

# CoENet: An Intelligent Deep Learning Framework for Medicinal Plant Leaf Image Classification

S.Selva Nidhyananthan <sup>1\*</sup>, D.Suganya<sup>2</sup>, V.Packiya<sup>3</sup>, D.Dharshini<sup>4</sup>, R.K.Divyasri Nachiar<sup>5</sup>

<sup>1</sup>Professor, <sup>2</sup>Research Scholar, <sup>3-5</sup>UG Scholar

Department of ECE, Mepco Schlenk Engineering College, Sivakasi, Tamil Nadu, India

\* Corresponding Author

## ABSTRACT

Given the dire threat of extinction facing many plant species, biodiversity conservation is essential; especially medicinal plants. People's awareness on alternative medicine makes them use therapeutic herbs with the guidance of herbalists. Integrating contemporary technology methods with conventional herbal knowledge will ultimately improve the therapeutic system to a larger degree. A CoExtensive model based on Multi-Scale deep parallel Convolution Neural Network is proposed which categorizes the medicinal leaf and enlightens the user on its attributes like therapeutic qualities, particularly concerning the illness it is intended to treat. This multi-scale approach boosts performance in tasks like object detection, image segmentation, and classification by analyzing the data at different levels of detail simultaneously. Traditional methods involve resizing the herbal image data which loses information or using separate CNNs for each scale which can be computationally expensive. The proposed architecture CoENet is developed to balance efficiency and network complexity. A comprehensive evaluation of the proposed methodology upon testing on the 'Medicinal Leaf Dataset' yields an accuracy of 99.73% and the 'Mepco Tropic Leaf Dataset' yields an accuracy of 97.2% and compared with pre-trained deep CNN architectures VGG19, InceptionV3, Xception to show the supremacy of the proposed approach of leaf classification.

**Keywords:** Medicinal Plant Leaf, Coextensive, Multi-scale deep parallel CNN, Classification accuracy.

## 1. INTRODUCTION

Medicinal plants have served as a cornerstone of healthcare for millennia, offering natural remedies for various types of ailments. Even before the introduction of allopathy among people, medicinal plants have been proven to be the only source of remedy to cure all types of diseases. Now-a-days people tend to be interested in organic and natural forms of living, leading to the increase in herbal therapies and the integration of plant-derived compounds into pharmaceutical drugs and it is proven to be more effective. However, the safe and effective utilization of these natural resources has its roots in the accurate identification of the underlying plant species. Traditional methods of plant identification often rely on the expertise of botanists, can be time-consuming, require extensive training [1], and expertise [6].

Recently many studies contribute to advancing the field of plant identification and offer valuable insights into the application of deep learning for agricultural and botanical purposes, potentially revolutionizing herb classification methodologies [2]. By analyzing the image at different scales concurrently, the Multi-Scale Parallel Deep (MP-DCNN) architecture captures a richer and more comprehensive set of features [19]. MP-DCNN potentially requires less preprocessing as it can analyze information at different scales within its architecture but has its downfall in network complexity. The proposed model CoENet is developed to address these by using MP-DCNN for its architectural base and the repetitive use of basic layers of Convolution networks (ConvNet) such as Convolution and pooling layers along with the use of Fully Connected [FC] layers which thereby reduces the network complexity.

The first section of this paper provides an introduction to Medicinal Leaf Classification. The second section includes relevant works on Medicinal Leaf classification; the third section contains methodology; the fourth section analyzes the model's performance; and a conclusion in section five.

## 2. BACKGROUND STUDY

Deep learning (DL) is explored in papers [4], [5] as a potential solution due to its ability to learn complex patterns from data. Existing plant leaf classification models often sacrifice compactness [7] for high accuracy. DeepPlantNet, a novel deep learning architecture with specific design choices, demonstrates superior performance across different classification schemes (eight-class and three-class) compared to existing models [8]. Usage of Deep Transfer

Learning leverages the challenge of data scarcity and helps to overcome it [9]. HTSD (High-Level Triangle Shape Descriptor), a deep learning model utilizing convolutional and fully connected layers, effectively learns robust and discriminative features directly from leaf images, leads to higher classification accuracy [10].

Transfer learning facilitates knowledge transfer from diverse pre-trained models and federated averaging aggregates updates for better generalization. FTL (Federated Transfer Learning) is tested on a rice-leaf disease dataset, demonstrating higher accuracy compared to traditional machine learning and federated learning approaches. Analysis is carried out on both balanced and unbalanced data distributions [11]. Multiscale parallel deep CNNs show promise for improved plant leaf classification, addressing both species and disease identification. This tackles the limitations of traditional methods that struggle with differentiating diseases and species due to variations in scale and location. This architecture utilizes multiple parallel streams to analyze leaf images at different scales, enabling the model to capture both global and local features of the leaf [3]. Convolutional Neural Networks (CNNs) have emerged as the leading method for achieving high accuracy in leaf classification, surpassing traditional approaches on the Flavia dataset [12].

Successful development of such automated systems such as the Ayurleaf model could have significant benefits in facilitating proper identification and utilization of medicinal plants. Ayurleaf utilizes a Convolutional Neural Network (CNN) to automatically classify medicinal plants based on leaf image physical constituents [13]. Accurate identification of maize leaf diseases is crucial for optimal crop yield, but traditional methods are time-consuming and require expertise. Here, deep convolutional neural networks (CNNs) are adopted as a potential solution [14]. The use of rough sets could lead to efficient classification with reduced reliance on complex feature engineering. Applying rough sets might enable accurate classification while potentially reducing the need for complex feature engineering techniques compared to traditional methods [15]. Soybean crops are susceptible to various leaf diseases, impacting overall yield. Traditional plant leaf classification methods require expertise and are time-consuming. Deep learning offers a promising alternative for automated and accurate classification based on analyzing image features [16], [17].

Traditional plant leaf classification methods often struggle with distinguishing fine-grained differences between closely related species. The features from different pre-trained CNN models are combined to improve classification performance at both the genus and species level

[18]. The challenges of plant identification while combining dataset images from various sources, often lead to imbalanced class distributions where some species are vastly over-represented compared to others. To address the class imbalance issue, oversampling, under-sampling, and transfer learning techniques within a convolutional neural network (CNN) classifier are employed [19]. Acquiring and labeling large datasets can be expensive and time-consuming, especially in biological research. Deep low-shot learning, is a technique for training accurate models with limited training data [20]. This research purports to focus on computer vision methods for Ayurvedic plant recognition, based on its title and distribution locations. The utilization of "feature extraction methods" suggests the study investigates the method by which computer algorithms can identify relevant aspects from images of these plants [21, 22]. It probably contrasts multiple methods of extraction, evaluating their efficacy, and accuracy in identifying Ayurvedic medicinal herbs. The establishment of automated tools or systems that help in the recognition of therapeutic plants could profit significantly from this research, which may have significant implications for researchers and practitioners of Ayurvedic medicine. These approaches can make the model highly complex too. Due to its ability to analyze data at many sizes within its architecture, MP-DCNN may require less preprocessing; however, this is offset by the network's complexity. The proposed model CoENet utilizes the structure of MP-DCNN which reduces preprocessing requirements and the network is less complex because of the involvement of CNN CNN-based feature extraction approach.

### 3. MATERIALS AND METHODOLOGY

#### 3.1 Dataset

Our proposed architecture CoENet is trained using the Medicinal Leaf Dataset and Mepco tropic Leaf dataset. The Medicinal Leaf Dataset contains 30 classes of Medicinal leaves which have localities all around Asia, have a total of 1855 images, each having 1600x1200 pixels, and some samples are shown in Fig 1. The Medicinal leaves in this dataset were captured using a Mobile camera (Model: Samsung s9+) [1]. The Mepco tropic Leaf dataset contains 50 classes which have its locality around the foothills of the Western Ghats in Tamil Nadu. It has a total of 3777 images and some samples are shown in Fig 2. These images were captured using mobile cameras and they are of different sizes [21]. The split for training-testing is 80-20% for both datasets.

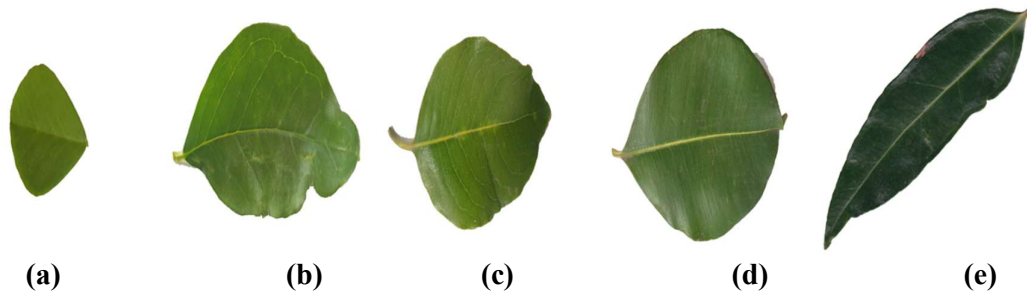


**Fig.1: Samples of Medicinal Leaf Dataset (a) Trigonella foenum-graecum (Fenugreek) (b) Punica granatum (Pomegranate) (c) Santalum album (Sandalwood) (d) Syzygium cumini(Jamun) (e) Syzygium jambosa(Rose apple)**



**Fig.2: Samples of Mepco Tropic Leaf Dataset (a) Avaram (b) Holy Basil (c) Ivy Gourd (d) Nalta Jute (e) Spiderwisp**

### 3.2 Methodology

The research uses a deep learning technique for the automated identification of therapeutic herbs. Architectures like InceptionV3, Xception, and VGG16 are used in architectural study.

#### 3.2.1. VGG16:

VGG16 consists of 16 layers. VGGNet is constructed with five sets of  $(3 \times 3)$  kernel-based convolution layers. After every convolution layer, Rectified Linear Unit activation function is used, and to reduce spatial dimension, max pooling works on  $2 \times 2$  kernels. At the end softmax layer of dimension  $1 \times 1 \times 1000$  is preceded by three fully connected layers of size 4096 units. The model is trained on the medicinal leaf dataset and the architecture is shown in Fig 3.

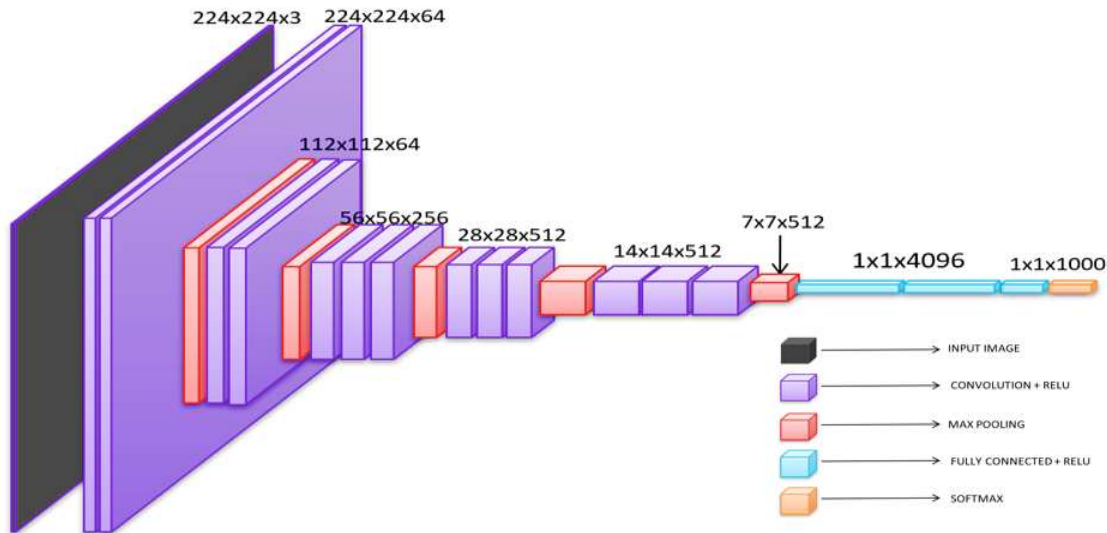


**Fig.3: VGG 16 Architecture**

### 3.2.2. InceptionV3 and Xception:

The Inception Network V3 learns intricate patterns with fewer parameters. The inception modules concatenate their outputs after performing parallel convolutions at various spatial scales. It efficiently captures both local and global characteristics, enabling the network to concurrently learn rich representations at multiple scales. InceptionV3 uses a variety of pooling techniques, such as average and standard max pooling, to downsample feature maps and capture spatial information at multiple scales. Depthwise separable convolution in inception architecture, splits the conventional convolution operation into two distinct operations such as depthwise convolution and pointwise convolution, differentiates it from Xception architecture which typically uses input images resized to a fixed size, often 299x299 pixels, with standard mean normalization. Depthwise convolution creates a series of intermediate feature maps by applying a single filter to each input channel. The intermediate feature maps are then combined using pointwise convolution, which applies a 1x1 convolution over all channels. The Inception V3 architecture shown in Fig.4 and the Xception model shown in Fig.5 are trained using both datasets.

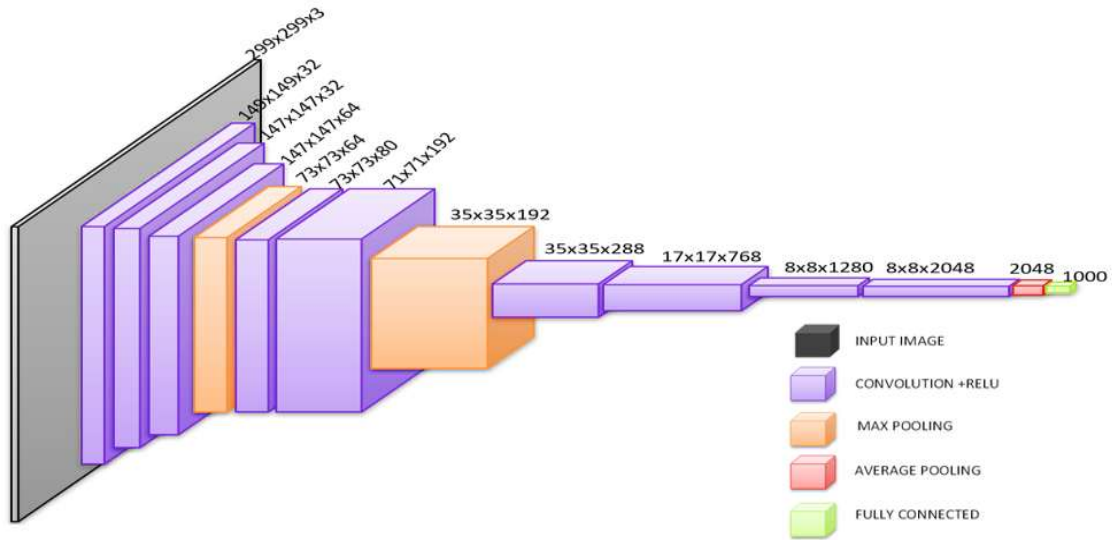


**Fig.4: Inception V3 architecture**

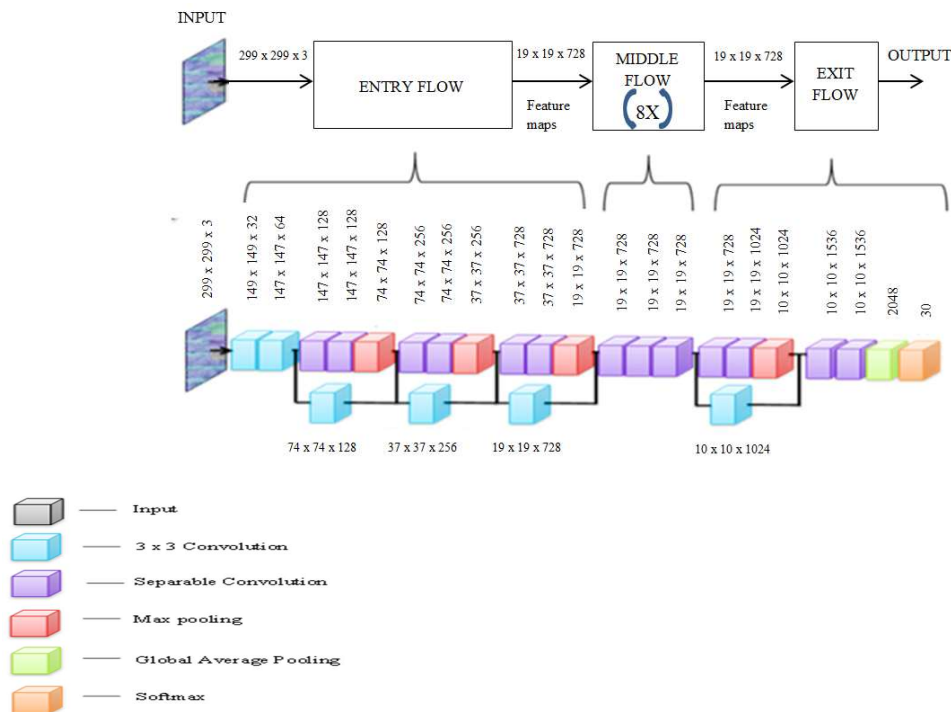


**Fig.5: Xception Architecture**

### 3.2.3. CoENet

In the proposed architecture CoENet – CoExtensive Neural Network, the input image is resized to three different sizes and fed to three branches of the architecture which has sets of convolution and pooling layers and culminate with concatenation layers for combining those three branches' outputs. The proposed architecture is shown in Fig 6. The first branch has the convolutional layer of filter size 3x3 at first followed by a series of filters of size 1x1, 3 x3, and 3 pooling layers of kernel size 2x2. The image of size 128x128x3 is fed to the second branch which has the filter size of 5x5 which is then followed by a series of filters of size 1x1, 3x3, and 5 pooling layers of kernel size 2x2. The image of size 256x256x3 is fed to the third branch which has the filter size of 7x7 which is then followed by a series of convolutional layers of filter size 1x1, 3x3, and 7 pooling layers of kernel size 2x2. The output of all the three branches is concatenated and fed to a series of convolutional layers, max pooling (MP) layers and FC layers.

#### *A. Resizing*

Before feeding the images into the convolutional layers, the architecture resizes each image to a standard size of 64x64, 128x128, and 256x256 pixels. As the number of operations increases with the number of pixels, processing, and training can be accelerated with smaller images. Typically, CNNs expect inputs of a fixed size. Resizing ensures all images conform to this requirement, simplifying the network architecture.

#### *B.Data augmentation*

A common challenge in the classification of images is having a relatively small dataset. The size of the dataset is essentially increased by augmentation. It is done by flipping and rotating the original images to create more images. More examples are given to the model to learn from, which improves generalization on unseen data. This makes the model less prone to overfitting on the specific training data and more likely to perform well on new, unseen leaf images. An augmentation factor of 10 is used to increase the number of images to avoid overfitting.

### C.Convolution

The size of the filters on the first, second, and third branches is 3x3, 5x5, and 7x7, respectively to locate characteristics and patterns within the image. A batch normalization (BN) layer and a ReLU layer come after each convolutional layer. CNNs frequently employ the BN technique to increase training speed and stability. It brings the outputs of the previous convolutional layer into a common range by standardizing them (by subtracting the mean and dividing by the standard deviation of the batch). This prevents problems like exploding or vanishing gradients and speeds up the network's learning process. Compared to the 3x3 convolution, the convolutional layer with the 5x5 filter size enables the network to capture features over a greater region of the image, possibly recognizing more complex patterns. Similar to this, a 7x7 filter is employed to find even larger and complex features in the image.

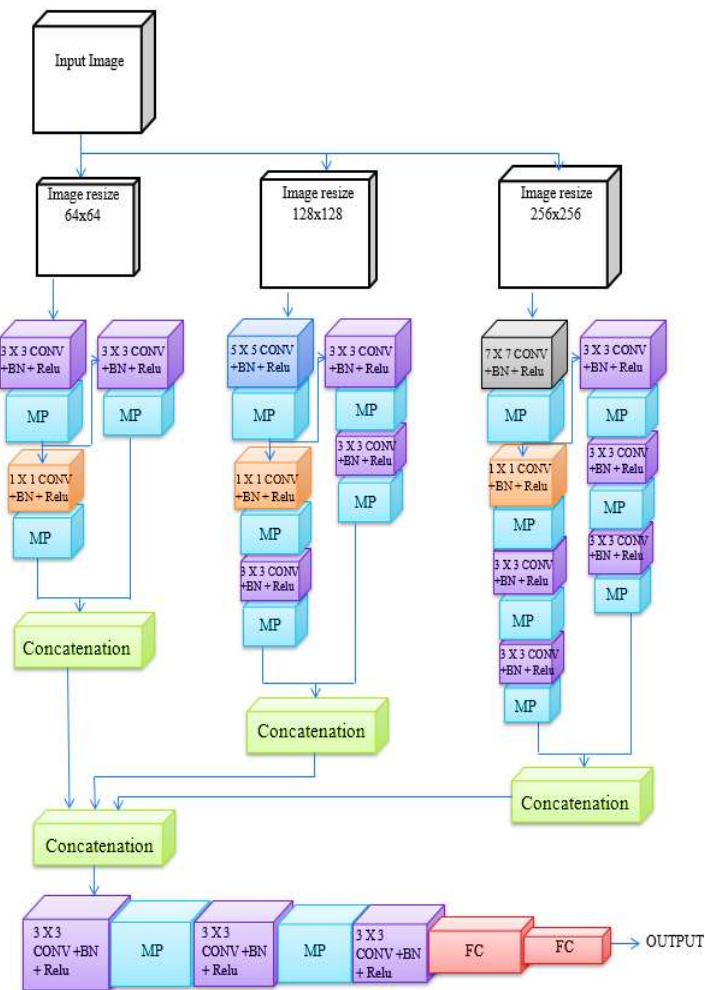


**Fig.6: CoENet architecture**

#### *D.Max Pooling:*

Max pooling selects the maximum value from a specific area of the feature map. As a result, the network becomes more efficient by having fewer parameters and calculations. Pooling layers downsample the feature maps, therefore reducing the dimensionality of the data. Max pooling helps the model to recognize features regardless of their small positional shifts. This is because it chooses the most significant value inside a small area, and even small feature movements won't alter this maximum value. This makes the model more robust to variations in the input data.

#### *E.Pointwise Convolution:*

The number of channels in the feature maps is decreased while retaining spatial information by using point-wise convolution. In this architecture, point-wise convolution is applied after the initial convolutional layers. Even though a 1x1 convolution has a small receptive field, it introduces additional non-linearity to the network through activation functions. By reducing the number of parameters, 1x1 convolutions can function as a regularization technique to stop overfitting. The network gains non-linearity when 1x1 convolutions are followed by non-linear activation functions (such as ReLU), which enables the network to learn complex relationships between features.

#### *F. Concatenation:*

Concatenation is a possible approach, where the feature maps from each resized image would be stacked together, creating a deeper feature map with a combined depth. As a result, the network might be able to learn features from different image resolutions in the same layer. The objective of the concatenation layer is to combine the features that have been extracted from various neural network branches or paths. In this architecture, feature maps from three distinct paths are combined by concatenation. The network can learn complementary representations that might not be picked up by individual routes alone by merging feature maps from several paths. Concatenation effectively raises the feature maps' dimensionality, providing the ensuing layers with richer and more diverse information. This can boost the model's overall performance and increase its ability to depict complex relationships within the data.

#### G. Fully Connected layers:

Classification is carried out using fully connected layers using the flattened output from the convolutional layer. They discover relationships between the corresponding leaf classes and the extracted features. The dropout of 0.25, and 0.2 respectively is introduced between each FC layer, and finally, Softmax classifier classifies the output.

## 4. RESULTS AND DISCUSSION

The purpose of this section is to discuss how well a proposed CoENet model can classify the medicinal leaves both datasets with high accuracy.

### 4.1. Data Collection

We have evaluated our model on two datasets. It began with a small number of classes and progressed to a larger number of classes. The Medicinal Leaf Dataset has thirty classes that contain 1,855 samples of medicinal leaves in which 1484 images are used for training and 371 images for testing. The Mepco tropic leaf dataset has fifty classes and consists of 3777 images of which 3021 images are used for training and 756 images are used for testing. By using augmentation, the imbalance between the training and testing data is resolved and CoENet is trained with an augmentation factor of 10 on both datasets. After augmentation, the total number of images in the Medicinal Leaf Dataset is 20405 and in Mepco Tropic Leaf Dataset is 41547.

### 4.2. Evaluation Metrics

Accuracy (*acc*), recall (*re*), precision (*pr*), and F1-score (*F1score*) value are the evaluation metrics used.

$$acc = \frac{\text{No. of correct predictions}}{\text{Total No. of predictions}} \quad (1)$$

$$pr = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positive}} \quad (2)$$

$$re = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (3)$$

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

### Confusion Matrix:

The confusion matrix shown in Fig. 7 is plotted against the true label and the predicted label to verify the model's performance for the Medicinal Leaf Dataset (Dataset 1) which contains 30 classes. It shows the accuracy of each class classification and only one image from the class *Hibiscus Rosa-sinensis* was misclassified. The confusion matrix for the Mepco Tropic Leaf Dataset (Dataset 2) contains 50 classes and the lowest rate of correct classification lies in the Madagascar Periwinkle class.

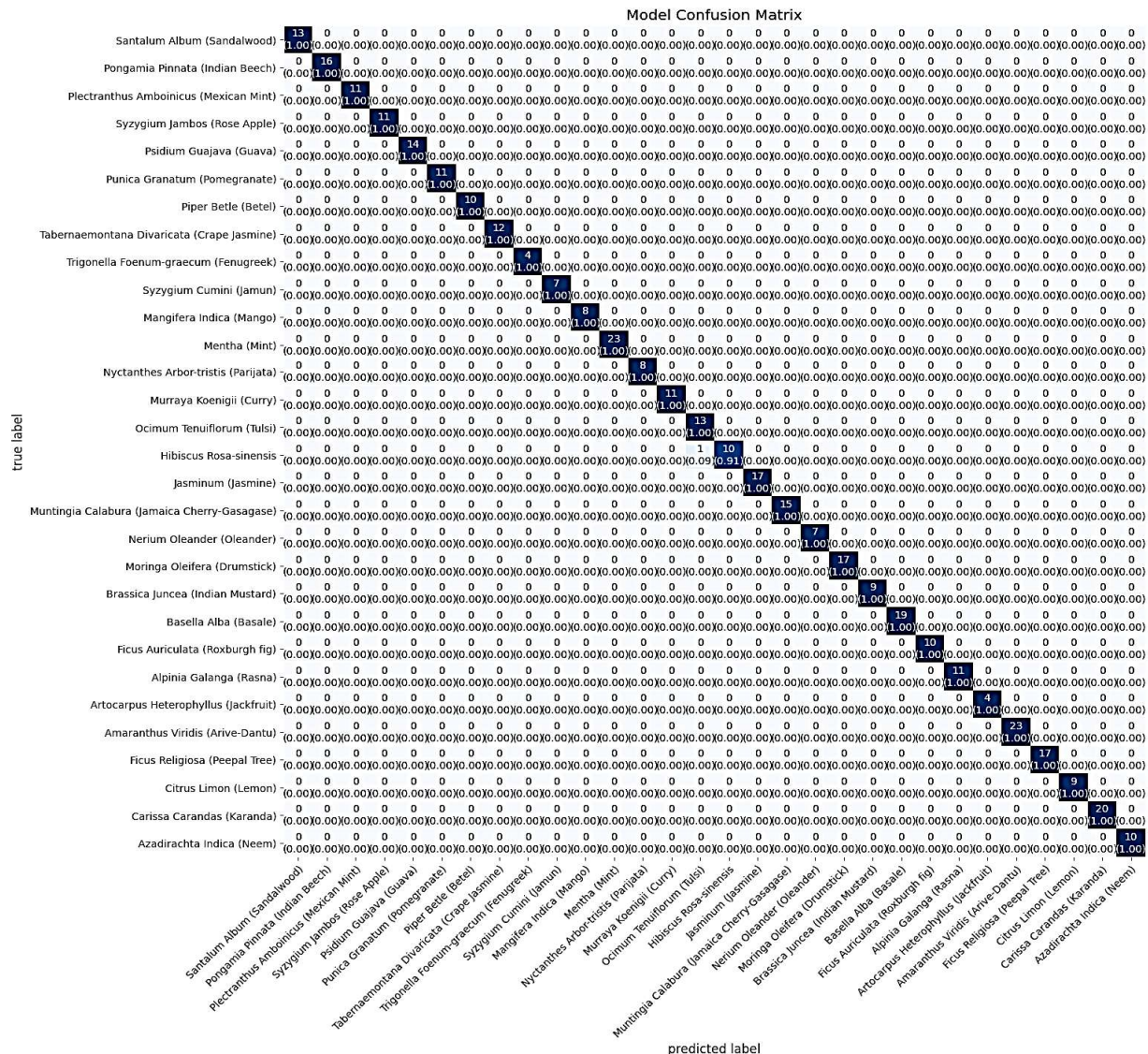


**Fig.7: Proposed Architecture's Confusion Matrix on Dataset 1**

**ROC curve:**

A Receiver Operating Characteristic curve (ROC) is used to evaluate how successfully a model classifies data. The trade-off between accurately classifying false positive rate and true positive rate is plotted on the curve. A ROC curve closer to the top-left corner indicates a better-performing model. This indicates that the model has a low false positive rate which misinterprets negative cases as positive and a high true positive rate, which accurately identifies positive cases. The ROC curve for CoENet, trained on both datasets is shown in Fig.8. The medicinal leaf dataset achieves an accuracy of 99.73%, **higher** than the accuracy of the Mepco tropic leaf dataset. Table 1 shows the evaluation metrics and we can observe that the proposed architecture CoENet acquires a remarkable accuracy of 99.73% compared to the baseline models such as VGG16, Xception, Inception V3, and MP-DCNN.

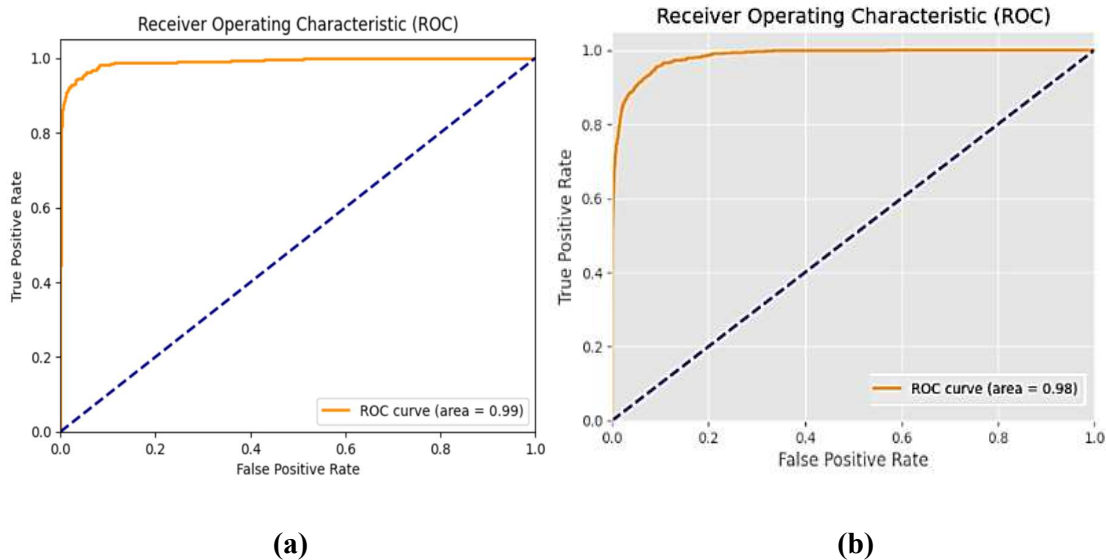


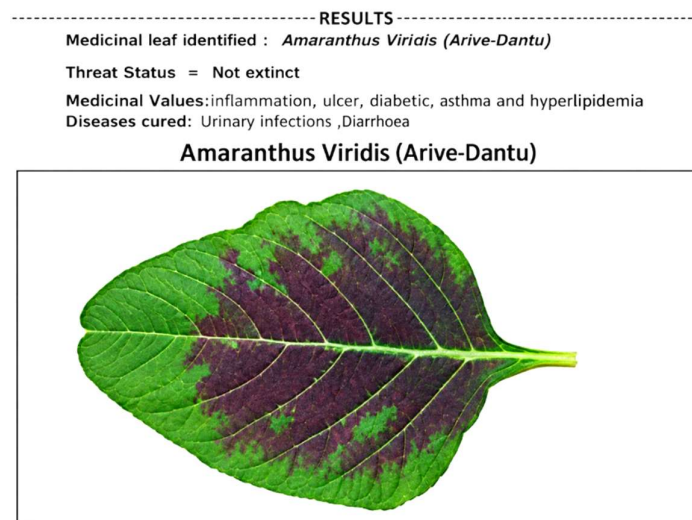
**Fig.8: ROC Curve (a) Proposed architecture's ROC curve on Dataset 1**  
**(b) Proposed architecture's ROC curve on Dataset 2**

**Table 1. Comparison of Evaluation metrics between baseline models and CoENet on both Datasets.**

| Models                   | Dataset        |             |             |             |                   |             |             |             |
|--------------------------|----------------|-------------|-------------|-------------|-------------------|-------------|-------------|-------------|
|                          | Medicinal Leaf |             |             |             | Mepco tropic Leaf |             |             |             |
|                          | Accuracy       | Precision   | Recall      | F1-Score    | Accuracy          | Precision   | Recall      | F1-Score    |
| VGG16                    | 93.07          | 0.93        | 0.93        | 0.93        | 87.76             | 0.88        | 0.88        | 0.88        |
| Inception V3             | 95.57          | 0.96        | 0.96        | 0.96        | 89.27             | 0.89        | 0.89        | 0.89        |
| Xception                 | 97.5           | 0.98        | 0.98        | 0.98        | 93.8              | 0.94        | 0.94        | 0.94        |
| MP-DCNN [3]              | -              | -           | -           | -           | 90.86             | -           | -           | -           |
| <b>CoENet (Proposed)</b> | <b>99.73</b>   | <b>1.00</b> | <b>1.00</b> | <b>1.00</b> | <b>97.2</b>       | <b>0.97</b> | <b>0.97</b> | <b>0.97</b> |

**Attribution:**

The proposed CNN-based architecture CoENet also displays the Threat status, Medicinal Values, and the diseases that will be cured by the specific medicinal leaf after its identification. The threat status of a medicinal leaf is determined by the International Union for the Conservation of Nature (IUCN) and has categories like Critically Endangered, Endangered, Vulnerable, Least Concern, and Not Extinct. The results of the attributions are shown in Fig.9 for the Medicinal Leaf Dataset and Fig.10 for the Mepco Tropic Leaf Dataset.

**(a)**

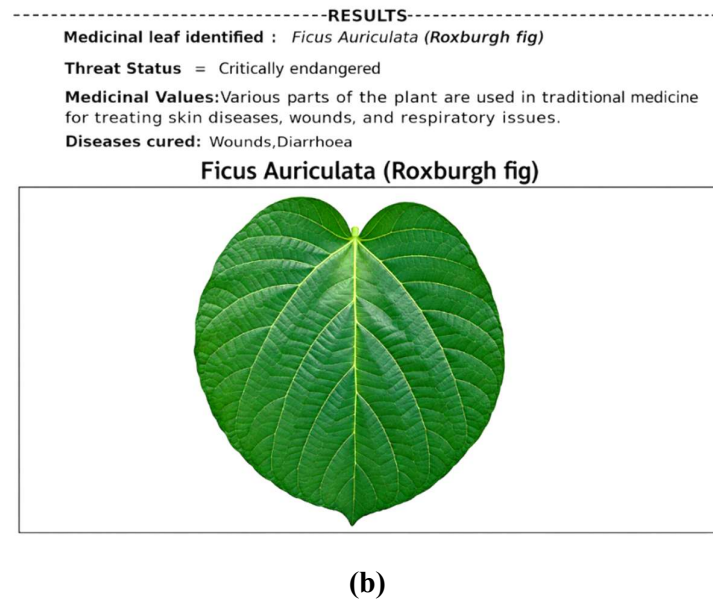
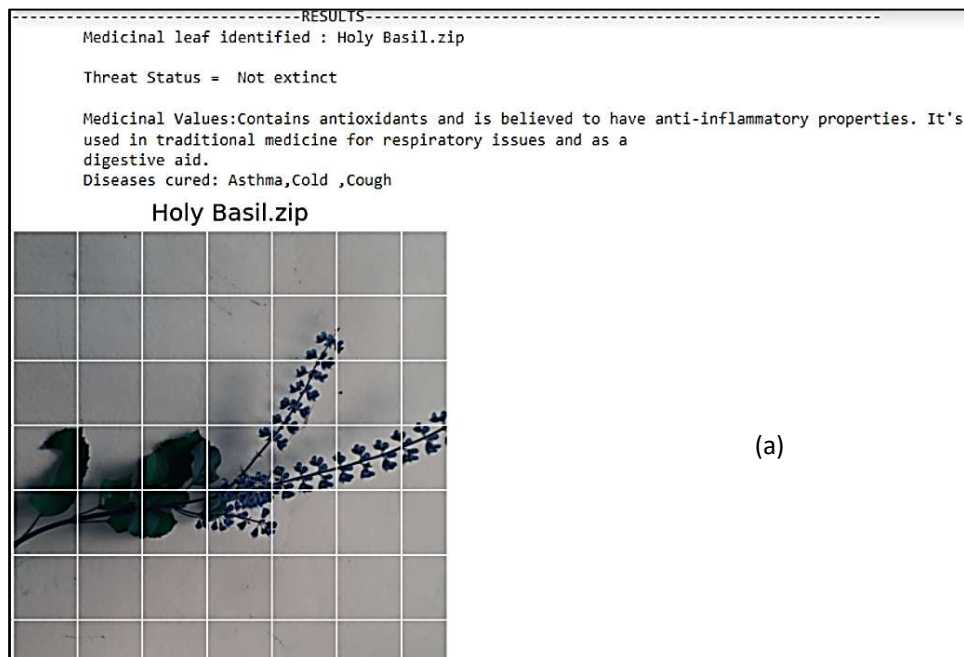


**Fig.9: Attribution results of CoENet on Medicinal Leaf Dataset (a) Amaranthus Viridis (b) Ficus Ariculata**



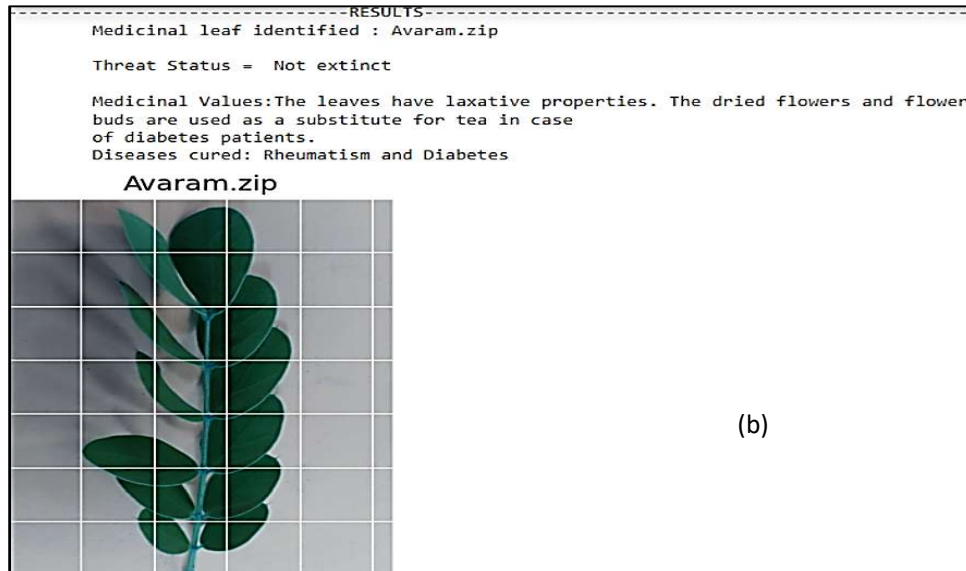


**Fig.10: Attribution results of CoENet on Mepco tropic Leaf Dataset (a) Holy Basil (b) Avaram**

### *Acknowledgment*

Our project participated in the Naan Mudhalvan - Niral Thiruvizha Hackathon, a prestigious event organized by TNSCST. We gratefully acknowledge the partial funding provided by TNSCST for this project.

### *Conflict of Interest*

The authors declare that they have no conflict of interest.

## **5. CONCLUSION:**

In this paper, we presented CoENet- Coextensive Neural Network, a deep learning network in which the feature extraction is carried out in three different parallel branches, and the results are accumulated to get higher accuracy. CoENet is created especially for classifying medicinal plants and displaying their attributes such as Threat status, Medicinal Value, and the disease that will be cured by those leaves. To attain remarkable accuracy, our research suggests a revolutionary design that makes use of methods like multi-scale parallel convolutional neural networks. After extensive testing and analysis, our model achieved an astounding 99.73% accuracy on the Medicinal Leaf Dataset and 97.2% accuracy on the Mepco Tropic Leaf Dataset.

CoENet performs far better than current state-of-the-art techniques. In comparison with well-known models such as Inception, VGG16, and Xception, our method shows notable enhancements. It also outperforms the MP-DCNN which has 90.86% accuracy on Mepco tropic Leaf dataset [3]. The use of augmentation, Pooling layers, and dropout significantly increases the model's accuracy during its development. These findings demonstrate the accuracy with which our suggested design can classify medicinal leaves, and they point to the wide range of sectors in which it may find use, including pharmacology and botany. The effectiveness of CoENet highlights the significance of utilizing advanced deep-learning techniques in the field of botanical research and medicinal plant classification. This model has a major societal impact in the field of assisted living. In the future, we plan to improve and fine-tune our model to tackle various challenges in this domain, which will eventually contribute to the progress of identifying and utilizing medicinal plants.

## 6. REFERENCES:

- [1] ROOPASHREE S, ANITHA J, "DeepHerb: A Vision-Based System for Medicinal Plants Using Xception Features", " IEEE Access, volume 9, pages 135927 – 135941, DOI: [10.1109/ACCESS.2021.3116207](https://doi.org/10.1109/ACCESS.2021.3116207)
- [2] AMGAD MUNEER, SULIMAN MOHAMED FATI, "Efficient and Automated Herbs Classification Approach Based on Shape and Texture Features using Deep Learning", " IEEE Access, volume 9, pages 196747 – 196764, DOI: [10.1109/ACCESS.2020.3034033](https://doi.org/10.1109/ACCESS.2020.3034033)
- [3] Russel Newlin Shebiah and Arivazhagan Selvaraj, "Leaf species and disease classification using multiscale parallel deep CNN architecture", " Neural Computing and Applications, volume 34, pages 19217-19237, DOI: 10.1007/s00521-022-07521-w
- [4] Wei Tan J, Chang S W, Abdul-Kareem S, Yap H J, Yong K T, "Deep learning for plant species classification using leaf vein morphometric", "IEEE/ACM transactions on computational biology and Bioinformatics, volume 17, issue 1, pages 82-90, DOI: 10.1109/TCBB.2018.2848653
- [5] Kanda P S, Xia K, Sanusi O H, " A deep learning-based recognition technique for plant leaf classification", " IEEE Access, volume 9, pages 162590-162613, DOI: 10.1109/ACCESS.2021.3131726
- [6] Wu P, Qian Z, " Leaf classification based on the convolutional neural network", "Journal of Physics: Conference Series, Volume 1820, No. 1, p. 012161, DOI:10.1088/1742-6596/1820/1/012161

- [7] Wagle S A, Harikrishnan R, Ali S H M, Faseehuddin M, “ Classification of plant leaves using new compact convolutional neural network models”, “ Plants, 11(1), 24, DOI: [10.3390/plants11010024](https://doi.org/10.3390/plants11010024)
- [8] Ullah, N, Khan J A, Al Qathrady, M., El-Sappagh, S, Ali F, “ An effective approach for plant leaf diseases classification based on a novel DeepPlantNet deep learning model”,” Frontiers in Plant Science, volume 14, 1212747, DOI:[10.3389/fpls.2023.1212747](https://doi.org/10.3389/fpls.2023.1212747)
- [9] Beikmohammadi A, Faez K, “ Leaf classification for plant recognition with deep transfer learning”,”2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), pages 21-26, DOI: 10.1109/ICSPIS.2018.8700547
- [10] Chengzhuan Yang, Lincong Fang, Qian Yu, Hui Wei,” A Learning Robust and Discriminative Shape Descriptor for Plant Species Identification”,” IEEE/ACM Transactions on Computational Biology and Bioinformatics, volume 20, [issue 1](#), pages 39 – 51, DOI: [10.1109/TCBB.2022.3148463](https://doi.org/10.1109/TCBB.2022.3148463)
- [11] Aggarwal M, Khullar V, Goyal N, Gautam R, Alblehai F, Elghatwary M, Singh A, “ Federated transfer learning for rice-leaf disease classification across multiclient cross-silo datasets”, ” Agronomy, volume 13, issue 10, 2483, DOI:10.3390/agronomy13102483
- [12] Ahmed S U Shuja, J Tahir M A, “Leaf classification on Flavia dataset: a detailed review”, “Sustainable Computing: Informatics and Systems, 100907, volume 40, DOI:10.1016/j.suscom.2023.100907
- [13] Dileep M R, Pournami P N, “AyurLeaf: a deep learning approach for classification of medicinal plants”,”TENCON 2019-2019 IEEE Region 10 Conference (TENCON), pages 321-325, DOI: 10.1109/TENCON.2019.8929394
- [14] Ahila Priyadharshini R, Arivazhagan S, Arun M, Mirnalini A, “Maize leaf disease classification using deep convolutional neural networks,”Neural Computing and Applications, volume 31, page 8887-8895, DOI:10.1007/s00521-019-04228-3
- [15] Zhang S, Feng Y, “Plant leaf classification using plant leaves based on rough set”, “International Conference on Computer Application and System Modeling (ICCASM 2010),volume 15, pages 15-521, DOI: 10.1109/ICCASM.2010.5622528
- [16] Liu J, Yang S, Cheng Y, Song Z, ” Plant leaf classification based on deep learning”,”Chinese Automation Congress (CAC), pages 3165-3169, DOI:[10.1109/CAC.2018.8623427](https://doi.org/10.1109/CAC.2018.8623427)
- [17] AhilaPriyadharshini R, Arivazhagan S, Francina E C, Supriya S, “ Leaf Disease Detection And Classification System For Soybean Culture”, “2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT), pages 1-7, DOI: [10.1109/ICIICT1.2019.8741482](https://doi.org/10.1109/ICIICT1.2019.8741482)

- [18] Araújo V M, Britto A S, Brun A L, Koerich A L, Oliveira L E, “Fine-grained hierarchical classification of plant leaf images using fusion of deep models”,” IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI), pages 1-5, DOI:10.1109/ICTAI.2018.00011
- [19] Viraj K. Gajjar, Anand K. Nambisan, Kurt L. Kosbar, “Plant Identification in a Combined-Imbalanced Leaf Dataset”,” IEEE Access, volume 10, pages 37882 – 37891, DOI: 10.1109/ACCESS.2022.3165583
- [20] Lei Cai, Zhengyang Wang, Rob Kulathinal, Shuiwang Ji, “Deep Low-Shot Learning for Biological Image Classification and Visualization From Limited Training Samples”,” IEEE Transactions on Neural Networks and Learning Systems, volume 34, issue 5, pages 2528 – 2538, DOI: 10.1109/TNNLS.2021.3106831
- [21] Ahila Priyadharshini, R., Arivazhagan, S., & Arun, M. (2021). Ayurvedic medicinal plants identification: a comparative study on feature extraction methods. In Computer Vision and Image Processing: 5th International Conference, CVIP 2020, Prayagraj, India, December 4-6, 2020, Revised Selected Papers, Part II 5, pages 268-280, Springer Singapore, DOI: 10.1007/978-981-16-1092-9\_23.
- [22] Khuat, P. T., & Van, H. T. (2026). A unified EfficientSwinB-based framework for medicinal plant recognition and safflower germplasm classification. *Scientific Reports*, 16, 11791. <https://doi.org/10.1038/s41598-026-42449-4>.