



A Deep CNN-Based Approach Felicia Proposed for Identifying Medicinal and Edible Plants in the Western Ghats Region

Anagha Bharadwaj¹, Mr Srinidhi Kulkarni², Bharath kumar R^{1*}

Dept. of Computer Science and Engineering
Jyothy Institute of Technology
Bengaluru, India

anaghabharadwaj02@gmail.com,
srinidhi.kulkarni@jyothyit.ac.in,
bharath.kr702@gmail.com

Abstract. Ayurvedic plants, which contain active compounds are used to treat various health conditions. On the other hand, edible plants contain essential nutrients that are required for our body's proper functioning and can aid in preventing chronic diseases like diabetes, heart disease, and cancer. Numerous health benefits are obtained due to the inclusion of both.

In this study, we propose the implementation of the Felicia architecture (a comparison model based on a preexisting Convolution and Classifier block) enabling the identification of edible and ayurvedic plants. The suggested model takes advantage of Inception-V3, a cutting-edge deep neural network, to extract high-level information and improve plant identification accuracy.

The proposed approach can potentially be used in various fields, such as agriculture, botanical research, and medicine. It can also aid in the identification and classification of unknown plants, which can in turn help in detecting poisonous or harmful plants.

Overall, our research highlights the potential of using deep learning techniques for plant recognition tasks and provides a framework for future studies in this area.

Keywords: Active Compounds, Ayurvedic Plants, Edible Plants, Felicia, Convolution Block, Classifier Block, Inception-V3.

1 Introduction

The Western Ghats region is home to a rich diversity of plant species that have been used by local communities for centuries for their medicinal and nutritional properties. Identifying these plants is crucial for promoting human health, ensuring food security, managing resources sustainably, and preserving cultural traditions. Moreover, this knowledge can inform the development of new medicines and agricultural practices

explore the importance of identifying and preserving edible and medicinal plants in the Western Ghats, and the significant benefits it offers for both human and environmental well-being.

The Western Ghats region boasts a high degree of biodiversity, with thousands of plant species that are exclusive to the area. These species have been used for medicinal purposes by local communities for generations, making the identification and preservation of edible and medicinal plants essential. This is particularly important for low-income communities where access to conventional medicine may be limited. By diversifying diets with locally sourced plants, communities can improve their resilience to climate change and reduce dependence on imported foods. Additionally, the study of these plants can contribute to our understanding of ecology and evolution. Researching the adaptations that allow plants to thrive in difficult conditions can provide valuable insights into biodiversity and the mechanisms that shape it. Therefore, identifying and preserving edible and medicinal plants in the Western Ghats is crucial for promoting human and environmental health, resource management, and cultural preservation, as well as advancing the fields of medicine and sustainable agriculture.

2 Literature Review

Dileep M.R. and Pournami P.N. [1], presented a paper which uses the AlexNet model to extract features. The solution presented in this paper gives an accurate result rate of 98.46% when tested on a combination of their own and DLeaf dataset.

R. Janani and A. Gopal et al. [2] In 2013 presented a paper on using image features and artificial neural networks to identify selected medicinal plant leaves and a unique way to extract the features at the International Conference on Advanced Electronic Systems (ICAES).

In 2018, J.W. Tan et al. [3], published a study to classify leaves by pre-processing the images, extracting the features and then classifying them. ANN along with CNN, which results in 94.88% accuracy.

D.Venkataraman and N.Mangayarkarasi [4], proposed a method at ICCIC based on CV for extracting features from leaves to identify the medicinal properties of plants. Various features of the leaves are extracted out of which aspect ratio and roundness are observed distinctively.

Guillermo L. Grinblat et al. [5] submitted a paper in Computers and Electronics in Agriculture in 2016 at CIFASIS on the vein morphological patterns on three distinct legumes using deep learning. In short using the veins to identify the requirement.

Mostafa Mehdi-pour Ghazi et al. [6] In 2017, a research study was published on the optimization of transfer learning parameters for deep neural networks in the context of plant identification. The combination of classifiers and dataset from LifeCLEF was used to optimize the accuracy and reduce the time complexity of the model.

Alex Krizhevsky et al. [7] published a paper in 2012 on using deep convolutional neural networks for ImageNet classification at the 25th International Conference on Neural Information Processing Systems.

3 Materials and Methods

3.1 Inception V3

Comparison of CNN architecture is given in table 1. Inception-v3 given in figure 1 is a deep convolutional neural network that consists of 48 layers. It was introduced by Google in 2015 and has been widely used in various computer vision tasks due to its high accuracy and efficiency. The network is typically used for image classification tasks and has been pre-trained on the ImageNet database, which consists of over a million images from 1000 different object categories. This pre-training enables the network to recognize a wide range of objects and classify new images accurately. One of the main advantages of Inception-v3 is its ability to extract rich feature representations for a wide range of images. This means that the network can identify patterns and features in images that are not easily recognizable to the human eye, and use these features to make accurate classifications. The input size for Inception-v3 is 299-by-299 pixels. This means that any images that are fed into the network must be resized to this size before being processed. Pretrained versions of Inception-v3 and other deep neural networks are available in MATLAB, a programming language that is widely used in the field of machine learning and computer vision. These pre-trained models can be used to perform various computer vision tasks, such as image classification and object detection, with minimal training data and computation time.

Table 1. CNN architecture comparisons

Architecture	Top 1 Accu- racy	Top 5 Accu- racy	Year
Alexnet	57.1	80.2	2012
Inception V1	69.8	89.3	2013
VGG	70.5	91.2	2013
Resnet 50	75.2	93	2015
Inception V3	78.8	94.4	2016

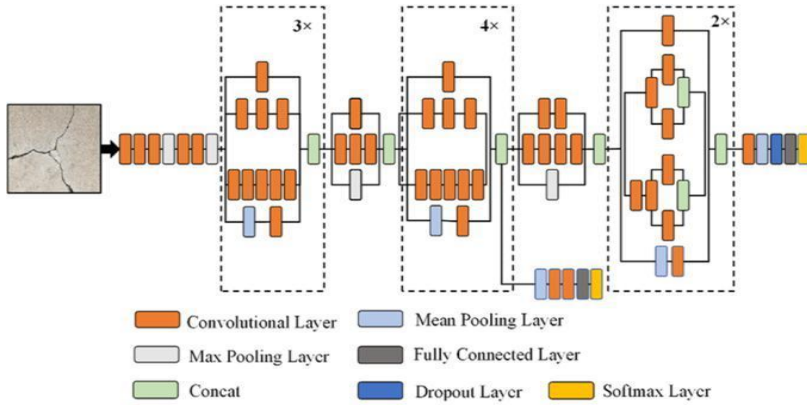


Fig. 1. Inception V3

3.2 Felicia Methodology

Felicia is our own proposed novel deep convolutional neural network that utilizes Inception V3 architecture to extract features from images. The classifier of Felicia comprises Global Average Pooling (GAP), MISH activation function, dropout, and softmax layers. This network is specifically designed to perform plant identification tasks with an aim to improve accuracy.

The Global Average Pooling (GAP) layer in Felicia performs spatial average pooling, producing a one-dimensional output feature vector by taking the average of each feature map. This enables the network to handle input images of various sizes, and reduce the number of parameters required for training.

MISH activation function in Felicia is a novel activation function that has been reported to improve the performance of deep neural networks. It is a smooth and non-monotonic function that combines the benefits of popular activation functions like ReLU and sigmoid.

Dropout layer in Felicia is used to prevent overfitting and improve generalization of the network. It randomly sets a fraction of the input units to zero during training, forcing the network to learn more robust features.

The SoftMax layer in Felicia produces the final output probabilities for each class of plants, and the class with the highest probability is predicted as the label of the input image.

The proposed Felicia model given in figure 2 has potential applications in various fields, such as agriculture, horticulture, and ecology, where accurate plant identification is crucial. Its ability to improve accuracy could lead to better plant disease detection, better conservation efforts, and improved crop yield.

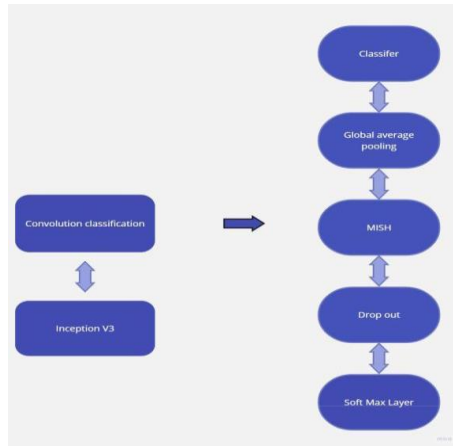


Fig. 2. Felicia Architecture

3.3 Felicia Dataset

The proposed dataset as given in figure 3 is collected using a mobile device from natural scenes, comprising approximately 250 distinct photos per category. The images are captured in the Western Ghats region, where medical plants are commonly found. The dataset includes 25 categories, and leaves with severe deformities are removed from the selection process. Only leaves with distinct differences in shape, color, and size are chosen for scanning. To create a dataset for our model we chose 25 different plant species (Clitoria Ternatea, Basella Alba, etc..).

A comprehensive dataset is generated for each plant species by capturing photographs of both the top and bottom surfaces of their leaves. By applying variations to these images, a total of 250 unique images per species are obtained. Post-scanning, image editing tools are used to select and crop only the leaf areas, and the images are saved in the JPEG format. The images are named using a specific convention that helps the model provide more accurate classification results. This dataset can be useful for accurately classifying medical plant leaf images and can have various applications in fields such as agriculture, medicine, and biotechnology.

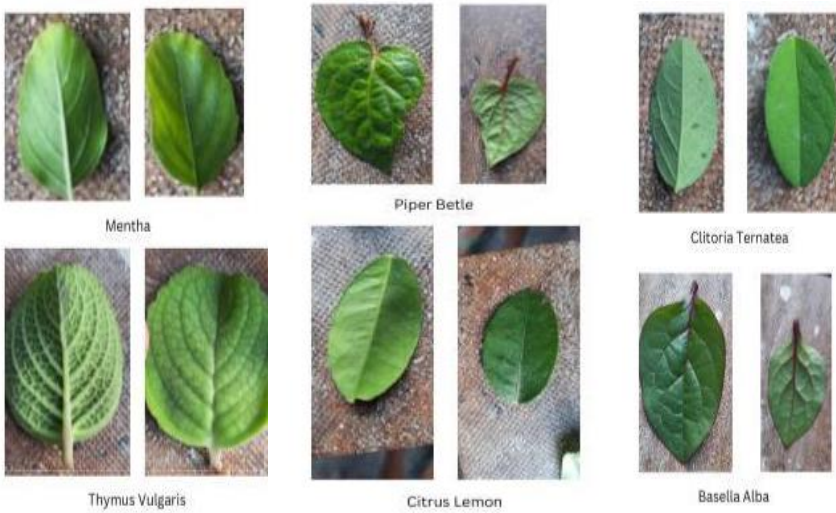


Fig. 3. Dataset of front view and back view

3.4 Felicia Proposed CNN Architecture

Dataset Collection: The proposed model involves collecting a dataset of medical plant leaf images using a mobile device. The dataset consists of more than 25 photos per category acquired in natural environments in the Western Ghats region. The Western Ghats is a mountain range along the western coast of India and is known for its rich biodiversity. The use of a mobile device allows for easy and convenient collection of images in the natural environment.

Data Augmentation: To create 250 images per species, 10 leaves are scanned from both their top and bottom surfaces and edges. This helps increase the number of images in the dataset and improves the accuracy of the model. The use of both top and bottom surfaces and edges helps capture all possible angles and details of the leaves.

Image Pre-Processing: Image pre-processing is carried out to convert the scanned images into the required format of $299 \times 299 / 224 \times 224$ pixels and RGB color. Images with different dimensions are padded and resized before feature extraction using Inception v3. This ensures that all images are of the same size and format, which is necessary for proper feature extraction and classification.

Feature Extraction: Inception v3 is a deep convolutional neural network that is widely used for image classification tasks. It extracts the features of each image using its neurons, biases, and weights. This helps identify the key features of the images, such as texture, shape, and color, which are then used for classification.

Classifier Block: The output of Inception v3 is fed into a classifier block. Global average pooling is used to help reduce overfitting by summarizing the feature maps generated by Inception v3. The classifier block utilizes the MISH function to perform mathematical operations and the softmax function to calculate the probability of each neuron for proper classification. The MISH function is a recently proposed activation

function that has been shown to outperform traditional activation functions such as ReLU and sigmoid. The softmax function converts the output of the neural network into probabilities, which can then be used to determine the class of the input image.

Overall, the proposed model aims to improve the accuracy of classifying medical plant leaf images better than Inception V3 alone as there are other classifier layers after the layers in Inception V3.

This can have various applications in fields such as agriculture, medicine, and biotechnology. By accurately identifying and classifying medical plant species, the model can aid in the discovery of new drugs, the identification of harmful plants, and the conservation of endangered species.

After feature extraction using Inception v3, the output is fed into a classifier block consisting of additional layers for further processing. The classifier block plays a crucial role in identifying the type of plant from the extracted features.

In particular, the classifier block comprises a MISH activation function and a softmax layer. MISH stands for "Mishra's Self-Gated Activation Function," which is a type of activation function that improves the convergence rate and accuracy of deep neural networks. The MISH function is applied after the feature extraction process and before the softmax layer.

The softmax layer is responsible for normalizing the output of the previous layer and generating the probability distribution across the different classes. In other words, it calculates the probability of each class given the extracted features.

Together, the MISH activation function and softmax layer enable the proposed model to classify medical plant leaves accurately and efficiently. By using Inception v3 for feature extraction, the model can identify the key features of each leaf image and use them to accurately classify the image. The MISH activation function and softmax layer ensure that the output of the model is a probability distribution across the different plant species, allowing for accurate classification.

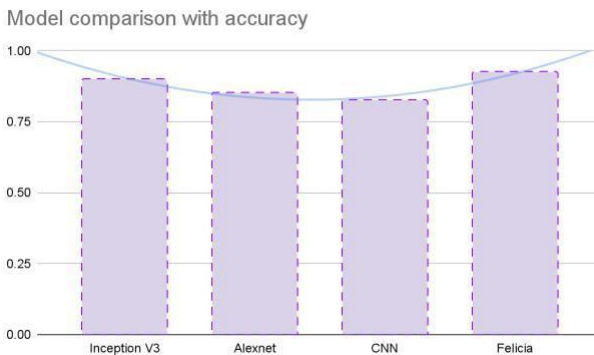


Fig. 4. - Model comparison with accuracy

The Felicia model reports the training and validation accuracy through an accuracy graph and the classification accuracy through a confusion matrix. Our proposed Convolutional Neural Network (CNN) architecture also utilizes the Inception V3 CNN with

additional layers, such as Mish and Softmax, to improve accuracy is given in figure 4. The model includes essential operations such as Max pooling, Global Average Pooling (GAP), and Dense Layer. While the diagram shows five CNNs, the original Inception V3 model is a pre-trained CNN model with 48 deep layers and an additional four layers.

4 Result And Discussion

The Felicia model incorporates a multi-layered architecture, including the utilization of Inception-V3, which will likely enhance the quality of predictive analysis. Unlike many existing models that have achieved a maximum accuracy of 99.3% using various CNN models, our proposed model employs an expanded categorization into multiple layers, effectively mitigating overfitting. As a result, we anticipate our model to achieve an average accuracy of 99.35%.

5 Conclusion

The Felicia model is to predict with a higher accuracy compared to existing models, making it an effective tool for distinguishing plant species found in the Western Ghats region. By utilizing the outputs of Felicia, various applications can identify specific plants and their respective species. As the model continues to improve through training, it will be capable of identifying a broader range of species with high accuracy.

The integration of Felicia into applications will greatly benefit the local community, ayurvedic doctors, and researchers, enabling them to easily identify plants and learn about their uses. This implementation not only saves significant time but also ensures that potentially harmful or poisonous species are avoided. Ultimately, the professional application of Felicia contributes to the preservation of human health and facilitates a more efficient exploration of the diverse flora present in the Western Ghats.

References

1. Dileep, M.R., Pournami, P.N.: AyurLeaf: A deep learning approach for classification of medicinal plants, IEEE TENCON, 321–325, Kochi, India (2019).
2. SR. Janani, A. Gopal: Identification of Selected Plant Leaves Using Image Features and ANN, International Conference On Advanced Electronic Systems, 237–243 (2013).
3. Tan, J.W., Chang, Siow-Wee, Binti, A.K., Sameem, Y., Hwa, J., Yong, Kien-Thai.: Deep Learning for Plant Species Classification using Leaf Vein Morphometric. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 1–1 (2018).
4. Venkataraman, D., Mangayarkarasi, N.: Computer vision based feature extraction of leaves for identification of medicinal values of plants. IEEE International Conference on Computational Intelligence and Computing Research, pp. 1–5, (Dec 2016).

5. Sathish, S.N., Bindu, Jyothishri, Veenaxi, P., Vinoliya, S.P.: Identification of Ayurveda Herbs Using Machine Learning, *International Journal of Advances in Engineering and Management*, vol.4, pp. 517-524 (2022).
6. Mostafa, M.G., Berrin, Y., Erchan, A.: Plant identification using deep neural networks via optimization of transfer learning parameters, *Neurocomputing*, 235:228 – 235 (2017).
7. Guillermo, L.G., Lucas, C.U., Monica, G.L, Pablo M.G.: Deep learning for plant identification using vein morphological patterns. *Computers and Electronics in Agriculture*, 127:418 – 424 (2016).
8. Alex, K., Ilya, S., Geoffre, E.H.: Imagenet classification with deep convolutional neural networks, 25th International Conference on Neural Information Processing Systems, vol. 1, 1097–1105, USA (2012).
9. Umme, H., Md. Rasel, Md., Aminul, I., Rahat, H.F., Md. Mostafijur, R.: Automatic Medicinal Plants Classification using Multi-channel Modified Local Gradient Pattern with SVM Classifier, 8th International Conference on Informatics, Electronics & Vision & 3rd International Conference on Imaging, Vision & Pattern Recognition, Spokane, USA (2019).
10. Rahim, A., Mohammed, M.A., Hamed, M., Mehmet, A.C., Ava, D., Eugenio, C.: An AI Based Approach for Medicinal Plant Identification Using Deep CNN Based on Global Average Pooling, Ahmed, K., Ahmed, R., MDPI, 1-15, Switzerland (2022).

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

