting deep architectures tailored for texture classification.

Elmas [8] presented the utilization of deep learning techniques for identifying trees through bark images. A dataset comprising 24 686 images from 59 tree species. Employing seven pre-trained convolutional neural networks (CNNs), including AlexNet, DenseNet201, ResNet18, ResNet50, ResNet101, VGG16, and VGG19, the research showcases the potential of transfer learning methods for tree species identification. The findings reveal that transfer learning offers fast and accurate solutions to classification tasks. While the average accuracy of all networks ranges from 93.21% to 95.89% concerning the image-to-data ratio, the two most successful networks achieve an average accuracy of 99.46%.

Liu et al. [9] in their research paper worked on plant identification based on transfer learning from a deep CNN using an ImageNet dataset that contains fruits and flower images. Here research adapts the ResNet-50 model by modifying its last three layers. Later fine-tuning on this pretrained network was performed using flower and fruit images. The proposed network is evaluated on two botanical datasets: the Oxford Flowers dataset, which includes 102 classes, and the HNPlant dataset, consisting of 20 classes. By optimizing the hyperparameters, they achieved high classification accuracies of 92.4% on the Oxford-102 dataset and 95.0% on the HNPlant-20 dataset, demonstrating the model's effectiveness and superiority in automated plant identification.

Bindushree et al. [10] proposed a medicinal plant recognition technique utilizing images of flowers and leaves. Testing is performed on nine medicinal plants with a dataset of 300 images per class. The preprocessing is done to enhance images; later segmentation is also done to extract shape and texture features from flowers and leaves. These features were then used to train classifiers including FRCNN, RCNN, VGG16, and VGG19. The method succeeded in getting accuracy rates of 96.3% with FRCNN, 94.04% with RCNN, 92.4% with VGG16, and 93.2% with VGG19. Additionally, the study provides descriptions of the medicinal benefits of the identified plants.

Ghazi et al. [11] in their research paper worked on dataset LifeCLEF 2015 plant task dataset to evaluate the performance of deep neural networks. The dataset contains 91 758 labeled images of various plant attributes of 1,000 species. The dataset's diversity in terms of plant attributes such as leaf, flower, stem, and fruit makes it challenging. They divided the training data into 70 904 images for training and 20 854 for validation. They fine-tune pretrained deep convolutional neural networks of AlexNet, GoogLeNet, and VGGNet using the LifeCLEF 2015 plant task dataset. Transfer learning and the best classifiers' predictions were combined to improve performance. Fine-tuning GoogLeNet and VGGNet performed better than AlexNet, with VGGNet achieving the highest accuracy of 78.44%.

Ming et al. [12] in their research paper explained the use of Raman spectroscopy in conjunction with support vector machine modeling for the identification of easily confused mineral-based traditional Chinese medicines. The researchers created SVM-based models to classify the nine mineral TCMs that are frequently misunderstood. The study emphases on how the study of mineral TCMs can be helped by the integration of methods such as PCA, SVM, PSO, and GA. The recognition of the TCMs based on SVM models exhibits excellent performance and robust prediction ability.

Dahigaonkar and Kalyane [13] in their research paper examined the identification of Ayurvedic medicinal plants based on image processing methods. Researchers developed an intelligent system using feature vectors to identify plants based on characteristics that differentiate various species, such as shape, color, and leaf texture, to overcome this problem. Support vector machine classification and feature extraction were part of the process. With SVM, the study's accuracy was 96.66%.

Kumar et al. [14] in their research paper present an effective method based on digital image processing for the correct identification of Ayurvedic plants using their leaves. A database of leaf images was developed by analyzing leaf characteristics such as shape, color, and texture. The researchers developed classifiers that could accurately discriminate plant species, i.e., 99% with fresh leaves and over 94% with dried leaves.

Akter et al. [15] presented the fuzzy local binary pattern and fuzzy color histogram. Both were later combined with a PNN classifier. They used this method on a dataset that included 2448 leaf photos from herbal plants. Each leaf image was 270 by 240 pixels. The classification accuracy attained by this method was 74.5%.

Arai et al. [16] in their article explained the SVM classifier in combination with the discrete wavelet transform. This combination was used to extract translation-invariant features from a dataset of eight distinct ornamental plants in Indonesia. In this, they achieved a remarkable accuracy rate of 95.8% by employing an SVM classifier in combination with the discrete wavelet transform.

Sun et al. [17] in their research paper worked on deep learning for plant identification in a natural environment and obtained the BJFU100 dataset in a natural environment using mobile phones. This dataset comprises 10 000 images of 100 different ornamental plant species. They developed a deep learning model consisting of 26 layers and eight residual building blocks for the purpose of uncontrolled plant identification. Their model achieved an impressive recognition rate of 91.78% when tested on the BJFU100 dataset.

Goeau et al. [18] in their research paper proposed a new classification task using the Plant CLEF dataset, which is part of the Pl@net project. Numerous researchers have both theoretically and practically developed systems for plant identification [19], [20].

Josef et al. [21] in their research paper conducted experiments to assess the performance of three network architectures: Inception v3, ResNet50, and DenseNet201. They used a clean dataset consisting of 256 288 samples from 10 000 different plant species. Achieving an accuracy rate exceeding 90%, they observed that DenseNet outperformed the other models.

Additionally, Danzi et al. [22] in their research paper employed the PlantCLEF 2015 and PlantCLEF 2017 datasets to propose a novel loss function that incorporates the hierarchical relationships of the taxonomic tree into the deep learning objective function. This approach shows promise for classification tasks involving multilevel labels.

Akter et al. [34] in their research proposed a convolutional neural network-based approach for the classification of medicinal plants. Their study involved the creation of a novel dataset comprising leaf images of 10 Bangladeshi medicinal plant species. This dataset, consisting of 34 123 training images and 3,570 test images, was augmented to enhance the training process. The model, trained on the augmented dataset, achieved a promising accuracy of 71.3% on the test set, demonstrating the feasibility and effectiveness of CNNs in medicinal plant classification.

Almazaydeh et al. [35] in their research developed a system for identifying medicinal plant species from leaf images using a

Mask R-CNN model. Trained and tested on a publicly available dataset from Mendeley containing 1800 images of 30 different species. The model achieved an average accuracy of 95.7%, highlighting the effectiveness of Mask R-CNN for automated plant identification tasks.

Anubha et al. [40] in their research investigated plant species recognition by comparing traditional image processing and deep learning methods. The study utilizes four datasets: Folio, Swedish Leaf, Flavia, and a real-time dataset named Leaf12. The deep learning approach employs pretrained CNN architectures such as VGG16 and VGG19, using their learned weights for feature extraction before feeding them into classifiers such as logistic regression. The study demonstrates the superior accuracy of deep learning models, particularly VGG architectures, compared with traditional methods.

Tiwari et al. [107] conducted a systematic review of deep learning applications for medicinal plant species classification and recognition, analyzing 31 studies published between 2018 and 2022. Most studies utilized private leaf datasets and leveraged CNNs, often employing transfer learning with pretrained models, for feature extraction and classification. The article focuses on the broad application of deep learning for medicinal plant classification. The author mentions that CNN was the most used deep learning classifiers (used in 64.5% of the papers reviewed). The article also mentions transfer learning as a popular technique for feature extraction (used in 83.8% of the studies).

Pukhrambam and Sahayadhas [43] proposed a system for automatically identifying medicinal plants from images using deep learning. The study utilizes the Indian Medicinal Plants, Photochemistry, and Therapeutics benchmark dataset, along with an additional dataset. The methodology involves training a CNN with DenseNet architecture to classify the images. The authors report achieving a 99.56% recognition rate on the IMPPAT dataset and 98.51% on the Manipuri dataset. This high accuracy highlights the effectiveness of DenseNet for this task. However, the article acknowledges limitations, including the potential for reduced accuracy when dealing with images captured in varying conditions (lighting, angles, etc.).

Chanyal et al. [47] in their research concluded that automated identification of medicinal plants from leaf images using machine learning and deep learning. The review highlights the effectiveness of ANN, achieving up to 98.9% accuracy in some studies. Future research should focus on diverse datasets with varied lighting and backgrounds to enhance the robustness and accuracy of these classification systems.

Abera et al. [33] in their article explored the use of medicinal plants. The study identifies 49 medicinal plant species used to treat various human ailments. The author interviewed 30 key informants and 165 community members about the medicinal plant species. The data collected was then quantified and verified using several preference ranking methods.

Chen et al. [49] in their research identified a need for multifaceted conservation of rapidly disappearing medicinal plant species. The study highlights the potential of biotechnology, including tissue culture and micropropagation, to increase yields and alleviate pressure on wild populations. Ultimately, Chen et al. advocate for a comprehensive approach that integrates conservation efforts, sustainable harvesting practices, and biotechnological advancements to ensure the long-term availability of these valuable resources.

Dat et al. [54] in their research presented a novel approach for leaf recognition by combining EfficientNet and MobileNet architectures. The study utilized a dataset of 10 000 images encompassing 20 Vietnamese herb species, captured in various natural conditions. U-Net model segmented leaf images from their backgrounds to enhance feature extraction. Then, pretrained EfficientNet B0 and MobileNet V1 models, were chosen for their lightweight architecture and robust performance. The use of lightweight CNN architectures such as EfficientNet and MobileNet allows for deployment on devices with limited computational resources. Furthermore, the study demonstrated that the proposed MMCNN model outperforms existing state-of-the-art methods in leaf recognition tasks. The dataset, while substantial, is limited to Vietnamese herb species, potentially limiting the generalizability of the findings to other geographical regions or plant species.

While a significant amount of research has been conducted on leaf classification, Ambulkar et al. [119] highlight the lack of focus on medicinal plant leaves. The authors discuss various feature extraction methods, including Canny edge detection and Gabor wavelets, as well as classification algorithms such as PCA and PNN, drawing from a range of previous studies. Although the article does not present a novel study with its own dataset and methodology, it serves as a valuable resource for understanding the current state of leaf classification research and identifying potential areas for future investigation, particularly regarding medicinal plant identification.

Bonnet et al. [62] in their research discussed a competition focused on identifying plant species from images. The dataset primarily featured around 1,000 species. The study used a cross-domain classification approach. The training set included many herbarium sheets and a smaller set of field photos, aiming to bridge the gap between the two domains. Additionally, the dataset incorporated five morphological and functional traits for each species, potentially aiding in identification.

Huang et al. [120] presented a novel dataset of images featuring Chinese medicinal blossoms. The study focuses on creating a dataset of 12 common and economically significant blossoms used in traditional Chinese medicine. The dataset comprises 1,716 images categorized into 12 classes, divided into training, validation, and test sets at an 80:10:10 ratio. The authors utilized data augmentation techniques, including Gaussian filtering, brightness adjustments, rotations, and noise addition, to enhance the model's performance. The methodology involves using CNNs, specifically the AlexNet and InceptionsV3 models, for image classification. However, the article's limitations include a relatively small dataset size and the lack of detailed results and analysis of the classification performance using different CNN models.

Ullah et al. [31] found that LRP is more effective than LIME and SHAP for explaining deep learning models trained on structured data. This effectiveness is observed both locally at the sample level and holistically across the entire testing set. Additionally, LRP demonstrates a significant computational advantage, being considerably faster than both LIME and SHAP. This speed makes LRP potentially suitable for real-time applications.

Jayanka et al. [69] presented a study on the use of CNN for the identification of Ayurvedic herbal plants in Sri Lanka. The authors utilized a dataset of images depicting leaves from 17 different Ayurvedic plant species. Here, preprocessing steps involved background removal and resizing of all images to a uniform dimension of 256 $\times$ 256 pixels. The study explored the performance of CNNs using both RGB and grayscale images, as well as multi-layer neural networks with RGB images. The results indicated a high degree of accuracy, with the CNN trained on RGB images achieving the highest accuracy of 97.71% in recognizing the Ayurvedic plant leaves. While the study demonstrates the limitations such as the need for a larger and more diverse dataset encompassing various growth stages and environmental conditions.

Table I provides a concise overview of various studies, highlighting the specific plant attributes utilized (e.g., leaf, bark, trunk, flower, etc.) and the chosen feature extraction methods employed, which range from established techniques such as digital morphological features and Zernike moments to powerful deep learning architectures such as VGG16, ResNet variations, and EfficientNet, showcasing the diverse approaches in this field and the strong presence of CNN based methods. This literature review highlights a significant shift in medicinal plant identification and classification, moving from traditional machine learning methods such as support vector machines, random forests, and K-nearest neighbors, which relied on manual feature extraction, to the power of deep learning. This review found that plant identification based on single attributes, especially leaf images, achieves the highest accuracy, with bark images showing similar promise. While multiattribute methods are promising, they need further development in terms of data and accuracy to match the effectiveness of single-attribute techniques. Deep learning, particularly CNNs, has emerged as a powerful tool for this task, able to learn complex features directly from images.

The reviewed studies overwhelmingly favor deep learning techniques for classification and recognition tasks, with CNNs demonstrating superior effectiveness compared with other methods, especially in single-attribute identification using leaf or bark images. While alternative approaches such as segmentation and hybrid models exist, the prevalence and success of CNNs solidify their position as a powerful and preferred tool for analyzing and classifying medicinal plants, paving the way for robust and accurate identification systems, particularly for multiattribute identification, which requires further development.

III. Research Gap

The study highlights several critical research gaps within the domain of plant identification.

1) *Limited Attribute Focus:* Existing AI-based systems designed for plant identification predominantly rely on a single plant attribute, notably leaves. Unfortunately, these systems overlook the potential of leveraging additional essential plant attributes such as stems, roots, flowers, petals, seeds, etc. All these attributes are also crucial for comprehensive plant identification and further, it can help to accurately assess the medicinal properties of the plant.
2) *Multiattribute Challenges:* The accuracy of AI-based systems so far is noteworthy when focused on a single attribute, particularly leaves (achieving an accuracy of approximately 95%–97%). However, extending this level of accuracy to identification based on multiple attributes presents a substantial challenge. The transition to multiattribute identification poses a significant obstacle in maintaining similar high levels of accuracy.
3) *Medical Property Prediction:* There is a lack of research on AI systems specifically designed to identify the remedial properties of plants for treating specific conditions, such as skin diseases. Developing such systems would require integrating multiattribute analysis with knowledge of traditional medicine.

IV. Methodology

Fig. 1 illustrates the methodology of our innovative system. Methodology encompasses an integrated system composed of three pivotal components: user interface, an AI analyst, and administration. Initially, the user interface facilitates the collection of training images sourced from online repositories as well as field surveys conducted at diverse locations. The AI Analyst component advanced the study by deploying a deep convolutional neural network to pinpoint distinct plant attributes, developing a preprocessed template from an existing database, and performing back-end data aggregation for pattern recognition. The authenticated dataset was then divided into subsets for training and testing to assess the performance of the trained medicinal plant classifier. The classifier's output provided insights into the relationships between the medicinal attributes of plants and their potential as skin disease treatments, with the validation of results steered by expert analysis. Where correlations were substantiated, the process was deemed complete; if not, the model was subject to reiteration with new datasets. During this stage, a suite of machine learning algorithms was also applied to produce a variety of evaluative metrics and reports.

Finally, the Administration section was responsible for stakeholder verifications via login credentials, addition, and customization of datasets for new medicinal plants, verification of datasets and outcomes by experts, and an expanded study and analysis of additional medicinal plants and their geographical distribution for improved data preprocessing.

A. Novel Deep CNN Model

This research introduces a novel deep CNN model specifically designed for plant classification and the identification of medicinal properties. Building upon the robust Inception ResNet-V2 architecture, the model incorporates additional layers and techniques to enhance performance accuracy and robustness, exceeding the capabilities of standard architectures.

Crucially, we have introduced specific modifications to improve the model's resilience to various image disturbances

TABLE I
USED ATTRIBUTE AND FEATURE EXTRACTION TECHNIQUES

Ref No.	Author	Year	Attribute Used	Technique Used
[1]	Chen et al.	2021	Leaf	ModelArt, EasyDL
[2]	Kadiwal et al.	2022	Leaf	CNN
[3]	Sharmila et al.	2022	Leaf	CNN
[4]	Kumar et al.	2021	Leaf	Dense121, InceptionV3, VGG16, Xception, VGG19, and MobileNet.
[5]	Karna Hari Priya et al.	2020	Leaf	PNN
[25]	Zhang et al.	2018	Leaf	GoogleNet
[15]	Akter and Hosen et al.	2020	Leaf	Attention-based feature map
[32]	Abdollahi et al.	2022	Leaf	Morphological, Texture, and Shape Feature Extraction
[35]	Almazaydeh et al.	2022	Leaf	Resnet101 with FPN(Feature Pyramid Network
[36]	Al-Qurran et al.	2022	Leaf	InceptionV3, ResNetV2 and Inception ResNetV2.
[40]	Anubha Pearline et al.	2019	Leaf	VGG16, VGG19, InceptionV3 and Inception ResNetV2
[42]	Azeez et al.	2019	Leaf	InceptionV3, ResNet, MobileNet and Inception ResNetV2
[43]	Banita Pukhrambam et al.	2022	Leaf	DenseNet
[56]	Diqi and Mulyani et al.	2021	Leaf	Susuki Algorithm
[57]	Sheelarani et al.	2022	Leaf	VGG16
[64]	Haryono et al.	2020	Leaf	CNN-LSTM
[66]	Huang et al.	2021	Leaf	AlexNet, InceptionsV3
[67]	Indrani et al.	2020	Leaf	SqueezeNet
[68]	Islam et al.	2019	Leaf	YOLOV2
[69]	Jayanka et al.	2020	Leaf	Multi-layer perceptron (MLP), CNN
[71]	Joshi et al.	2021	Leaf	ResNet50
[76]	Little et al.	2020	Leaf	SeResNeXt-101, ResNet-50,SeNet-154
[79]	Malik et al.	2022	Leaf	EfficientNet-B2
[81]	Muneer and Fati et al.	2020	Leaf	Zernike, Hu(shape), Texture (GrayLevel Co-Occurrence Matrices (GLCM))
[84]	Oppong et al.	2022	Leaf	AlexNet, Inceptionv3, DenseNet201, GoogleNet, Resnet101, Resnet50, Mobilenetv2, VGG16 and VGG19
[85]	Patil et al.	2020	Leaf	MobileNetV2 and VGG16
[88]	Paulson and Ravishankar et al.	2020	Leaf	VGG16 and VGG19
[90]	Pudaruth et al.	2021	Leaf	Inception-v3
[92]	Pushpanathan et al.	2022	Leaf	VGG16, VGG19, ResNet50, EfficientNet B0 and EfficientNet B7
[94]	Quoc and Hoang et al.	2020	Leaf	VGG16, VGG19, Resnet50, InceptionV3, Densenet121, Xception and MobileNetV2
[96]	Roopashri and Anitha et al.	2021	Leaf	VGG16, VGG19, InceptionV3 and Xception
[98]	Sachar and Kumar et al.	2022	Leaf	MobileNetV2, InceptionV3, and ResNet50
[101]	Shahmiri et al.	2022	Leaf	VGG16, VGG19, Resnet50, InceptionV3, Densenet121, Xception, MobileNetV2
[107]	Tiwari et al.	2022	Leaf	AlexNet, VGG-19, ResNet-101, and DenseNet201
[117]	Aldakheel et al.	2024	Leaf	YOLOV2
[6]	Widians et al.	2023	Bark	VGG16
[7]	Carpentier et al.	2018	Bark	BarkNet 1.0
[8]	Bahadır Elmas et al.	2021	Bark	Convolutional neural networks, AlexNet, DenseNet201, ResNet18, ResNet50, ResNet101, VGG16, and VGG19
[118]	Afsharpour et al.	2024	Fruit	CNN
[99]	Senevirathne et al.	2020	Leaf and Flower	FRCNN(Faster Recurrent Convolutional Neural Network)
[11]	Mostafa Mehdipour Ghazi et al.	2017	Flower, leaf, stem, fruit	GoogLeNet and VGGNet performed better than AlexNet, with VGGNet
[10]	Bindushree et al.	2023	Flower, leaf	FRCNN, RCNN, VGG16, and VGG19.
[9]	Liu. et al.	2022	Flower, fruit	ResNet50

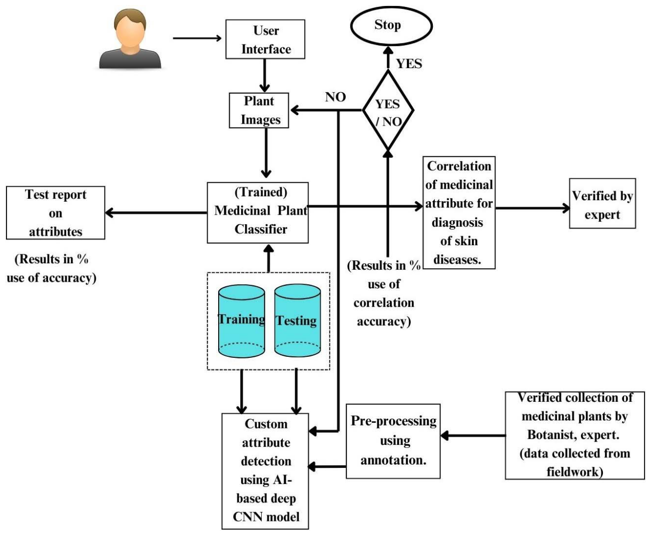

Fig. 1. Methodology for ML classification for detecting medicinal plants and their use for skin diseases.

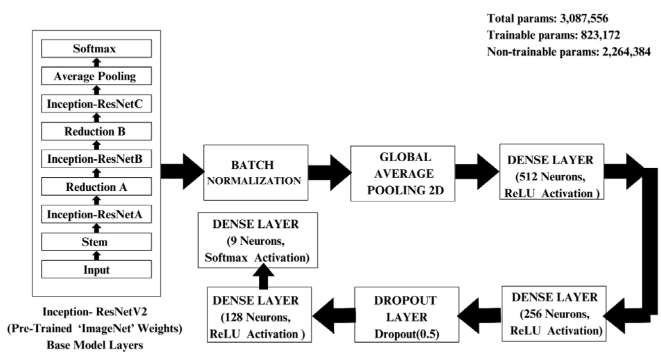

Fig. 2. Novel deep CNN model for plant classification and identifying medicinal properties.

commonly encountered in real-world applications, such as covered, fuzzy, rain-affected, and strongly sunlit images.

This addresses a significant gap in generalization, as the model demonstrates enhanced adaptability to real-world scenarios.

The model shown in Fig. 2 incorporates several significant enhancements, including a custom output layer specifically designed for the distinct classes within our dataset, and freezing the base layers to utilize the advanced features learned from the extensive ImageNet database without alteration. We integrated batch normalization and pooling strategies to improve feature representation and added multiple dense layers following the global average pooling for finer feature processing, necessary for precise classification tasks. The pretrained Inception ResNet-V2 model is used with "ImageNet" weights. It is later connected with four dense layers. The neural network layers modified and added on the Inception ResNet-V2 are progressively decreasing in neuron number such that the number of neurons varies from 512 to 256 (then a dropout of 0.5) to 128 and finally 9 for the class. There is a systematic "halving" of the number of neurons making a pyramid-like structure from 512 neurons to 128 neurons for improved accuracy and better feature extraction and generalization of the model. The model logic here uses transfer learning,

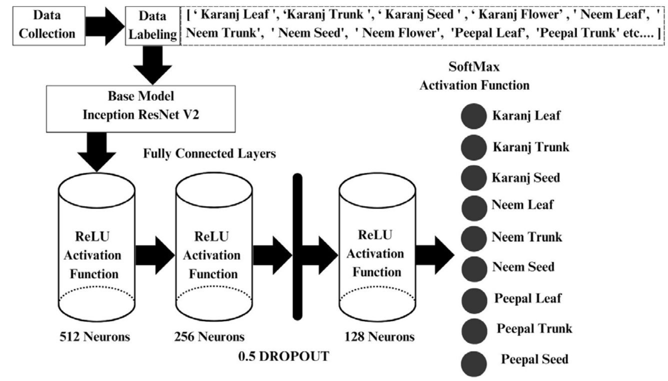

Fig. 3. Training phase of the novel deep CNN model.

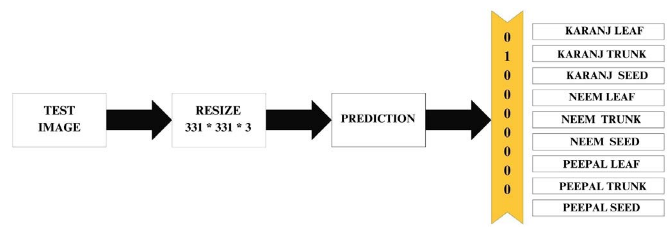

Fig. 4. Testing phase of the novel deep CNN model.

training is done using Tensorflow and the model is imported from tensorflow.keras.applications.InceptionResNetV2 makes the import for the original top neural network as false, weights as "ImageNet" and input shape as (331,331,3).

Fig. 3 shows the training phase of the new model. The first two dense layers consist of 512 neurons and 256 neurons respectively with the ReLU activation function. DropOut layer with 0.5 dropout is also added next to it which is later connected with the one denser layer of 128 neurons with the ReLU activation function. The final output i.e. dense layer is of eight neurons with a SoftMax activation function. There are ReLU activation functions used in the hidden layer and the SoftMax activation function is in the output layer. The classification is based on one hot encoding.

Fig. 4 Shows the testing phase of the new model where if the identified image is Karanj trunk then for the order a Karanj leaf, Karanj trunk, Karanj seed, neem leaf, neem trunk, neem seed, peepal leaf, peepal trunk, and peepal seed. We get 0,1,0,0,0,0,0,0,0. When testing the input images are resized to 331 * 331 * 3 size and then sent to the model for prediction.

The model's optimization process integrates the Adam Optimizer, leveraging accuracy metrics for refinement.

The Adam optimizer equations

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (1)$$

$$v_t = \beta_1 v_{t-1} + (1 - \beta_1) g_t^2. \quad (2)$$

Equations (1) and (2) illustrate the iterative refinement of the momentum and adaptive learning rate, crucial for optimizing the model's performance.

Furthermore, employing the categorical cross entropy loss equation, as depicted by (3)–(5), facilitates the assessment of classification accuracy, essential for model evaluation and improvement.

The equation for categorical cross-entropy loss

$$\mathrm{CE} = -\sum_{i=1}^{i=N} y\_\mathrm{true}_i .\ \log(y\_\mathrm{pred}_i) \tag{3}$$

$$\mathrm{CE} = -\sum_{i=1}^{i=N} y_i .\ \log(\hat{y}_i) \tag{4}$$

$$\mathrm{CE} = -\left[y_1 \log(\hat{y}_1\ ) + y_2 \log(\hat{y}_2\ ) + y_3 \log(\hat{y}_3)\right]. \tag{5}$$

To enhance model training efficiency and prevent overfitting, an early stopping mechanism is incorporated.

The equation for regularization from early stopping

$$\hat{J}(\theta) = J(w^*) + \frac{1}{2}(w - w^*)^T H(w - w^*) \tag{6}$$

$$\nabla_w \hat{J}(w) = \ H(w - w^*) \tag{7}$$

Since

$$w^* = \arg\ \min_w J(w) \tag{8}$$

$$\nabla_w J(w; X, y)|_{w^*} = \ 0. \tag{9}$$

Represented by (6) through (9), this technique enables the restoration of optimal model weights while minimizing divergence from convergence, thereby enhancing generalization.

Training occurs in batches of size 2500 with a validation set across almost 10 epochs, augmented by an early callback strategy. This strategy depends on an exponential distribution, as delineated by (10) through (13), to probabilistically determine the occurrence of an early callback, thus optimizing training time.

To calculate early call-back, we first calculate the exponential distribution using the following equation:

$$\mathrm{f}(x) = \lambda\ *\ \exp(-\lambda x) \tag{10}$$

where

1) λ (lambda) is the rate parameter, which determines the average rate at which events occur. It is the reciprocal of the mean time between events ($1/\mu$).
2) x is the time variable.

For the exponential distribution, the CDF is given by

$$\mathrm{F}(x) = 1 - \exp(-\lambda x). \tag{11}$$

The probability of receiving a callback before or at a specific time t is given by the CDF

$$P(\text{callback} \le t) = F(t) = 1 - \exp(-\lambda t). \tag{12}$$

To calculate the early callback probability, you need to specify a threshold time, say T. The early callback probability is the probability that a callback occurs before or at time T

$$P(\text{early callback} \le T) = F(T) = 1 - \exp(-\lambda T). \tag{13}$$

We use TensorFlow's ImageDataGenerator as a fundamental tool for preprocessing and augmenting the data, which improves the model's ability to generalize across diverse datasets. Furthermore, the integration of an early stopping mechanism for protecting against overfitting ensures the model's convergence towards optimal performance. The resulting convergence of these tactical adjustments is a model that not only performs better classifications but also provides information about the beneficial properties of plants, demonstrating the effectiveness of transfer learning in enabling quick and effective training with better performance results.

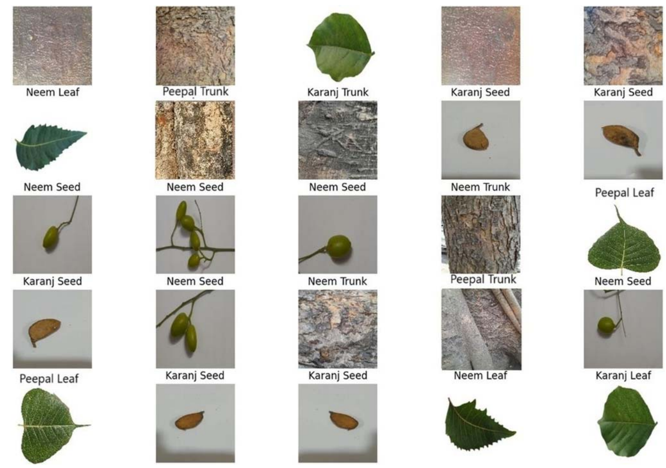

Fig. 5. Sample images from the dataset.

B. Dataset

Datasets are essential to foster the development of several computational fields, giving scope, robustness, and assurance to results. At the outset, in collaboration with botanists, a concerted effort was made to describe and refine the distinct features of medicinal plants that warranted investigation and focus. To expedite and simplify the data collection process, a customized mobile application was developed, affording researchers the flexibility to gather data both with and without its utilization. The dataset was enriched and diversified with the inclusion of plant species sourced from Maharashtra Nature Park, Dharavi, and the Veermata Jijabai Bhosale Botanical Udyan in Mumbai.

Before inputting images into the image training module, they undergo thorough scrutiny by experts. Following this, an image preprocessing step is implemented, which includes cropping, resizing, augmentation, and normalization. These steps are guided by annotations provided alongside the images. By adhering to these preprocessing procedures, the image data is refined and standardized, ensuring its suitability for training within the image training module. Through this, we plan to collect images of four key medicinal trees: Neem, Karanj, Peepal, and Moh. But later, we narrowed our focus to three key medicinal trees Neem, Karanj, and Peepal due to challenges in locating enough Moh trees. Fig. 5 shows that the data collection efforts are centered on gathering images depicting various attributes of each plant for comprehensive analysis and study.

This study leverages a meticulously curated dataset comprising 22 500 images representing three prominent medicinal plant species indigenous to Maharashtra, India: Peepal, Karanj, and Neem [28]. These species were specifically selected due to their extensive applications in traditional medicine. The dataset ensures comprehensive representation by encompassing 2,500 images per species, systematically distributed across three key attributes: leaves, trunks, and seeds. Images were captured using mobile phones and cameras against plain backgrounds to facilitate initial model training. This controlled setting aids in isolating the

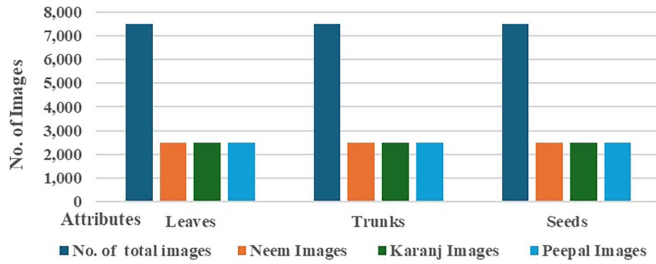

Fig. 6. Plant species representation.

plant features and minimizing the influence of background noise. However, we acknowledge the limitation of this approach for real-world applications. In future work, we plan to expand the dataset and training methodology to encompass images with diverse and complex backgrounds. This will enhance the model's robustness and generalizability, enabling it to accurately identify medicinal plants in more challenging, real-world scenarios.

Fig. 6 illustrates that the dataset is balanced, with an equal number of images per species and attribute. This balanced distribution is essential for training a robust and unbiased model.

After data is collected, the dataset was partitioned into training and testing subsets. A common 80%–20% split was employed, allocating 80% of the data (18 000 images) for model training and the remaining 20% (4,500 images) for evaluating model performance. The collected images were meticulously labeled according to their corresponding attributes (e.g., Karanj Leaf, Karanj Trunk, Neem Trunk). Each unique attribute was then assigned a numerical identifier to facilitate classification.

V. Results and Discussion

In our comprehensive literature review, we explored the methodologies utilized for the identification and classification of plants. A prominent focus among these methodologies is the categorization process. To address this, we evaluated the efficacy of three distinct models: VGG16, MobileNet-V2, and InceptionResNet-V2, in the realm of plant identification. Our investigation encompassed both single-attribute and multiattribute approaches, aiming to discern the most suitable model for versatile plant classification tasks.

A. Results With Single Attribute

From a literature review, we observed that these three models VGG-16 [40], Mobile Net-V2 [40], and Inception ResNet-V2 [36] performed identification effectively on leaf images. Therefore, we decided to train and test these models using our dataset [28]. Importantly, these models achieved accurate results within reasonable processing times, demonstrating their efficiency in tree identification tasks.

In Table II, we first assessed the model's performance on leaf images. Then, we proceeded to utilize trunk images as input to gauge the models' effectiveness. Our findings revealed a discernible variance in performance. Particularly, Mobile Net-V2

TABLE II
Comparison of CNN Models on a Single Attribute (Leaf or Trunk)

Attribute Used →	Leaf Images					Trunk Images				
Parameter →	Accuracy (%)		Loss (%)		Time (Sec)	Accuracy (%)		Loss (%)		Time (Sec)
Model ↓	Train	Test	Train	Test		Train	Test	Train	Test	
VGG-16 [40]	97.14	96.53	2.3	2.4	560.7	50	20	59.32	62.42	998
Mobile Net-V2 [85]	98	98	0	0	494.1	100	57	0.002	1.42	855
Inception ResNet-V2 [36]	100	90	0	1.4	409.8	99	100	0	0	719

Fig. 7. Training accuracy and loss of mobile Net-V2 model on trunk images.

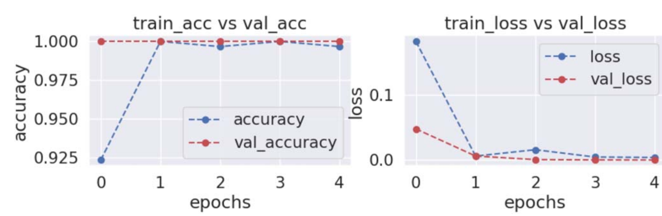

Fig. 8. Training accuracy and loss of inception ResNet-V2 model on trunk images.

and Inception ResNet-V2 exhibited adeptness in plant recognition when utilizing trunk images alongside leaf images.

Fig. 7 highlights the stark contrast between the MobileNet-V2 model's training accuracy of 100% and its testing accuracy of 57%. Furthermore, while the training loss remained low at 0.002, the testing loss was notably higher at 1.429, with an execution time of 855 s.

Overall, the mobile Net-V2 model's performance raises concerns about overfitting and poor generalization.

Conversely, in Fig. 8, the inception ResNet-V2 model shows good performance, with both training accuracy and testing accuracy of 100%. Moreover, the training as well as testing loss were minimal at 0, with an execution time of 719 s. The overall performance of the Inception ResNet-V2 model is highly impressive, representing perfect accuracy and minimal loss on both training and testing datasets.

Fig. 9 indicates the results of CNN models' flexibility in accommodating diverse plant attributes beyond only leaves, thus amplifying their efficacy in comprehensive plant identification systems. Consequently, we opted to assess a model on multiple attributes concurrently.

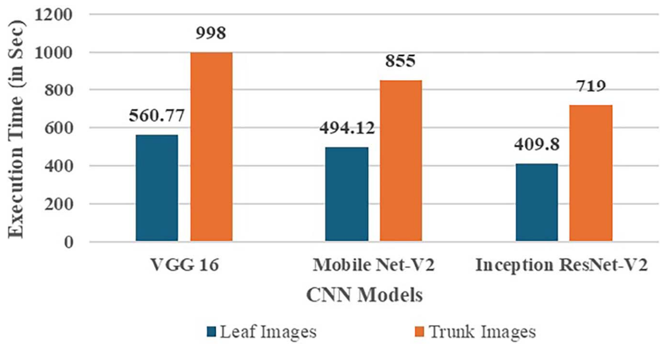

Fig. 9. Comparison of time taken by different CNN models.

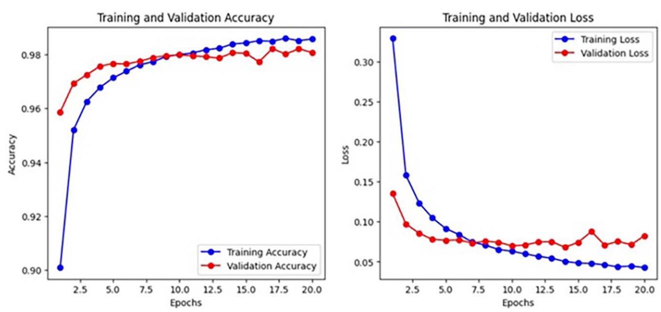

Fig. 10. Training and testing accuracy and loss of novel deep CNN model with two attributes on Peepal tree.

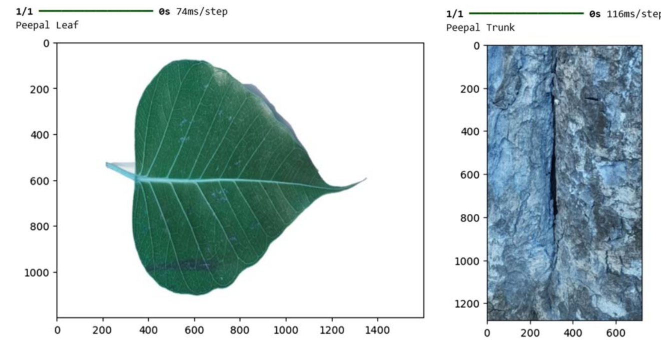

Fig. 11. Result of novel deep CNN model with two attributes on Peepal tree.

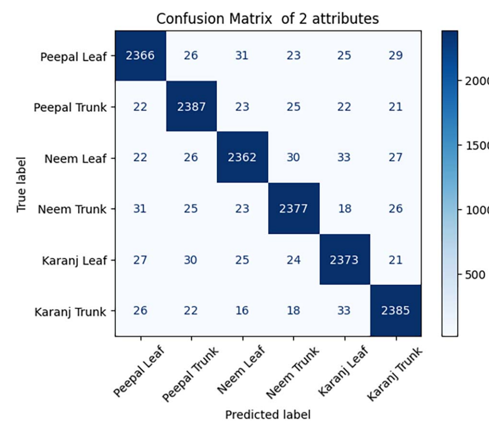

Fig. 12. Novel deep CNN model confusion matrix with two attributes on Peepal, neem, and Karanj tree.

We supplied a database of combined images of leaves and trunks as input to the models and evaluated their performance. Interestingly, the Mobile Net-V2 model exhibited complete failure in identifying plants within a database comprising two attributes. In contrast, the Inception ResNet-V2 model outperformed the Mobile Net-V2 model, prompting our decision to enhance the Inception ResNet-V2 model's capabilities in handling multiattribute features of plants.

B. Results With Multiattribute

Based on the outcomes mentioned above, we have chosen to enhance the Inception ResNet-V2 architecture to develop a novel deep CNN model customized for plant classification and the identification of medicinal properties. The novel deep CNN model was first tested on combined leaf and trunk images, showcasing exemplary performance.

Fig. 10 shows that the model's accuracy rates and scoring both are around 98% in the training and testing phases. The losses were also minimized to an almost nonexistent level, with the training loss recorded at a low 0.033% and the testing loss at an infinitesimal 0.10%. These results essentially approach a 0% loss, underscoring the model's precision and consistent accuracy in identifying images of Peepal plant leaves and trunks. Fig. 11 shows the result of novel deep CNN model with Peepal leaf and trunk images.

Fig. 12 shows the confusion matrix depicting the model's classification performance in six categories: Karanj leaf, Karanj trunk, neem leaf, neem trunk, Peepal leaf, and Peepal trunk.

Table III shows the dataset size of 2500 samples per class, the model exhibits outstanding accuracy and precision, achieving flawless classification with no misclassification.

TABLE III
PRECISION, RECALL, AND F1- SCORE MATRIX FOR TWO ATTRIBUTES

Plant Attribute	Precision	Recall	F1-Score	Support
Peepal Leaf	0.95	0.95	0.95	2500
Peepal Trunk	0.94	0.94	0.94	2500
Neem Leaf	0.95	0.95	0.95	2500
Neem Trunk	0.94	0.94	0.94	2500
Karanj Leaf	0.95	0.95	0.95	2500
Karanj Trunk	0.94	0.94	0.94	2500

Following the primary success, we enhanced the application of the same model to integrate a trio of attributes, namely leaves, trunks, and seeds, to explore performance enrichments through multiattribute analysis. The results are noteworthy, Fig. 13 shows that the model achieves 99.60% training accuracy and 97.91% testing accuracy. The training loss is 0.03% and the testing loss is 0.09%. Notably, the model demonstrates consistent precision and accuracy in identifying images of different attributes of Karanj, neem, and Peepal trees.

Fig. 14 displays the results of the novel deep CNN model with three different attributes for different trees, i.e. neem leaf, Karanj seed, and Peepal trunk.

The training pace of the novel deep CNN model exhibited remarkable efficiency across each epoch, consistently achieving superior accuracy in classifying plants within notably reduced training durations. This underscores the novel deep

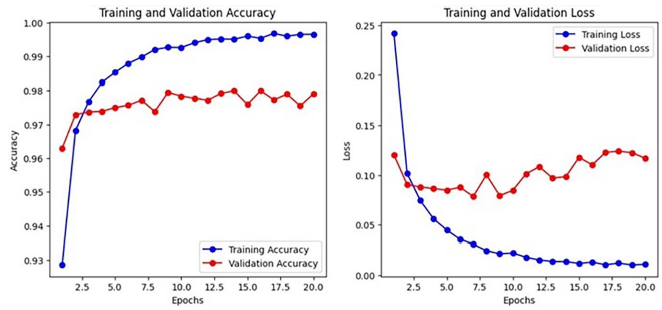

Fig. 13. Training and testing accuracy and loss of novel deep CNN model with three attributes on Karanj tree.

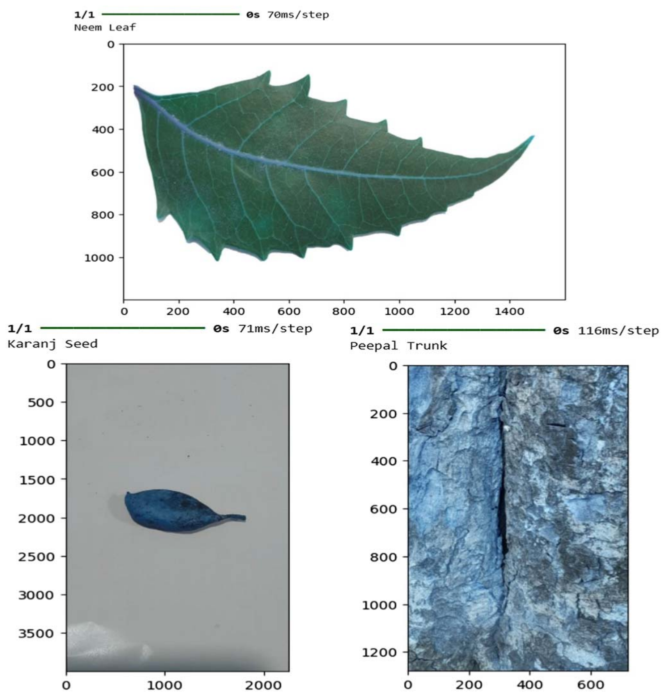

Fig. 14. Result of novel deep CNN model with three attributes of different trees.

TABLE IV
PRECISION, RECALL, AND F1- SCORE MATRIX FOR THREE ATTRIBUTES

Plant Attribute	Precision	Recall	F1-Score	Support
Karanj Leaf	0.9235	0.9230	0.9232	2500
Karanj Seed	0.9161	0.8865	0.8463	2500
Karanj Trunk	0.8723	0.8715	0.8719	2500
Neem Leaf	0.9568	0.9575	0.9672	2500
Neem Seed	0.8932	0.8975	0.8923	2500
Neem Trunk	0.8756	0.8779	0.8741	2500
Peepal Leaf	0.9300	0.9290	0.9295	2500
Peepal Seed	0.8900	0.8905	0.8902	2500
Peepal Trunk	0.9312	0.9348	0.9344	2500

CNN architecture's competitive advantage over the other models for classifying medicinal plants sourced from the dataset.

Fig. 15 shows the confusion matrix depicts the model's classification performance in nine different categories: leaf, trunk and seed of Karanj, neem, and Peepal. As shown in Table IV, with a

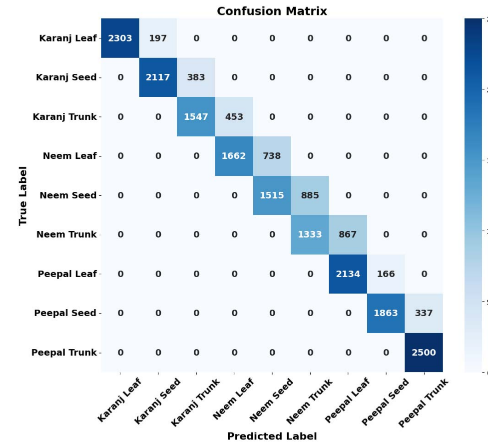

Fig. 15. Confusion matrix for three attributes on Karanj, neem, and Peepal tree.

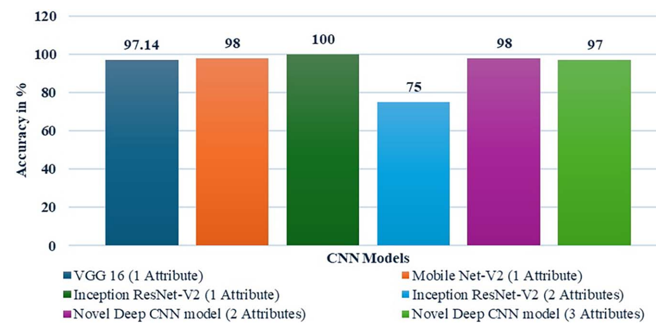

Fig. 16. Accuracy comparison of different CNN models with novel deep CNN model.

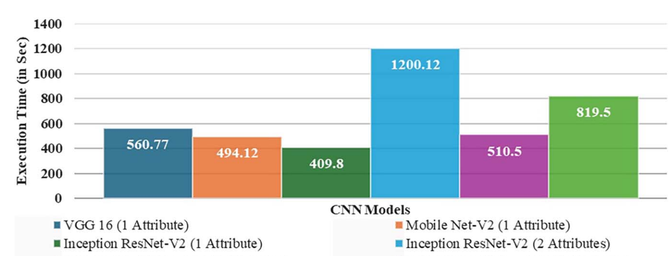

Fig. 17. Execution time comparison of different CNN models with novel deep CNN model.

dataset size of 2500 samples per class, the model exhibits outstanding accuracy and precision, achieving flawless classification with no misclassification.

Figs. 16 and 17 present a detailed comparison of CNN models, which were scrutinized in our investigation, and benchmarked against the newly developed CNN model, focusing on critical performance measures such as accuracy, loss, and execution time. Based on all the results, we can confidently assert that our novel deep CNN model exhibits robust predictive capabilities, not limited to single attributes but extending to multiattributes as well. Whether utilizing a single attribute or multiple attributes, the model consistently delivers precise and reliable predictions, showcasing its adaptability and potential for diverse applications in plant classification and identification. Besides its exceptional predictive accuracy, our model enriches its utility

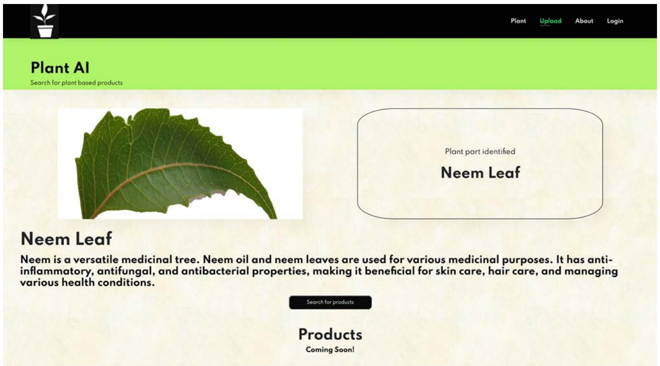

Fig. 18. From leaf to remedy: innovative tree detection and skin disease treatment recommendations.

by offering preliminary remedial suggestions for skin conditions linked to a specific plant identified. We used a novel deep CNN model to reliably recognize the plants based on distinguishing characteristics such as leaves, trunks, and seeds. To improve the actual utility of this classification, we linked an existing Medicinal Plant Dataset [28] from Kaggle that connects each recognized plant species to its known medicinal properties. This database contains thorough information about the medical uses, active compounds, and traditional applications of each plant. By comparing the CNN model's plant identification to the medicinal properties database, we gain important information into the possible medicinal uses of the detected plants, bridging botanical classification and pharmacological applications. The integration of this model into an accessible, intuitive web platform "Plant AI" further democratizes its advantages, allowing individuals, regardless of their expertise, to benefit from its features with ease.

Fig. 18 shows the model's availability on a user-friendly platform paves the way for its extensive adoption and use, leading to increased public knowledge and improved health management concerning plant-derived treatments for skin diseases. This provides a precious tool for individuals seeking natural and traditional remedial options, underscoring the critical role of our model in fostering better health outcomes and awareness of ethnomedicinal practices.

VI. Conclusion

In summary, our study tackles critical challenges related to medicinal plant identification based on multiple attributes. Given the enormous diversity of plant species around the world, the accurate identification of medicinal plants using any part of the plant bears significant implications for botanical study and conservation initiatives. Crucially, due to the high frequency of skin diseases, the identification of beneficial plants for skin care becomes imperative in formulating effective remedies. This interdisciplinary methodology, merging botany with computer science, opens new avenues for inventive applications in sectors such as agriculture, healthcare, and ecological preservation. It can be summarized that the proposed model can be used to assist in dermatological diagnosis. This research helps in preserving the ancient Indian tradition.

Future Scope

In addition to expanding the dataset to include more diverse backgrounds, future work will explore the integration of explainable AI techniques. This will involve implementing methods such as layer-wise relevance propagation or gradient-weighted class activation mapping to provide insights into the model's decision-making process and enhance its transparency [119]. This will be essential for building trust in the model's predictions and facilitating its adoption in real-world healthcare settings.

Acknowledgment

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