Exploring Multi-Stage Deep Convolutional Neural Network for Medicinal Plant Disease Diagnosis

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Abstract. Medicinal plants play a crucial role in healthcare, but various diseases often threaten their cultivation. Early and accurate diagnosis of plant diseases is essential for maintaining plant health and ensuring sustainable production. Deep learning has emerged as a powerful tool for automated image-based disease diagnosis in recent years. This study explores using a multi-stage deep convolutional neural network (CNN) for medicinal plant disease diagnosis such as Squeeze-Net, Efficient-Net, and Res-Net50. The proposed framework involves several stages, where each stage performs increasingly complex feature extraction, allowing the model to learn fine-grained patterns associated with different plant diseases. In this study, they collected the data from the Mendeley Medicinal Leaf dataset, which contains 8 classes. They performed the results based on several parameters such as accuracy, precision, recall, and F1-score. By training on a dataset of medicinal plant images exhibiting various diseases, the Res-Net50 demonstrates robust performance, with a high classification accuracy of 98%.

Keywords: Medicinal Plant, Herbs, CNN, Deep Learning.

1 Introduction

Plants contribute significantly to Earth's biodiversity [1]. Plants that are utilized in the treatment and prevention of specific illnesses and ailments that affect people are referred to as medicinal plants [2,3]. A similar pattern of "size" and "shapes" could be seen in the many various kinds of herbal treatments, which might differ from one region to another [4-6]. From their roots to their leaves, these plants are very beneficial. Today, they still make use of the leaves of plants like Karpooravalli, Podina, Neem, Thudhuvalai, Basil, etc. [7], e.g. certain leaves can treat skin conditions, colds, and dyspepsia, and purify the blood.

Multi-deep Convolutional Neural Networks (CNN) are utilized to detect leaf images [12, 13]. To begin, MP is tough to identify because the bulk of them are found in deep forests with leaves that are almost similar to one another [14]. Choosing the wrong plant by mistake might result in a serious health problem that could lead to death. Plants can be recognized in a variety of ways [15]. Currently, plant identification is done by hand, which increases the possibility of mistakes [16]. To address this issue, a group of scientists collaborated to develop an automated system identification approach [17].

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Scientists have focused their attention on problems such as classifying plant leaf diseases, segmenting individual leaves, and grading their quality. This research discusses the creation of a multi-stage deep CNN system intended exclusively for the automatic evaluation of illnesses in MP.

This research explores the application of a multi-stage deep convolutional neural network (CNN) for identifying and diagnosing diseases in medicinal plants. Leveraging advanced models like ResNet-50, SqueezeNet, and EfficientNet, the study employs systematic pre-processing, segmentation, and feature extraction to enhance image-based disease classification. Using the Mendeley Medicinal Leaf dataset, encompassing eight classes, the ResNet-50 model achieved a remarkable accuracy of 98%, demonstrating its robustness in detecting plant diseases. The research contributes to automated, scalable, and efficient solutions for plant disease management, improving the sustainability and effectiveness of medicinal agriculture.

2 Literature Review

A through study conducted with focus on the identification of MP illnesses using ML and DL methodologies.

Diwedi et al., (2024) [18] presented an ECN-PTL architecture incorporating Progressive Transfer Learning and using a modified ResNet50. For this online compilation of MP species, they used the Indian Medicinal Plants Database (IMPLAD). By comparing the enhanced ResNet50 model OSVM classifier in the ECNN-PTL method to baseline models such as VGG16, VGG19, and ResNet50, they can see how it performs in terms of accuracy, precision, recall, error rate, and runtime. The training phase accuracy is 98.5% and the testing phase accuracy is 96.8% for the updated ResNet50+OSVM model.

Dey et al., (2024) [19] evaluated seven state-of-the-art DL algorithms for automatic plant identification using leaf images and recommended the most effective model based on a comparison analysis. Xception, InceptionResNetV2, InceptionV3, DenseNet201, ResNet50V2, VGG16, and VGG19 were all trained with a lot of caution. When comparing the models, they found out something important: DenseNet201 has the highest Normalized leverage factor ($\gamma\tau$) for PI at 0.19, which puts it at the top with an impressive 99.64% accuracy and 98.13% precision. The same model attains an impressive 97% accuracy in the PFI scenario, with a $\gamma\omega = 0.15$.

Roopashree et al., (2024) [20] investigated the potential of using GIS and ML methods to forecast the naming of endangered MP in certain areas. They used a variety of supervised algorithms, including Extra Tree Classifier (EXTC), Random Forest (RF), bagging classifier, extreme gradient boosting (XG-Boost), and k closest neighbor (KNN), among others. Based on its superior performance compared to other models, EXTC is the model chosen for soil classifications (99.01% accuracy rate) and subregion classifications (98.76% accuracy rate).

Lakshmanarao et al., (2024) [21] presented a comprehensive strategy for MP recognition that integrates classical approaches with DL features derived from VGG16 architecture, including form, texture, statistics, and color characteristics. When the final dataset was ready, it was processed using ML models such as Support Vector Machine (SVM), RF, Decision Trees (DT), Logistic Regression (LR), and KNN to identify distinct species of MP. An RF model with a 98.3% accuracy and a 98% f1 score for MP categorization was found to be the best-performing model via comparison analysis.

Islam et al., (2024) [22] provided a reliable, precise, and workable method for identifying MP using images taken of them on smartphones. To identify the plants, the suggested method used an SVM and a cascaded architecture to extract features from a pre-trained ResNet50 model that had been tuned using Particle Swarm Optimization (PSO). Outperforming the state-of-the-art (99%), the proposed ResNet50-PSO-SVM network achieved 99.60% accuracy in classifying seven MP.

Pushpa et al., (2024) [23] suggested a hierarchical two-tiered approach for plant categorization to handle the problems of variance within inter-class and intra-class. An RF classifier is used to forecast which plant species belong to each category. In addition, the model's generalizability is evaluated using two datasets that were self-created—RTL80 and RTP40—and collected over 300 man-hours. Results from experiments show that the suggested hierarchical model outperforms state-of-the-art approaches, with an impressive accuracy of 94.54% on the GSL100 leaf dataset and 75.46% on the RTL80 and RTP40 real-time datasets.

Tyagi et al., (2023) [24] evaluated healthy and unhealthy MP leaves using three different CNN architectures of DL to create reliable classification models. Inception V3, VGG-19, and VGG-16 are the names of these CNN models. A lot of effort has gone into pre-training and fine-tuning these networks utilizing massive image datasets. In this study, they compare and contrast several methodologies to find the best fit based on their practicality, accuracy levels, and other relevant criteria.

Kavitha et al., (2023) [25] developed a DL model that uses vision to identify herb plants. From the Kaggle database, they choose six plants: betel, curry, tulsi, mint, neem, and Indian beech—despite the abundance of beneficial plants. Precision, accuracy, and recall are some of the metrics used to assess the DL model. So, with a 98.3% success rate, the DL model could recognize medicinal leaves.

Hajam et al., (2023) [26] used a three-component deep CNN consisting of VGG16, VGG19, and DenseNet201 to infer features from the input images of the MP dataset, which included images of 30 different kinds of leaves. To evaluate the models, quantitative tests were conducted using the Mendeley Medicinal Leaf Dataset. After fine-tuning, the VGG19+DensNet201 ensemble outperformed VGG19 and VGG16 in detecting pictures of MP, with improvements of 7.43% and 5.8%, respectively. Additionally, with a 99.12% accuracy rate on the test set, VGG19+DensNet201 could outperform its standalone counterparts.

Rapidly identifying and assessing diseases in MP are crucial for ensuring the quality and efficacy of herbal medicines. Traditional methods of plant disease detection are often labor-intensive, time-consuming, and require expert knowledge, which can be a barrier to timely intervention. The paper based on multi-stage deep CNN for automated assessment of MP disease detection addresses this issue by proposing a robust, automated system leveraging multi-stage deep CNNs. This approach aims to accurately detect and classify various MP diseases from leaf images, enhancing the speed and precision of disease diagnosis. By integrating multiple stages of DL models, the system can progressively refine its predictions, ultimately achieving higher accuracy and even reducing the over-processing overhead slowly. Moreover, the pervasive health analytics shall be enforced or generated for preventing the local weather or pollution impact on the Medicinal Plant Health. This automated solution holds the potential to revolutionize plant disease management in medicinal agriculture, offering a scalable, efficient, and reliable alternative to traditional diagnostic methods.

In this research, the authors provide some research objectives.

- To design and implement a multi-stage DCNN framework tailored for the detection and classification of diseases in MP.
- To collect a comprehensive dataset of medicinal plant images exhibiting various diseases and preprocess the images to enhance the model's performance in disease detection.
- To train the multi-stage CNN on the pre-processed dataset, optimizing hyperparameters to improve accuracy, precision, recall, and F1-score in disease detection.
- To compare the performance of the multi-stage deep CNN with traditional plant disease detection methods, demonstrating the superiority of the proposed approach in terms of accuracy and efficiency.

3 Proposed Methodology

A deep DCNN as well as an image-processing framework is used for the identification of diseases in MP. Within this structure, an image of an MP is used as the input information. In the first place, photos of MP are pre-processed to have the noise removed. It is the mean filter that is used in the process of noise elimination. The process of histogram equalization is used to improve the quality of images. A single image could be segmented into several sections or segments via the process of image segmentation. The process of determining the borders of an image is enabled by it. The algorithm known as K-Means is responsible for the segmentation of images. The principal component analysis method is used in the process of feature extraction. After that, the Squeeze, Efficient-Net, and ResNet-50 models are used to carry out the process of picture categorization. To determine the quality of the data that was obtained, recall, accuracy, and precision are used. Fig. 1 presents the block diagram of the suggested work.

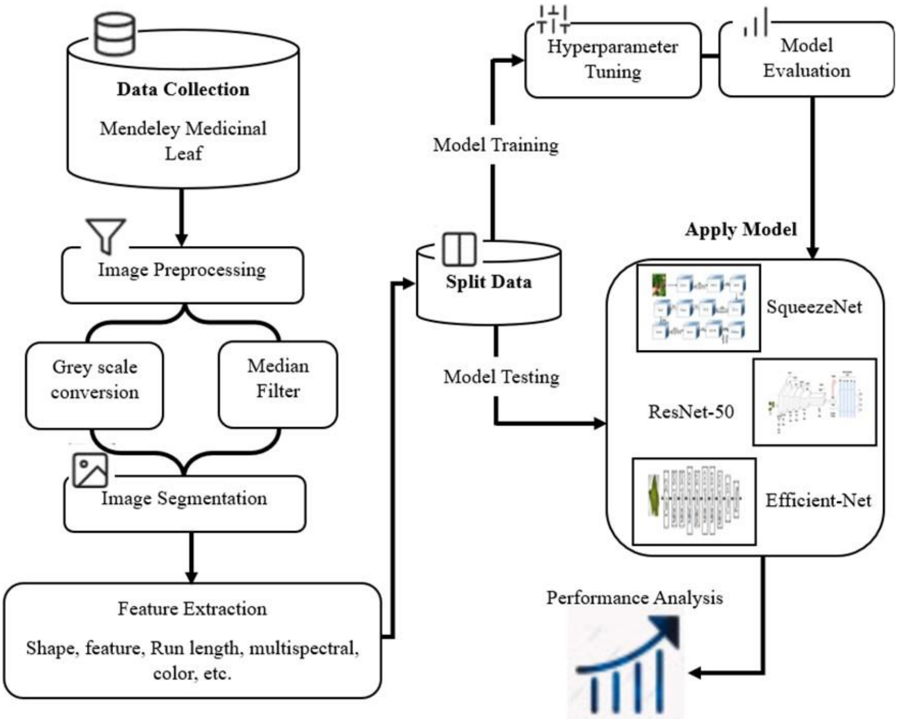


Fig. 1. Block diagram of proposed work

3.1 Dataset Used

The first stage in identifying plant species was gathering the necessary information. Finding appropriate sources for medicinal leaf datasets and settling on a dataset structure required a qualitative investigation. Several aspects impact the dataset selection process. These include the problem's nature, the data's availability and variety, and the dataset's relevance to the application. To generalize the methodology, they used the Mendeley Medicinal Leaf dataset, considered the standard dataset for categorizing medicinal plant leaves [27]. In this paper author considers a total of 8 classes such as Aegle marmelos (Indian bael fruit), Cycas circinalis, Pergularia daemia, Selaginella, Aegle marmelos bael, Dodonaea viscosa, Ajwain, and Cissus quadrangularis. Fig. 2 indicates the images of some of the diseases or classes.

3.2 Feature Extraction

The binary format of the plant image has digital morphological data that can be used to extract the desired shape features. Several other characteristics can be broken down into the form feature, such as the aspect ratio, rectangularity, eccentricity, diameter, thin factor, perimeter ratio, and irregularity.

Shape Features
The aspect ratio – A minimal bounding rectangle's (MBR) width-to-length ratio is the ratio of its maximum and minimum sides.
Rectangularity – It is calculated by dividing the size of the region of interest (ROI) by the size of the MBR.
Eccentricity – the ratio of the major inertia axis (EA) and the minor inertia axis (MA) of the ROI.
Diameter – the largest possible distance between two places on the leaf's edge.
Narrow Factor – It is defined as the proportion of diameter to physiological length.
Perimeter Ratio – perimeter as a percentage of the total length and breadth as specified by physiology.
Irregularity – A measure of dispersion or irregularity is the difference between the radius of the largest and smallest circles that can enclose the area.

Texture Feature Gray-level Co-occurrence matrices are used for texture feature extraction (GLCM). When it comes to analyzing textures, the GLCM is among the most often-used feature extraction methods.

(a) Cycas circinalis (b) Pergularia daemia (c) Selaginella

Fig. 2. Some diseases or, classes

Squeeze-Net is a sandwich of eight fire modules between two convolutional layers, as shown in Figure 8. The fire module consists of a squeeze convolutional layer with a filter of dimensions 1 × 1. It is fed to an expanded layer [31]. This layer contains a mixture of 1 × 1 and 3 × 3 convolutional filters. For each fire module, the number of filters gradually increases from the beginning to the end of a network. Max-pooling is performed after convolution1, fire4, and fire8 layers with a stride of two. It makes use of the ReLU activation function. It uses Dropout after module Fire9.

ResNet50 is a CNN design that avoids the vanishing gradient issue by learning from extremely deep structures via residual connections. The 50-layer design has ReLU activation functions, batch normalization layers, convolutional layers, and fully linked layers. Through the use of a skip connection, ResNet50 can learn both low-level and high-level characteristics by avoiding many network levels [33].

Efficient-Net is a family of deep CNN architectures called Efficient-Net was released. After that, it has shown breakthrough performance on several computer vision applications. With a compound scaling strategy, Efficient-Net optimizes the network's depth, breadth, and resolution all at once, resulting in great accuracy and computing efficiency. The two main networks of Efficient-Net are the backbone network, which does feature extraction from input images, and the head network, which does the final classification [35, 36]. To capture input spatial and channel-wise correlations, the backbone network includes a mix of mobile inverted bottleneck convolutional layers and squeeze-and-excitation (SE) blocks. For the last categorization, the head network employs fully linked layers in conjunction with global average pooling. Figure 10 shows the framework of the Efficient-Net method.

3.3 Performance Matrics

The confusion matrix of any DCNN model could be constructed using four separate detection variables. These detection variables are True positive (TP), true negative (TN), false positive (FP), and false negative (FN). Afterward, they take into account the metrics provided below to assess the efficacy of the proposed model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Recall = \left(\frac{TP}{TP+FN}\right) \tag{2}$$

$$Precision = \left(\frac{TP}{TP+FP}\right) \tag{3}$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

4 Result Analysis

Table 1 indicates the number of images contained by the train and validation dataset. In this number of images for training is 1215 and the number of images for validation is 655.

Table 1. No. of images contained by the train and validation dataset

Classes	No. of images by train dataset	No. of images by validation dataset
Aegle marmelos (Indian bael fruit)	141	91
Cycas circinalis	108	48

Pergularia daemia	183	73
Selaginella	168	98
Aegle marmelos bael	146	96
Dodonaea viscosa	74	24
Ajwain	135	85
Cissus quadrangularis	145	85
Timnospora cordifolia	115	55

4.1 Analyze the Models

The model performance on both the training and testing datasets for Squeeze-Net, Efficient-Net, and ResNet-50-CNN-scratch is shown by the curves in Fig. 3, Fig. 4 and Fig. 5.

The usual accuracy of training and validation curves for a Squeeze-Net and Efficient-Net model are shown in Fig. 3 and Fig. 4, respectively. At the beginning of the training epochs, the accuracy of both the training and validation processes is very poor, but it soon increases as the training progresses. On the other hand, the loss during training and validation both reduce at a quick rate. Throughout the training process, there is a steady rise in the correctness of the instruction. This suggests that the model is gaining a better understanding of the train data with each epoch that occurs. Furthermore, the validation accuracy shows an early improvement but soon returns to its previous level around 0.85. It would seem from this that the evaluation of the model on the validation set has reached a point where it is no longer substantially improving after a certain point. The difference between the accuracy of the train and the accuracy of the validation might be an indication of possible overfitting.

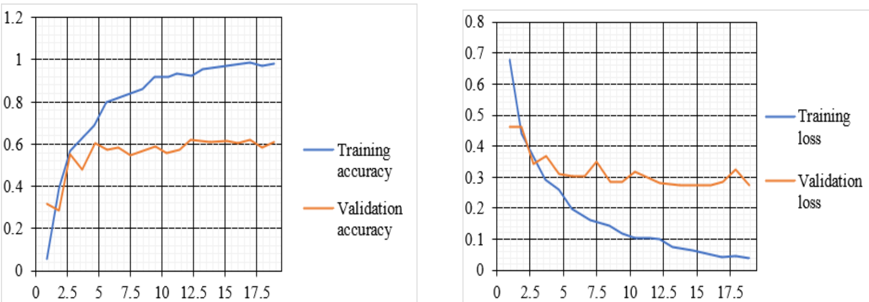


Fig. 3. Squeeze-Net model a) accuracy b) loss

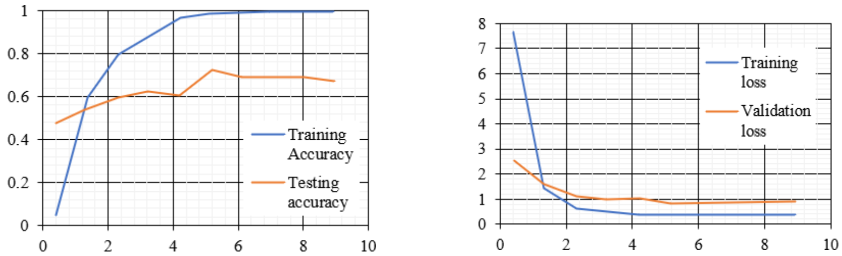


Fig. 4. Efficient-Net model a) accuracy b) loss

The accuracy of a ResNet-50 model during training and validation is most likely represented by Figures 18, respectively, throughout several epochs or iterations. The first improvement in train accuracy, as well as validation accuracy, provides evidence that the model is gaining information through the train data and can generalize successfully to data that it has not before seen. On the other hand, the training loss and the validation loss both decrease at a quick rate.

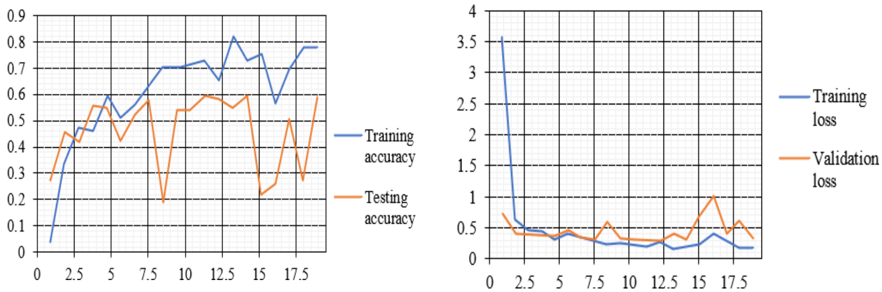
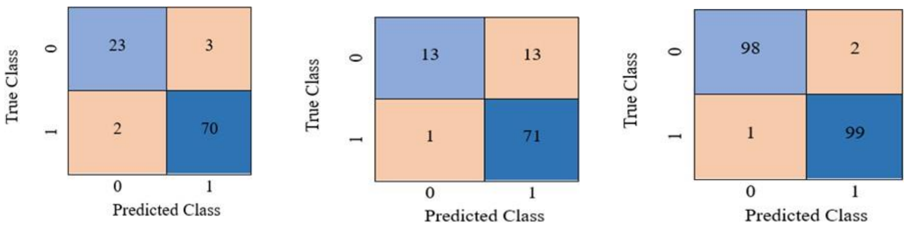


Fig 5. ResNet-50 model a) accuracy b) loss

A training dataset and a testing dataset are used to show the evaluation metrics for each of the suggested models for identifying sickle cells. These metrics values are presented in Tables 5 and 6. According to the findings shown in Table 5, the ResNet50 version produced the best results, with an accuracy rate of 98%. With a recall rate of 88% and an accuracy rate of 94.9%, Squeeze-Net obtained an F1 score of 90%. Figures 20 and 21 show the confusion matrix of each model and a graph of model performance on the training dataset.



(a) (b) (c)

Fig. 6. Confusion matrics of a) Squeeze-Net b) Efficient-Net c) ResNet-50 model

Table 2: Evaluation of the model using train dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Squeeze-Net	94.9	92	88	90
Efficient-Net	85.71	93	50	65
ResNet-50	98	98	99	99

Similarly, on the testing dataset, the ResNet50 version obtained the maximum evaluation, with an accuracy rate of 97.4%. With a recall rate of 91% and an accuracy rate of 92.5%, Squeeze-Net obtained an F1 score of 29%. A graph depicting the calculation of the model on the testing dataset can be seen in Fig. 7.

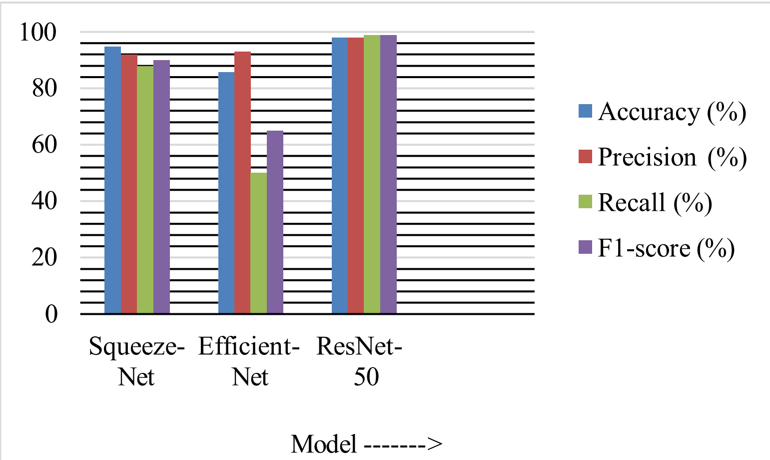


Fig. 7. Graph of model performance on the training dataset

Table 3: Evaluation of the model using the test data

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Squeeze-Net	92.5	92.4	91	29
Efficient-Net	97	97	97	97
ResNet-50	97.4	97	98.3	100

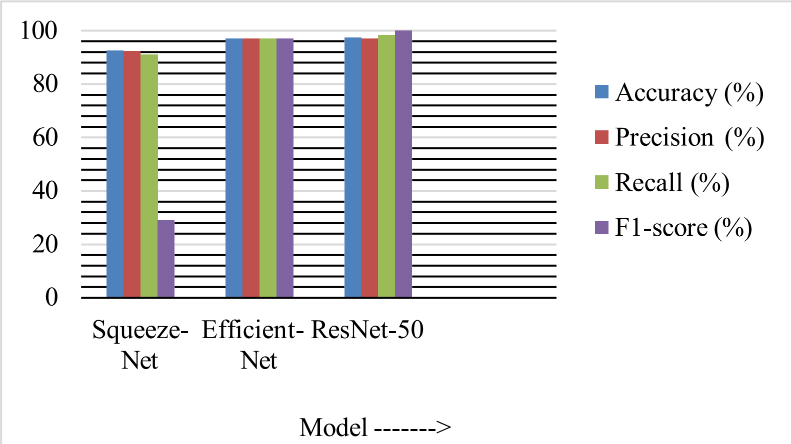


Fig. 8. Graph of model performance on the testing dataset

4.2 Comparison Analysis

The comparative study of the suggested model with the results of earlier investigations is shown in Table 4. When compared to the model used in the earlier research, the suggested model achieves a higher level of accuracy, which is 98%. This demonstrates that the model is effective. A comparison graph of the planned work with the work that has been done in the past is shown in Fig. 9.

Table 4. Comparison of the suggested model with previous work

Authors (Year) [Reference]	Medicinal Plant Used	Accuracy (%)
Thanikkal et al., [38]	Basil, Phyllanthus, Indian aloe, Pappaya, Gotu kola, Neem, Ginger, Thumba, Moovila	96
Latumakulita et al., [39]	Jarak, Jarak Merah, Miana, and Sesewanua	87.73
Our Work	Aegle marmelos (Indian bael fruit), Cycas circinalis, Pergularia daemia, Selaginella, Aegle marmelos bael, Dodonaea viscosa, Ajwain, and Cissus quadrangularis	98

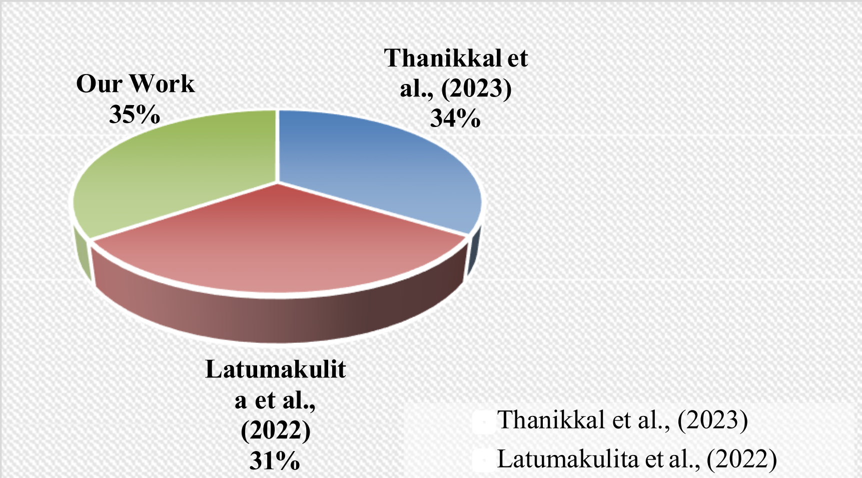


Fig. 9. Comparison pie-chart of previous work with current work

5 Conclusion

Medicinal plants are plants that are used to cure or prevent human illnesses or ailments. There are many various sorts of herbal treatments, and they might vary from location to place, producing a similar pattern of "size" and "shape". In conclusion, this study demonstrates the effectiveness of a multi-stage deep CNN in diagnosing diseases in medicinal plants. By employing multiple layers of feature extraction and classification, the proposed model achieves high accuracy in identifying various plant diseases. In this study, they collected the data from the Mendeley Medicinal Leaf dataset, which contains 8 classes. They performed the results based on several parameters such as accuracy, precision, recall, and F1-score. By training on a dataset of medicinal plant images exhibiting various diseases, the Res-Net50 demonstrates robust performance, with a high classification accuracy of 98%, recall of 99%, precision of 98%, and F1-score of 99%.

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