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Automatic Ayurvedic Leaf Classification System using Advanced Deep Learning Approaches

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***Abstract*—Plants are important component in traditional medicines and are useful for different diseases and healing the wounds. Classification of Ayurvedic medicinal plants is very important in number of fields such as healthcare, agriculture and environmental conservation. Leaves provide an important source of data for studies of plant biology. Plant leaf classification has been an important task and it is difficult due to several reasons. The classification of plants using digital leaf images has nowadays become an important research area in the automatic classification of plants. Many researchers have been focusing on the usage of different deep learning models in plant classification. InceptionV3, Inception-ResNetV2 and VGG16 were used as three convolutional neural network (CNN) architectures. The model is trained and tested with a dataset of more than 1000 images of medicinal leaves. The experimental results show that InceptionV3 obtained the highest accuracy of 95.17%, Inception-ResNetV2 achieved 89.78% accuracy and VGG16 achieved 88.11% accuracy. The recommended approach is to pre-process the leaf images and classify based on specific properties like texture and venation patterns, by extracting features by deep learning models. In addition, a graphical user interface (GUI) is developed to facilitate real time identification, which allows users to forecast the type of medicinal leaf, see its image and know about its applications.**

***Index Terms*—Medicinal Leaf Classification, Deep Learning, CNN, Image Processing, GUI Development.**

I. INTRODUCTION

Plants are an integral part of our human life and they serve many purposes like medicine, cosmetic, furniture etc. Ayurveda is an ancient system of medicine practice in India and exist from Vedic time. The important ingredients of the Ayurvedic medicines are plant leaves, root, bark etc. Medicinal value of large number of plants of Indian origin was identified. These plants are used in herbal medicines for the treatment of various diseases [1, 2]. The plants used for medicinal purpose are collected from forest, agriculture land, botanical garden etc. Identification of the real Ayurvedic plants of medicinal value is a big task. Identification of plants is done by a trained person or botanist by carefully examining the feature of the plants like leaves, shape, size, flowers, seeds, roots etc [3, 4]. The 2D views of the plant leaves have sufficient information to recognise the Ayurvedic medicinal plant among them. The leaves of medicinal plants can be easily collected and their images can be captured in different way using digital cameras, mobile phones or other digital appliances [5, 6].

Medicinal plants have been used since long time for the treatment of many diseases like cancer, diabetes, skins etc. [7, 8]. They play important role in human health. These medicinal plants contain bioactive compounds, extracts physiological effects on human body and hence they have therapeutic value [9]. Many of the medicinal plants are also used in food preparations as well as in traditional medicine extensively. Meanwhile, plant taxonomists are engaged in the classification of medicinal plants and are actively engaged in the discovery of new plants for human use all over the world [10, 11]. Plant discovery and naming is slow, thus the need for automated taxonomic classification. Despite their efforts, a significant number of species are still unknown [12, 13]. It is also difficult to identify the medical plant with the available techniques and also due to lack of awareness about these plants [14].

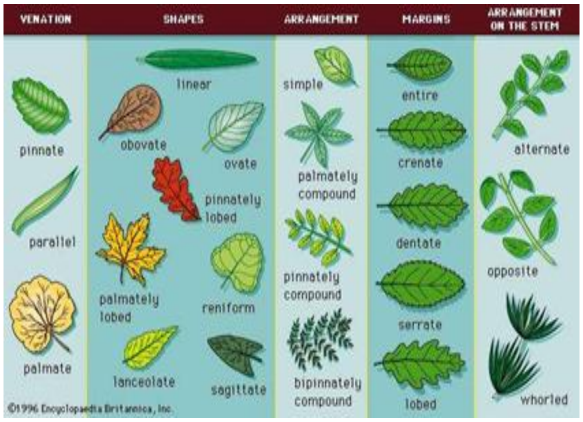


Fig 1. Types of leaf [https://www.britannica.com/science/leaf-plant-anatomy]

The leaf is a key object in plant taxonomy and a very wide field for research [15]. The different kinds of leaves are shown in Fig.1. Identification of plant leaves is important in classification [16]. Classification of plants helps in identification of various important medicinal plant species which leads to their preservation. To enhance the accessibility many researchers are digitising the identified species ensuring their availability in digital platform [17–19]. The macroscopic identification of medicinal plants is usually based on morphological and sensory characterisation of the plants. However, this method has some disadvantages such as needing more time of accumulation [20]. With the rapid development of science and technology, many methods have been emerged for automated recognition along with classifying of medical plants which includes DNA barcode, chemotaxonomy, image identification etc. [21]. The more important thing is to come up with a clever way to use computers to sort plants. Machine learning and deep learning are very important to create the computational model which will help us find medicinal plants accurately. However, only leaf shape, colour, texture and geometric properties are roughly explored for automatic plant identification [22, 23]. Automated plant classification can help in plant monitoring and new advances in computer science have made interdisciplinary research possible, including image processing, pattern recognition, artificial intelligence, and taxonomy. The identification and comparison of species relies heavily on the taxonomic nomenclature and categorisation of plants. Taxonomists worldwide have catalogued more than 300,000 plant species, many of which have medicinal and edible properties, while others are toxic and poisonous to humans [21, 24]. Moreover, many known and unknown plant species are becoming extinct. It is therefore important to identify, document and conserve rare plants for biodiversity conservation. The geographical distribution has a great influence on the study of plant diversity which affects the availability and survival of species [25, 26].

Traditionally, the task of plant identification is performed by human experts that analyse visual features to classify species. However, the advances in computer science provide a promising direction for the automation of the plant identification process based on image processing and pattern recognition and machine learning algorithms. Deep learning methods such as convolutional neural networks (CNNs) [16, 27, 28]. State-of-the-art architectures such as VGGNet [29], ResNet [30-32] and EfficientNet [33] have achieved remarkable performance on a variety of benchmarks. Although there are worldwide efforts in developing automated plant identification systems, most existing methods depend on semi-automated approaches that are either time consuming or require large human expertise. There is a growing need to develop a state-of-the-art, fully automated plant classification system with minimal human involvement to address these issues. Such a system should be equipped with state-of-the-art artificial intelligence techniques for improved accuracy and self-learning to improve itself continuously. The study highlights the need for automated taxonomic classification, particularly in the context of digitisation and conservation of species. The number of endangered and undiscovered plant species is increasing. Classification using deep learning can provide a promising solution for efficient plant identification and preservation.

II. REALTED WORK

Many approaches have been proposed to get the state-of-the-art plant identification. In this study, plant classification methods are classified according to feature selection approaches. The following section discusses popular methods adopted, including venation-based analysis, geometric and morphological methods and new non-imaging methods. Several researchers have proposed new techniques for automatic plant classification which are a huge development in the field.

Table 1. Literature Review of Plant Leaf Classification

Features	Classifier	Accuracy	Reference
Geometrical features	K-nearest neighbour	80%	[34]
Texture	Orthogonally local discriminant embedding	91.16%	[35]
Venation, and four different classifiers were used for classification.	Support vector machines (linear and Gaussian kernels), penalized discriminant analysis and random forests	92%	[36]
Leaf margin	Dynamic time warping	90% with 100 different species	[37]
Hu moments Annona Squamosa and Psidiuguajava	Support vector machine	86.6%	[38]

Rahim Azadmia et al. have classified different groups of medicinal plants by a novel image processing algorithm using intelligent ANN model [39]. Chun-qian Song et al . have used machine learning scheme for classification of thirty seven kinds of aerial parts of medical herbs based on ATR-FTIR [40]. D. T. N. Nhut et al. proposed a medicinal plant recognition using Vision transformer and BEiT [41]. Their results indicate that employing transformer-based architecture can considerably boost the classification accuracy over other methods. Xia-Feng Wang et al. [42] have proposed an efficient classification framework for classification of leaf images with complicated background. Manojkumar et al. proposed an image processing approach for Ayurvedic medicinal plants identification based on front and back scans of leaves [43]. They fused features of morphology, colour and texture and achieved 99% and 94.5% accuracy for green and dry leaves respectively using MLP classification. This work has shown the importance of multi-feature fusion in medicinal plant identification but the image data were captured in controlled environment. Moreover, Khan et al. demonstrated that an enhanced EfficientNet B4 deep learning model achieved an accuracy of 91.37% in classifying 80 species of medicinal plants from leaf images, suggesting the possibility of using AI-driven identification for the validation of traditional remedies in managing respiratory disorders [44]. In [45], Dinesh et al. proposed a Multi-Gradient Deep Convolutional Neural Network with Adaptive Support Vector Machine model, which attained 99% accuracy in the classification of maize leaf diseases namely Common Rust, Grey Leaf Spot, Blight and Healthy states, using the Kaggle Corn or Maize Leaf Disease Dataset.

S. Sharma et al. proposed an attention-based network AELGNet, which combines local and global features and uses CLAHE preprocessing to classify 80 Indian medicinal plant/leaf species with 99.71% accuracy [46]. S. Sachar et al. proposed a Lévy flight-enhanced Dragonfly algorithm for BRISK feature selection of medicinal leaf identification and achieved 88.6% accuracy on PlantVillage and 92.0% on a custom dataset using MLNN classifier [47]. R. Ding et al. developed a UAV-based YOLOv5s framework with data augmentation to identify four morphologically similar Gentiana medicinal species with mAP@0.5 of 0.889 on 640640 images and 0.798 in field surveys of 40 [48]. A. Dinesh et al. proposed a model M-D-C-A-S, which integrated multi-gradient deep CNN with adaptive SVM for maize leaf disease classification (Common Rust, Grey Leaf Spot, Blight, Healthy) with 99% accuracy, 100% precision, 99% recall and 100% F1-score on the Kaggle Maize dataset [49]. Pushpa et al. [51] proposed a hierarchical ML model by combining convolution (ResNet18), geometric, texture, shape, and multispectral features with Random Forest, achieving 94.54% accuracy on GSL100 (100 Indian medicinal plants) and 75.46% on real-time RTL80/RTP40 datasets. EEXR ensemble

(EfficientNet+Xception+ResNet) with HGAW segmentation and RBZR augmentation was proposed by G. B. Govindaprabhu et al. for 18 traditional Tamil medicinal plant leaves with 96.71% accuracy [52]. Tran et al. proposed incremental ResNet-18 (98.25% accuracy) and zero-shot CLIP (ViT-L/14@336px: 48% accuracy) for Vietnamese medicinal plant classification on Med Herb Lens dataset [53]. A. Churamani et al. [54] achieved 99.7% accuracy (WOA+ANN) on the Plant Village dataset for healthy/unhealthy plant leaf classification using GLCM+GLRLM features with WOA/PSO/BBA selection. N. S. Rani et al. proposed HerbSimNet (wavelet db1 features + 3 FC layers) for classifying 12 inter-class similar Indian medicinal plant leaves (1063 smartphone images) achieving about 60% test accuracy [55].

However, the available literature on the classification of Ayurvedic leaves has many limitations. Traditional machine learning methods based on manually designed features (e.g., texture or shape descriptors) are not robust to variations in leaf images due to lighting, occlusion or background noise, often resulting in accuracies below 90% in real-world scenarios. Deep learning models like EfficientNet or Vision Transformers are still being tested on general plant datasets instead of Ayurvedic datasets. This results in reduced generalisability for culturally relevant medicinal plants and ignores unique venation or texture patterns for species like Brahmi or Tulsi. Furthermore, few works deal with the requirement of real-time processing on resource-constrained devices. There is a lack of attention on Ayurvedic applications, such as associating classifications with therapeutic uses for diseases like diabetes, or skin conditions.

This work deals with identification and classification of medicinal plants like Tulsi, Lemon, Mint, Neem, Betel, Aloe Vera, Amla, Ashoka, Brahmi and Turmeric using Image Processing and Deep Learning techniques. The present work aims to overcome these limitations by developing a dedicated deep learning framework based on InceptionV3, Inception-ResNetV2 and VGG16 architectures, trained on a dataset of over 1000 Ayurvedic leaf images. We focus on robust pre-processing for noisy data inputs, and attain an accuracy up to 95.17%. Unlike previous approaches, this method includes Ayurveda specific features such as venation and texture for 10 important medicinal plants and provides a visual user interface (GUI) for real-time identification, and thus easy access to the plant images and applications. This work is done to improve conservation and practical utility in Indian healthcare and agriculture contexts by focusing on endangered or lesser-known species and performing tests on various imaging conditions.

III. MATERIALS AND METHODS

3.1. DATASET

The current study uses a tailor-made dataset created specifically for the purposes of this study. The Indian Medicinal Plant Dataset is a large collection of images of medicinal plants, collected from the Indian Medicinal Leaves Image Dataset by B.R. Pushpa et al. published on Mendeley Data [56]. The images were captured under different environmental conditions like different backgrounds and no constraints. This dataset contains 80 species of healthy medicinal herbs and for the present study 10 species-Tulsi, Lemon, Mint, Neem, Betel, Aloe Vera, Amla, Ashoka, Brahmi and Turmeric are selected and their leaf images of each are shown in Fig.2. More than 100 images for each selected species..

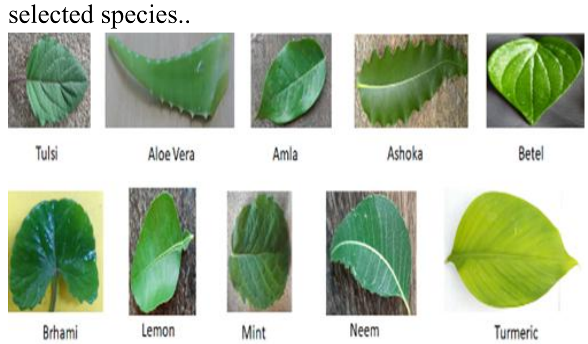


Fig.2 Sample images of Indian Medicinal Leaf Dataset

3.2. DATA AQUISITION

Each image was captured under different natural lighting conditions and from different angles with digital cameras and mobile devices, mimicking realistic plant identification scenarios. The photographs record the important morphological characters of the leaves i.e. shape, venation, texture and margin patterns which are important for correct classification. The images were annotated with the scientific and common names as depicted in Table 2 below. All images were pre-processed before analysis. Firstly, images were resized to 299 × 299 pixels to match the input requirements of deep learning models. Secondly, images were normalised to ensure consistent colour distribution. Thirdly, data augmentation techniques such as rotation and flipping were applied. This curation strategy ensures the dataset is appropriate for machine learning, improves the models' generalisability, and contributes to the overarching aim of building robust automated plant classification systems.

Table 2. Common name and scientific/ botanical of some Ayurvedic medicinal plants

Common Name	Scientific/Botanical Name
Tulsi	Ocimum tenuiflorum / Ocimum sanctum
Lemon	Citrus limon
Mint	Mentha arvensis
Neem	Azadirachta indica
Betel	Piper betle
Aloe Vera	Aloe barbadensis miller / Aloe vera
Amla	Phyllanthus emblica / Emblica officinalis
Ashoka	Saraca asoca
Brahmi	Bacopa monnieri
Turmeric	Curcuma longa

3.3. METHODOLOGY

Deep Learning Approach

Deep learning is a subset of machine learning technique, use deep neural network to automatically learn hierarchical feature of raw image data. Traditional image processing techniques use handcrafted features while deep learning technique processes photos and filters out noisy data. Deep learning translates images to images using deep neural networks for classification. Deep learning is known for detection and classification of plant images that has been achieved by classical image processing over the years. It is a computational model that learns to classify images directly. It attains high accuracy, and the capacity to handle large image datasets. Plus, it has the built-in GPU compatibility and pre-trained neural networks just can't do what it can.

The study proposed and validated a set of experiments for an automated plant classification system. We used state-of-the-art Deep Learning models such as Inception V3, VGG16 and ResNet50 for accurate classification. Key biometric indicators such as False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER) and Genuine Acceptance Rate (GAR) were used to provide comprehensive evaluation of model reliability and accuracy in differentiating plant species.

3.3.1. Inception ResNet V2

Inception ResNet V2 is based on a similar architectural backbone as Inception ResNet V1, with the main difference being in the configuration of the Inception and Reduction blocks. These Inception blocks use fewer computational resources than their Inception V4 counterparts through streamlined parallel convolutions and residual pathways. After each Inception block, the filter expansion by a 1×1 convolution (without activation functions) is used to scale the filter bank dimensionality to match the input size of the next layer. In Inception ResNet models, the Inception blocks replace the traditional pooling layers with the residual connections. The reduction blocks still use the pooling mechanisms to reduce the dimensions. To optimise for single-GPU training, we omit batch normalisation after summation operations, which curtails the model complexity. Both architectures have the same design of reduction blocks but different stem design and training hyper-parameters. Interestingly, Inception ResNet V1 has the same computational footprint as Inception V3, whereas Inception ResNet V2 is similar to the computational footprint of Inception V4. The Architecture of Inception ResNet V2 Model in Deep Learning is depicted in Fig. 4 below.

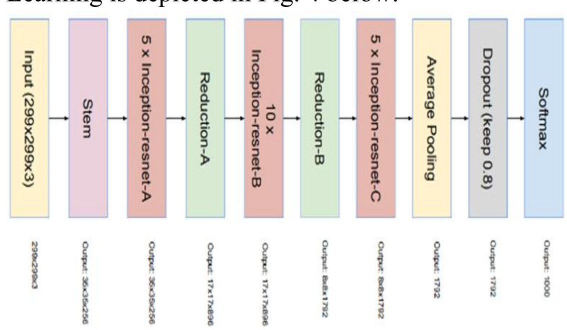


Fig. 4. Architecture of Inception ResNet V2 Model in Deep Learning.

3.3.2. Inception V3

Inception V3 is a progression of Inception V2 with specific changes and improvements like using RMSprop optimiser, using batch normalisation in the fully connected layer of the auxiliary classifier, breaking down 7×7 convolutions into smaller kernels for efficiency and adding label smoothing as a regularizer. Figure 5: Architecture of Inception V3 model in Deep Learning. This regularisation scheme penalises the classifier for being too sure about its predictions, and results in an observable reduction in error rate of around 0.2%.

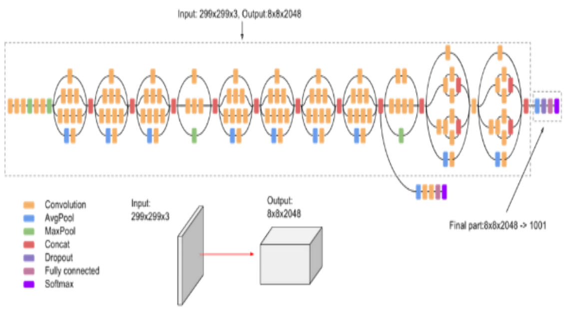


Fig. 5. Architecture of Inception V3 Model in Deep Learning

3.3.3. VGG16 (Visual Geometry Group)

This description describes a popular convolutional neural network (CNN) architecture for image classification. The structure contains 16 layers-13 convolutional and 3 fully connected as shown in Figure 6. The convolutional and max-pooling layers are combined in a systematic manner and the softmax is applied at the output for the probability distribution. The model is trained on a dataset of more than one million images, across multiple classes of objects. Input pre-processing Resizes images to 299×299 RGB pixels and subtracts the mean RGB values per pixel of the training set only. The processed image then passes through convolutional layers that use 3x3 and 1x1 filters to apply linear transformations to the input channels. 3×3 convolutional operations use a stride of 1 and spatial padding of 1. Then max-pooling with a 2x2 window and stride of 2. Softmax activation is used only in the last layer..

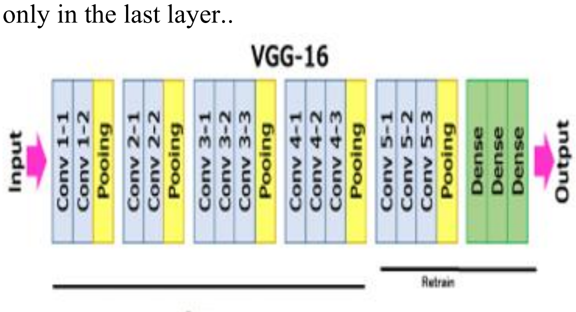


Fig. 6. Architecture of VGG16 Model in Deep Learning.

3.4. PROPOSED SYSTEM

The proposed system leverages advanced convolutional networks (CNN) architecture Inception ResNet V2, Inception V3, and VGG16 techniques, to achieve the high accuracy in identifying and classifying Ayurvedic medicinal leaves and displaying photos with their scientific and botanical names in our proposed system. This framework addresses the limitation of previous work by focussing on specialized dataset of 6900 photos from 10 key Ayurvedic plants (Tulsi, Lemon, Mint, Neem, Betel, Aloe Vera, Amla, Asoka, Brahmi and Turmeric) that were first resized to 299*299 in order to meet the requirements of the approach. Data pre-processing included normalization using the following formula for pixel value scaling:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x is the pixel intensity. This allows consistent feature extraction across different lighting conditions. Transfer learning was performed to optimise model performance by pre-training with image ImageNet weights and fine-tuning the top layers. Optimisation was done by Adam algorithm. Table 3 below shows key hyper parameters of each models. The batch size is set to 32 to fit the GPU memory.

Model summaries were generated post training to check the layer configuration. Highest validation accuracy of 95.17% was achieved using Inception V 3 which is calculated using standard formula. The precision was also calculated using the standard formula reaching 94.8% for Inception V3. The best model was saved as a .h5 file..

Table 3. Comparison of key hyper parameters and architectural characteristics used for fine-tuning the InceptionV3, Inception-ResNetV2, and VGG16 models

Parameter	InceptionV3	Inception-ResNetV2	VGG16
Batch Size	32	32	32
Learning Rate	0.001	0.0001	0.001
Dropout Rate	0.5	0.5	0.5

Optimizer	Adam	Adam	Adam
Epochs	10	10	10
Input Size	299×299×3	299×299×3	224×224×3
Number of Dense Layers	2 (512, 10)	2 (512, 10)	3 (512, 512, 10)
Activation (Output)	Softmax	Softmax	Softmax

For deployment, prediction utilized a pickle-serialized array storing class labels and botanical names. The image prediction function loaded the .h5 model and pickle data, pre-processing input images via resizing and normalization before inference and the result was generated using a random technique from the test set for demonstration. A Graphical user interface (GUI) built with Tkinter, facilitated real time uploads. The outcome was a set of photos with both the expected and real names. The architecture of proposed system is shown in Fig. 7.

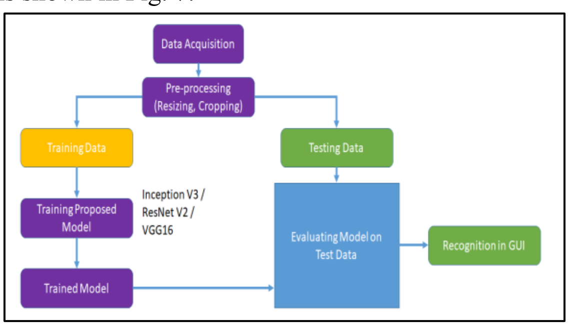


Fig. 7. Architecture of Proposed System.

IV. RESULTS AND DISCUSSION

4.1. Inception ResNet V2

In this study, we proposed a deep learning method for the general classification of plant leaves. The model used is Inception ResNet V2 applied to Indian Medicinal Leaf dataset with 30 dense layers and preconfigured weights for convolution and fully connected layers. Training of the model took 20 epochs to achieve an accuracy of 89.78% on validation. Figure 8 shows that the validation loss is higher than the training loss, which means that the model is better suited for new data than training data.

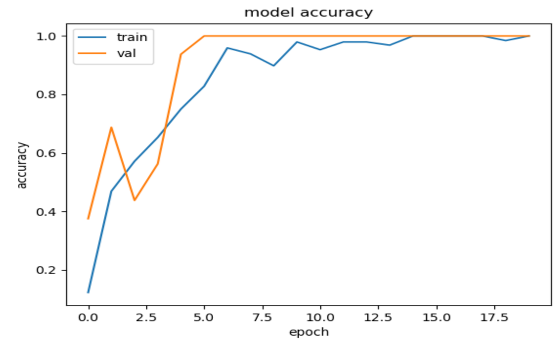


Fig. 8. Training and Validation Accuracy Curves for Inception ResNet V2.

4.2. Inception V3

This work aims to present a deep learning approach for general plant leaf classification. The model used is Inception V3 which was pre-trained with 30 dense layers with convolutional and fully connected layer weights which were constant on Indian Medicinal Leaf dataset. The model was trained for twenty epochs and achieved a validation accuracy of 95.17%. Fig. 9 displays the Training and Validation Accuracy Curves of Inception V3..

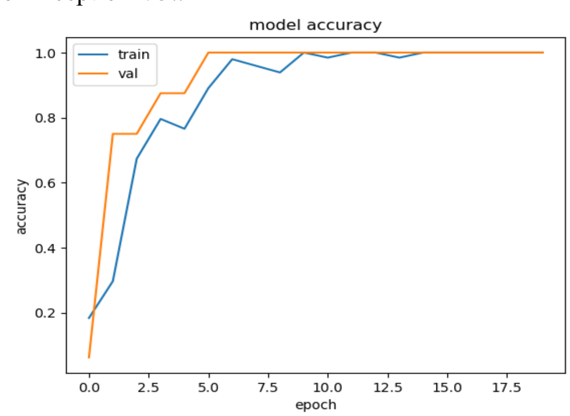


Fig. 9. Training and Validation Accuracy Curves for Inception V3.

4.3. VGG16

The purpose of this paper is to propose a deep learning approach for large-scale plant leaf classification.

The model used is VGG16 which is pre-trained and implemented on Indian Medicinal Leaf dataset and weights are fixed for 30 dense layers, convolutional and fully connected layers.

The training took 20 epochs to reach a validation accuracy of 88.11%.

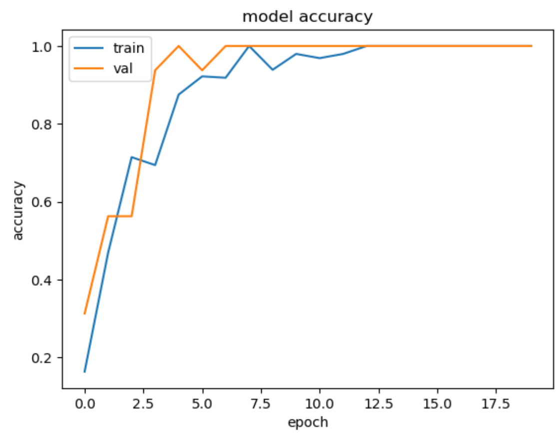
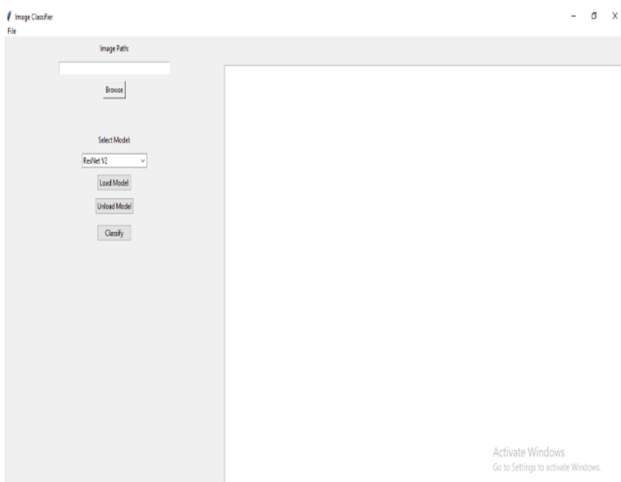


Fig. 10. Training and Validation Accuracy Curves for VGG16

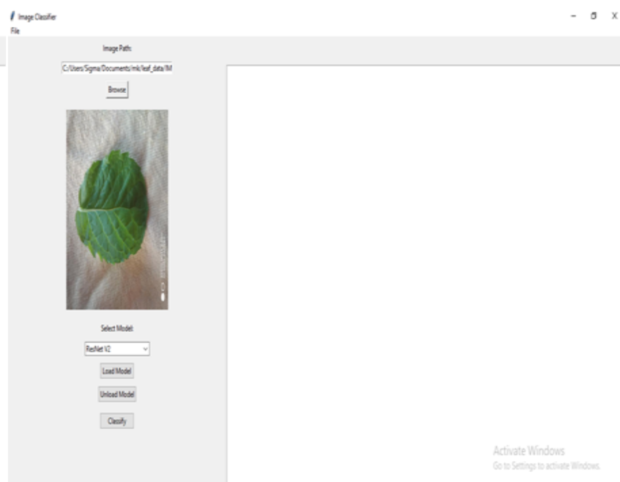
Fig.10. displays the graphical user interface (GUI) implementation and sample images of the actual and predicted output of the image data. Table 4. includes accuracy and support values for 80 different leaf types, showing the total accuracy of the model for each column value. The accuracy of each model is used in the present study is displayed in Table 4.

Table 4. Accuracy of Each Model

Dataset	Accuracy	Epoch	Model
Indian	95.17	20	Inception V3
Indian	89.78	20	Inception ResNet V2
Indian	88.11	20	VGG16



(a)



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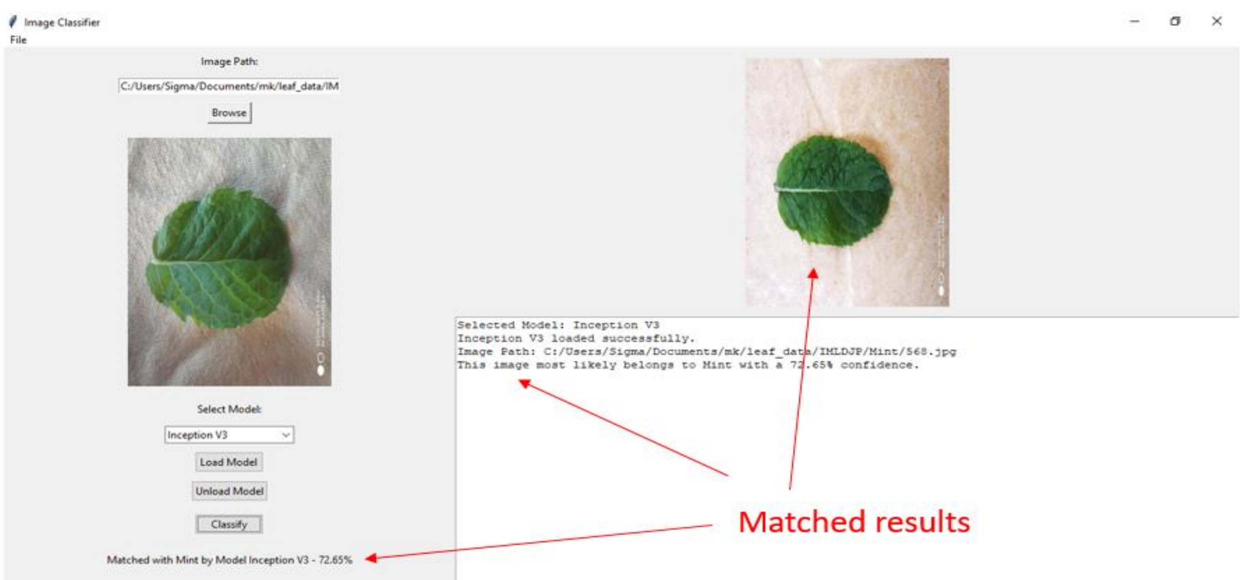

(c)Fig. 11. Screenshot of GUI Implementation

V. CONCLUSION

This study introduces a deep learning-based approach for classification of Indian Medicinal Leaves using three popular convolutional neural network architectures, i.e., Inception V3, Inception ResNet V2 and VGG16. The models were trained using transfer learning with pre-trained weights and fine-tuned on a dataset having more than 1000 images of medicinal leaves. The validation accuracies achieved were 95.17%, 89.78% and 88.11% respectively. The improved classification performance of Inception V3 is due to its efficient multi-scale feature extraction capabilities while Inception ResNet V2 and VGG16 also showed strong classification performance useful in practical applications. The model was trained for 20 epochs to ensure the model convergence without overfitting. An intuitive graphical user interface was also designed to support leaf identification and the information on leaf applications, improving the usability of the system for stakeholders. This work shows the potential of deep learning techniques for plant image classification tasks and provides a foundation for future growth with larger datasets and real-time applications.

REFERENCES

[1] R. K. Sharma and B. Dash, Charaka Samhita, Varanasi, India: Chowkhamba Sanskrit Series Office, 2019.
[2] K. R. Kirtikar and B. D. Basu, Indian Medicinal Plants, 2nd ed., Dehradun, India: International Book Distributors, 2018.
[3] H. Soltis and P. Soltis, "Plant phylogeny and the origin of major biomes," American Journal of Botany, vol. 101, no. 10, pp. 1601–1615, 2014.
[4] A. K. Jain, Medicinal Plants, New Delhi, India: National Book Trust, 2017.
[5] S. Wu, F. Bao, E. Xu, Y. Wang, Y. Chang and Q. Xiang, "A leaf recognition algorithm for plant classification using probabilistic neural network," IEEE International Symposium on Signal Processing and Information Technology, pp. 11–16, 2007.
[6] S. Kumar, "Leafsnap: A computer vision system for automatic plant species identification," European Conference on Computer Vision, pp. 502–516, 2012.
[7] World Health Organization, WHO Traditional Medicine Strategy 2014–2023, Geneva, Switzerland, 2013.
[8] I. Ahmad, F. Aqil and M. Owais, Modern Phytomedicine, Weinheim, Germany: Wiley-VCH, 2006.
[9] B. B. Aggarwal and Y. J. Surh, Spices: Chemistry and Health Benefits, CAB International, 2012.
[10] P. H. Raven, R. F. Evert and S. E. Eichhorn, Biology of Plants, 8th ed., W. H. Freeman, 2013.
[11] M. Christenhusz and J. Byng, "The number of known plant species in the world," Phytotaxa, vol. 261, no. 3, pp. 201–217, 2016.
[12] Royal Botanic Gardens, Kew, State of the World's Plants Report, 2022.
[13] CBD Secretariat, Global Biodiversity Outlook 5, Montreal, Canada, 2020.
[14] P. K. Warrier, Indian Medicinal Plants: A Compendium of 500 Species, Orient Blackswan, 2015.
[15] J. Cope, D. Corney, J. Clark, P. Remagnino and P. Wilkin, "Plant species identification using digital morphometrics," Expert Systems with Applications, vol. 39, no. 8, pp. 7562–7573, 2012.
[16] M. Grinblat, L. Uzal, M. Larese and P. Granitto, "Deep learning for plant identification using vein morphological patterns," Computers and Electronics in Agriculture, vol. 127, pp. 418–424, 2016.
[17] D. H. Janzen et al., "Digital biodiversity documentation," Nature, vol. 546, pp. 30–32, 2017.
[18] GBIF Secretariat, "Global Biodiversity Information Facility," 2023.
[19] Encyclopedia of Life, "Digital biodiversity archive," 2022.
[20] H. A. El-Gayar and M. Soliman, "A comparative study of image descriptors for plant identification," Pattern Recognition Letters, vol. 83, pp. 196–204, 2016.
[21] A. Kress, K. J. Erickson, F. Jones, N. Swenson and R. Perez, "Plant DNA barcodes and applications," Proceedings of the National Academy of Sciences, vol. 102, no. 23, pp. 8369–8374, 2005.
[22] S. Prasad, P. P. S. S. Rao and B. K. Mohanty, "Leaf recognition using texture features," Procedia Computer Science, vol. 58, pp. 152–159, 2015.

[23] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, 2015.
[24] P. H. Raven, "Plant diversity and conservation," Science, vol. 324, no. 5925, pp. 1275–1276, 2009.
[25] C. Mora et al., "How many species are there on Earth and in the ocean?" PLoS Biology, vol. 9, no. 8, 2011.
[26] IPBES, Global Assessment Report on Biodiversity and Ecosystem Services, 2019.
[27] A. Krizhevsky, I. Sutskever and G. Hinton, "ImageNet classification with deep convolutional neural networks," Advances in Neural Information Processing Systems, pp. 1097–1105, 2012.
[28] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," International Conference on Learning Representations, 2015.
[29] K. He, X. Zhang, S. Ren and J. Sun, "Deep residual learning for image recognition," Proceedings of CVPR, pp. 770–778, 2016.
[30] C. Szegedy et al., "Rethinking the Inception architecture for computer vision," Proceedings of CVPR, pp. 2818–2826, 2016.
[31] C. Szegedy, S. Ioffe, V. Vanhoucke and A. Alemi, "Inception-v4, Inception-ResNet and the impact of residual connections on learning," AAAI Conference on Artificial Intelligence, 2017.
[32] M. Tan and Q. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," Proceedings of ICML, pp. 6105–6114, 2019.
[33] A. Dosovitskiy et al., "An image is worth 16×16 words: Transformers for image recognition at scale," International Conference on Learning Representations, 2021.
[34] A. Kadir et al., "Leaf classification using shape, color and texture features," International Journal of Computer Trends and Technology, vol. 1, no. 3, pp. 225–230, 2011.
[35] Z. Wang et al., "Plant recognition using orthogonal locality preserving projection," Pattern Recognition Letters, vol. 33, pp. 447–454, 2012.
[36] J. Yanikoglu et al., "Automatic plant identification from leaf images," Machine Vision and Applications, vol. 25, no. 6, pp. 1369–1383, 2014.
[37] M. Cerutti et al., "Leaf margin recognition using dynamic time warping," Pattern Recognition, vol. 47, no. 2, pp. 546–557, 2014.
[38] S. S. Priya and P. Srinivasan, "Plant recognition using Hu moments and support vector machine," International Journal of Computer Applications, vol. 136, no. 4, pp. 15–20, 2016.
[39] R. Azadmia et al., "Medicinal plant classification using ANN and image processing," Computers and Electronics in Agriculture, vol. 186, 2021.
[40] C. Song et al., "Classification of medicinal herbs using ATR-FTIR and machine learning," Spectrochimica Acta Part A, vol. 222, 2019.
[41] D. T. N. Nhut et al., "Medicinal plant recognition using Vision Transformer and BEiT," Expert Systems with Applications, vol. 235, 2024.
[42] X. Wang et al., "Leaf classification under complex backgrounds," IEEE Access, vol. 10, pp. 104321–104334, 2022.
[43] P. Manojkumar et al., "Ayurvedic medicinal plant identification using morphology, color and texture fusion," Multimedia Tools and Applications, vol. 80, pp. 31587–31612, 2021.
[44] M. Khan et al., "EfficientNet-based medicinal plant classification for respiratory disease applications," Scientific Reports, vol. 13, 2023.
[45] A. Dinesh et al., "Multi-gradient CNN with adaptive SVM for maize leaf disease classification," Computers and Electronics in Agriculture, vol. 214, 2023.
[46] S. Sharma et al., "AELGNet: Attention-enhanced medicinal plant classification network," Expert Systems with Applications, vol. 236, 2024.
[47] S. Sachar et al., "Dragonfly optimization-based BRISK feature selection for medicinal plant identification," Knowledge-Based Systems, vol. 275, 2023.
[48] R. Ding et al., "UAV-based medicinal plant recognition using YOLOv5s," Computers and Electronics in Agriculture, vol. 218, 2024.
[49] A. Dinesh et al., "Deep CNN and adaptive SVM for maize disease classification," Neural Computing and Applications, vol. 36, pp. 12457–12475, 2024.
[50] B. R. Pushpa et al., "Hierarchical machine learning model for Indian medicinal plant classification," Ecological Informatics, vol. 80, 2024.

[51] G. B. Govindaprabhu et al., "EEXR ensemble model for traditional medicinal plant classification," IEEE Access, vol. 12, pp. 42055–42071, 2024.
[52] T. Tran et al., "Incremental learning and CLIP for medicinal plant recognition," Expert Systems with Applications, vol. 244, 2024.
[53] A. Churamani et al., "WOA-ANN based plant disease classification using texture descriptors," Computers and Electronics in Agriculture, vol. 211, 2023.
[54] N. S. Rani et al., "HerbSimNet: Lightweight deep learning model for medicinal leaf classification," Applied Soft Computing, vol. 150, 2024.
[55] B. R. Pushpa et al., "Indian Medicinal Leaves Image Dataset," Mendeley Data, Version 1, 2023.
[56] J. Deng et al., "ImageNet: A large-scale hierarchical image database," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255, 2009.