A Customized Robust Deep Learning Approach for Efficient Medicinal Plant Recognition

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Abstract. Medicinal plants are a significant source of healthcare in both traditional and modern medicine, and their identification remains a significant challenge due to morphological similarities between foliage and the lack of comprehensive databases. Traditional classification methods, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), do not perform well under these conditions. To overcome these deficiencies, the current research paper presents a powerful and customized transfer learning model based on the EfficientNetV2_B1 backbone. It is a Squeeze-and-Excitation (SE) attention architecture, which scaled the architecture to improve the way features are represented and is trained together with 30 percent dropout and L2 weight regularization, which discourages overfitting. This model was trained and tested on three different sets of Bangladeshi medicinal plants. Data augmentation was performed to ensure the model is not readily influenced by the variations in position, size, brightness, and angle. The proposed individualized model demonstrated superior functioning compared to the baseline and the current practices and had the capacity to tackle the issues related to foliage similarity. The proposed model achieves 99.57%, 97.52%, and 99.60% accuracy on three distinct datasets. In addition, the model has been employed to achieve a macro and weighted F1 score of around one point, which is a measure of its reliability and accuracy in the classification of medicinal plants.

Keywords: Medicinal plants, Deep learning, Transfer learning, Image classification, EfficientNetV2 B1.

1 Introduction

In Ancient times, people used medicinal plants to treat common infectious diseases. Some of these traditional medicines are still used as part of the daily regimen for various ailments [1]. Around 80% of people use medicinal plants for their traditional treatment, and they are also the best sources for many types of medicines, according to the World Health Organization (WHO) news [2]. The Malaysian people not only use herbal plants in cooking but also take advantage of them in medicine. This useful knowledge should

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be spread among the public so that they can acquire the positive effects [3]. To know about the existence of medicinal plants around us, Identification in the environment is necessary [4].

Several studies claim that the presence of phytochemicals, like Glycosides, Alkaloids, Flavonoids, Tannins, Terpenoids, Phenolic compounds, Steroids, contributes to medicinal properties in the different habitual treatments [5]. In modern health services for protective and therapeutic applications antioxidant potential of herbal plant species holds bright prospects [6]. Nowadays, several techniques are used to detect plants automatically, such as through foliage and flowers with their colors, outlines, and patterns. Currently, Leaf-based plant species detection systems are commonly used [4], [7], [8]. Measurements for visual shapes in images that are provided by texture features [3]. However, using traditional methods, manually identifying and studying plant classification can be time-consuming and inaccurate [9].

To gain an exact and optimal classification, the absence of a publicly available dataset specifically tailored for Bangladeshi medicinal plants is a liability [8]. Plant recognition based on pictures is a difficult approach because of the difficulty of morphologically similar foliage. Thus, there are many algorithms used in plant identification that perform with low accuracy [7]. Conventional approaches like applying SVM, KNN, and random forests have weaknesses in classifying medicinal plants. However, convolutional neural networks (CNNs) specialize in extracting high-level features [10]. Six transfer learning pretrained models were evaluated in this study: Bit s-r50x1, Inception v3, Inception ResNet v2, Nasnet large, ResNetv1 152, and mobilenet v2 130 224, which are pre-trained using a bulk dataset earlier, can decrease the training time and achieve better performance even on a small amount of data [11].

A combination of MobileNet and ResNet50 is a hybrid model good for feature extraction, and integration of MobileNetV2 with a Squeeze-and-Excitation (SE) block is also a hybrid model that is good to enhance features [11]. Pre-trained VGG16 with data augmentation and fine-tuning of deeper layers can increase accuracy gradually [12]. Proper image pre-processing plays an important role in gaining satisfactory results. In image classification, Deep learning models have validated its efficiency, besides transfer learning-based models that can simplify training complexity and data amount requirements [13]. This study will propose a custom model based on the EfficientNet V2 B1 backbone that is augmented with an attention mechanism. To demonstrate a strong performance, we apply this proposed customized model on three distinct Bangladeshi medicinal plant datasets.

2 Literature Review

Medicinal plants have received extensive focus in recent years in conventional medicine, biodiversity conservation, and pharmaceutical research, due to their influence on classification and identification. Specifically, by using deep learning, researchers have developed Models to exactly determine botanical varieties based on image data such as foliage, flowers, and stalks. These are a few of the most recent papers we have analyzed that are suitable for this study.

Medicinal plants have typically been the subject of intensive research and consideration, as a result of their vital role in maintaining people's lives [14]. Since the lack of limited modern health care, developing countries most often use medicinal plants for their traditional primary treatment [13]. Plant recognition involves differentiating slightly changing leaves, flowers, and fruit features. The bulk of these methodologies focus on distinct variations in leaf features [15]. Accurate identification of medicinal plants is important for avoiding the adverse effects on healthcare protection and medication efficacy due to the different operational conditions and cultivation environments [16].

K. L. D. Viet et al. [9] used the VNPlant-200 dataset to evaluate the performance of the federated learning architecture in identifying medicinal plants. The training images are shared among 10 clients using either the identical distribution (IID) or the non-independent and identical distribution (Non-IID) method to simulate distributed data in federated learning. By utilizing deep learning classifiers and federated algorithms, such as FedAvg and FedProx, to cooperatively train and enhance a global model for medicinal plant identification. This study declares that ConvNext performs best for IID data, and also respectively ResNet50 is excellent for Non-IID data.

To handle intrinsic variability in the images of medicinal plants, differences in illumination, occlusions, and morphological variations within plants, H. Bouakkaz et al. [17] proposed a hybrid model that combines Inverted Residual Blocks and Residual Blocks to increase feature extraction and develop classification accuracy. Binary Chimp Optimization (BCO) algorithms select relevant features from the feature map to ensure that exactly crucial features are used in classifications. Combines features from all network modules, refining representations, and boosting Serial-based feature fusion applied.

B. R. Pushpa et al. [18] proposed three hybrid models. The 1st model consists of combining VGG16 and MobileNet via an early fusion strategy for feature extraction, with classification conducted by a KNN classifier. The 2nd model is the combination of MobileNet and ResNet50 for feature extraction, and at last, the 3rd model integrates MobileNetV2 with a Squeeze-and-Excitation (SE) block to enhance features.

Using CNN on 39 classes of medicinal and aromatic plants, S. E. M et al. [12] had proposed a baseline custom model with 44.94% accuracy that is gradually increased using pre-training VGG16 with data augmentation and fine-tuning of deeper layers. The model achieves a peak validation accuracy of 95.24% while further enhancements are attached to Squeeze-and-Excitation (SE) blocks, GRUs, Transformer modules, and Dilated Convolutions.

To create a fast, simple, and accurate system, K. A. Sahib et al. [11] work on six pretrained transfer learning models that are tested on the Indonesian Medicinal Plant dataset with 100 classes and 10,000 images. The images are 128×128 pixels. Splitting it into 60% training data and 40% validation data. Boosting validation accuracy by 5.2% compared to previous methods, the Bit s-r50x1 model performed best with a secured 99.62% accuracy.

H. Chanyal et al. [19] reviewed the spreading use of medicinal plants in healthcare products and the need for accurate automatic classification systems. Along with image processing techniques, it also shows that early plant disease identification is essential because plant diseases influence the growth of their unique species. This study reviewed Obstacles like small datasets, controlled environments, and the need for varied images with complicated backgrounds. To recognize leaf patterns, many automated procedures are used. Machine Learning and Deep Learning methods. This study discusses how to improve accuracy, support medicine, and ecological conservation using ML and Deep Learning approaches.

U. Khaira et al. [20] proposed the I-NusaPlant mobile-based application for identifying medicinal plants in Indonesia. They use 5000 image data with 20 classes and apply a pre-trained model that is MobileNetV2, and achieved an accuracy of 100%. The mobile-based application uses only 17% of the CPU, besides working on all Android versions 8.0 (Oreo) to 13 (Tiramisu).

G. R., N. P, and S. R. [21] differentiated five distinct classes of medicinal plant Species using a pretrained deep learning (DL) method that is InceptionV3 with transfer learning. This study achieved 96.67% accuracy in identifying five classes of plant Species, though the model is limited due to the tiny number of classes.

3 Proposed Methodology

The proposed methodology allows for the development of a deep learning model for the accurate classification of medicinal plant leaf images. The workflow starts with data preparation. Three datasets are considered for this study. The EfficientNetV2-B1 is considered the base model to design the deep learning-based framework. This model architecture is a transfer learning based that reuses knowledge learned from the dataset. In this study, a model with a custom classification head is proposed, which significantly improves the accuracy and training time.

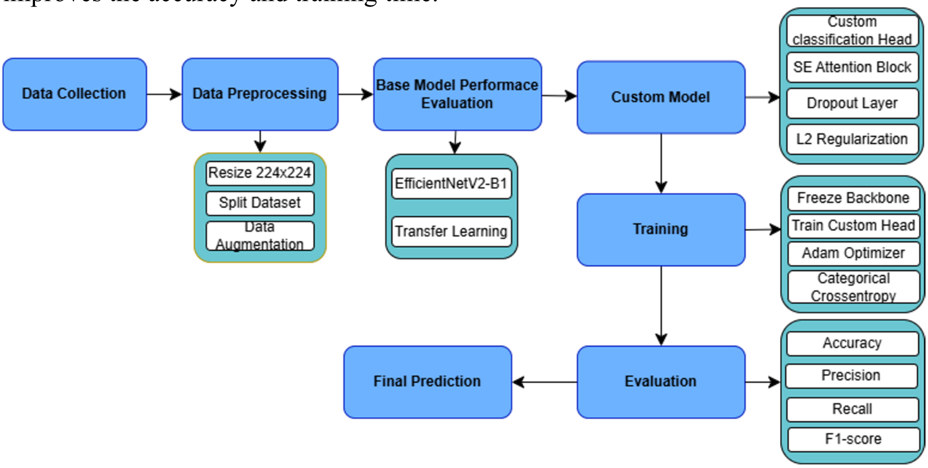

Fig. 1. Workflow of the proposed methodology.

3.1 Dataset Description

To complete any identification task using machine learning and deep learning models, gathering data is an essential step. In this study, we have gathered three different datasets on Bangladeshi medicinal plant identification from online research platforms. All data were collected from various places in Bangladesh, including Dhaka, Sirajganj, and Savar [22][23][24]. A few classes of rare, endangered, and threatened medicinal plants exist in this study [24]. Images were taken under different environmental lighting and at different times by keeping the background white. Details about datasets are provided in the table below.

Table 1. Summary of the Dataset Used in this Study

Dataset No.	Number of Classes	Number of Images
Dataset 1 [22]	16	3,494
Dataset 2 [23]	10	2,029
Dataset 3 [24]	10	5,000
Total	—	10,523

In addition, Dataset 1 and Dataset 3 have been photographed on a white background. On the contrary, Dataset 2 has real-life, complex backgrounds.

3.2 Data Preprocessing

Preprocessing enhances both the quality of data and the performance of Machine learning and Deep learning models. In this study, to manage the massive dataset size to ensure data stability among samples, all images were resized to 224×224 pixels (RGB) fixed resolution. The datasets are divided into training (70%), testing (20%), and validation (10%) data. Data augmentation is applied to the training dataset to generate approximately 600 images per class for balance. Data augmentation was conducted immediately, including the following parameters: rotation range = 25°, width shift range = 0.1, height shift range = 0.1, shear range = 0.15, zoom range = 0.2, horizontal flip = True, brightness range = [0.8, 1.2], and fill mode = “nearest” from Keras ImageDataGenerator. These modifications changed the images in terms of position, size, brightness, and angle are very significant to make the model more robust to several real-life conditions and prevent overfitting.

3.3 Proposed Model Architecture

The EfficientNetV2-B1 is used as the base architecture for medicinal plant leaf classification. Study shows that the transfer learning-based model performs well in the classification task [25]. The EfficientNetV2-B1 model takes an input image size of 240×240×3. This model consists of multiple EfficientNet blocks with convolutional, batch normalization, and activation layers. The base EfficientNetV2-B1 model uses a SoftMax layer to output the class probabilities in the output layer. To improve the capacity of the base model, we designed a custom model based on the EfficientNetV2-B1 architecture. This proposed model includes a custom classification head on top of the frozen EfficientNetV2-B1 backbone. This model architecture includes the following.

A) **Squeeze-and-Excitation (SE) Attention Block:**
The SE block is a lightweight attention mechanism that enhances the representational power of a convolutional network. The SE block recalibrates channel-wise feature responses to emphasize informative features and skip less useful ones. This attention mechanism works in two main steps:

Global Average Pooling (Squeeze): Global average pooling captures the global distribution of the feature map that summarizes the spatial information. This process condenses the spatial dimension into a single numerical value per channel of the feature map. Mathematically, for a feature map where *H* is the height, *W* is the width, and *C* is the number of channels, the pooled value for the c-th channel is:

$$s_c = \left(\frac{1}{H * W}\right) \sum_{\{i=1\}}^{H} \sum_{\{j=1\}}^{W} F\_c(i,j) \qquad (1)$$

Excitation (Fully Connected + ReLU): In the excitation step, a small fully connected layer with a non-linear activation (ReLU) is applied to the channel descriptor S_c to capture channel-wise dependencies:

$$z_c = ReLU(W_1 * s_c) \qquad (2)$$

Here, W_1 denotes the learnable weights of the fully connected layer and z_c is the intermediate excitation vector for the c-th channel.

Channel Recalibration (Scaling): Finally, the learned channel-wise attention weights are applied to the original feature map to recalibrate it:

$$\hat{X}_c = X_c * \sigma(W_2 * z_c) \qquad (3)$$

where X_c is the feature map of the c-th channel, z_c is the excitation vector obtained from the fully connected layer, W_1 and W_2 are learnable weights, and σ is the sigmoid activation function that produces attention weights in the range [0, 1].

B) **Fully Connected Dense Layers with Dropout**: Two dense layers form the trainable head:

• Dense layer with 512 units and ReLU activation
• Dense layer with 128 units and ReLU activation

Dense layer activations:

$$z = W_x + b, \ a = ReLU(z) \qquad (4)$$

Dropout regularization:

$$\tilde{a}_i = a_i * m_i, \ m_i \sim Bernoulli(1 - p) \qquad (5)$$

C) **L2 Regularization**: All dense layers include L2 regularization to prevent overfitting:

$$L_{total} = L_{data} + \lambda \sum_{i}^{H} w_i^2 \qquad (6)$$

where L_{data} is the standard cross-entropy loss, w_i are the trainable weights, and λ is the regularization coefficient.

D) **Output Layer (Softmax):** The output layer generates predicted probabilities for each class using the SoftMax activation. Let the input to the output layer be

$$z = [z_1, z_2, \dots., z_k]$$

where K is the number of classes (num_classes). The softmax function converts the raw scores into probabilities:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_i}}, \quad i = 1, 2, \ldots, K \tag{7}$$

Here, $\hat{y}_i$ represents the predicted probability of the input belonging to class i. The sum of all predicted probabilities over K classes is 1, ensuring a valid probability distribution:

$$\sum_{i}^{k} \hat{y}\_i = 1 \tag{8}$$

These predicted probabilities are then used to compute the cross-entropy loss during training:

$$L_{CE} = -\sum_{i=1}^{k} y_i \log(\hat{y}_i) \tag{9}$$

where y_i is the true label in one-hot encoding. One-hot encoding ensures that only the probability corresponding to the true class contributes to the loss. This output layer allows the model to perform multi-class classification and provides interpretable class probabilities for each input sample.

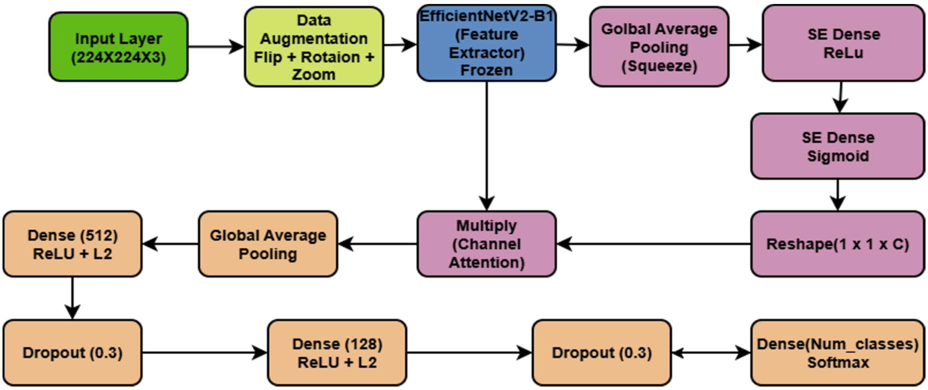

Fig. 2. Proposed Model Architecture with output layer

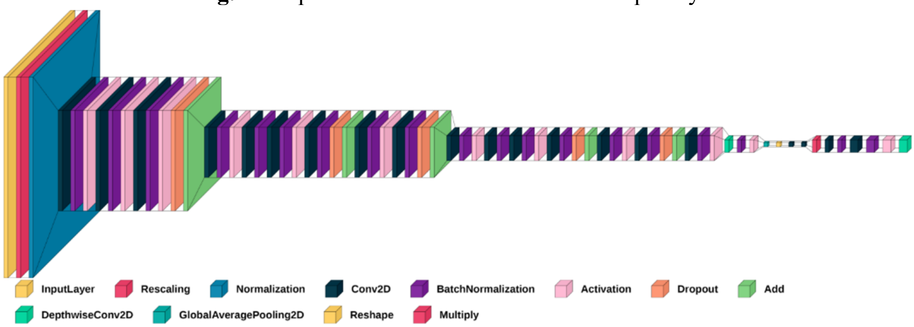

Fig. 3. Visualization of the first 20 convolutional layers of the Proposed Model

Table 2. Summary of Model Architecture

Hyper-Parameter	EfficientNetV2-B1	Proposed Model
Input Size	240×240×3	224×224×3
Number of params	7.09M	7.86M
Trainable params	0.165 M	0.928 M
Backbone / Architecture	EfficientNetV2	EfficientNetV2 + SE Attention
Loss function	Categorical Crossentropy	Categorical Crossentropy
Optimizer	Adam	Adam
Learning Rate	0.001	0.001
Drop Out	None	30%
Regularization	None	L2
Output Layer	Softmax	Softmax

3.4 Training Strategy

The model was trained using EfficientNetV2-B1 as a pretrained backbone. The feature extraction layers were frozen, and the classification head was fine-tuned. The batch size was 64 and ran for 30 epochs. L2 Regularization techniques are applied to prevent overfitting and for the model's generalization. Data was augmented, which includes flipping, rotation for better generalization. Early stopping with a patience of 5 was applied to avoid unnecessary training.

Table 3. Training Strategy and Hyperparameters

Hyperparameter / Setting	Value
Batch Size	64
Epochs	30
Dropout	30%
Data Augmentation	Flip, Rotation
Early Stopping	Yes, patience = 5
Pretrained Model	EfficientNetV2-B1
Frozen Layers	Backbone frozen, head trainable
Framework / Hardware	TensorFlow, GPU (T4)

3.5 Performance Evaluation

To evaluate the performance of the proposed model, several standard metrics were considered. These include:

- **Accuracy**: Assesses the general suitability of the model to the classification of samples in classes.

• **Precision**: Measures the ratio of the number of correctly predicted positive samples to the total number of predicted positives, which demonstrates that this model is trusted to make correct positive predictions.

• **Recall** (Sensitivity): Measures the model's ability to properly detect all actual positive samples.

• **F1-score**: The harmonic mean of precision and recall, which is a balanced measure of the performance of a model.

4 Result And Discussion

The performance of the proposed model was evaluated on three different datasets. The result is compared with the baseline EfficientNetV2-B1 model, as well as existing work reported in the literature. Multiple evaluation metrics, such as training accuracy, testing accuracy, macro F1 score, and weighted F1 score, were considered to assess the effectiveness of the model.

The performance of the models in terms of the classes was analyzed using the confusion matrix (Fig. 4, Fig.5, & Fig. 6) for both the baseline and the proposed models. The greatest concentration of the predictions is on the diagonal, which means that most of the classes with a high level of accuracy on the baseline model. The confusion matrix of the baseline EfficientNetV2-B model is shown on the left side of each figure. There were additional limited instances of misclassification, especially in Datasets 2 and 3 in the baseline model. However, the custom model overcame the situation and the misclassification in both data sets decreased, highlighted in Fig. 5 and Fig. 6. The proposed model (compared to EfficientNetV2-B1) offers a more discriminative ability, as it generates a cleaner confusion matrix with fewer off-diagonal elements. These results align with the accuracy and F1 scores reported, which, in addition, prove the usefulness of the proposed approach.

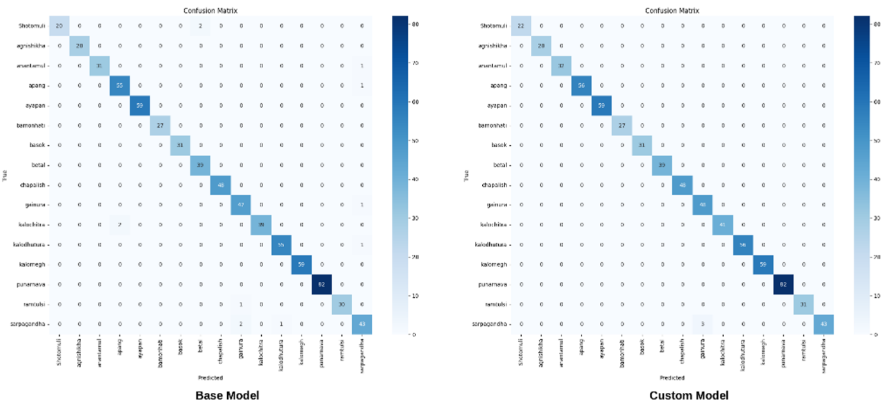

Fig. 4. Confusion matrix of the base model and custom model on Dataset 1.

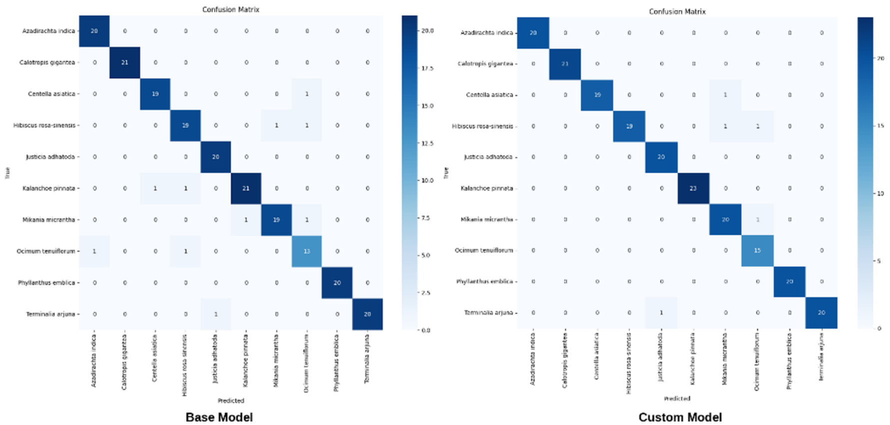

Fig. 5. Confusion matrix of the base model and custom model on Dataset 2

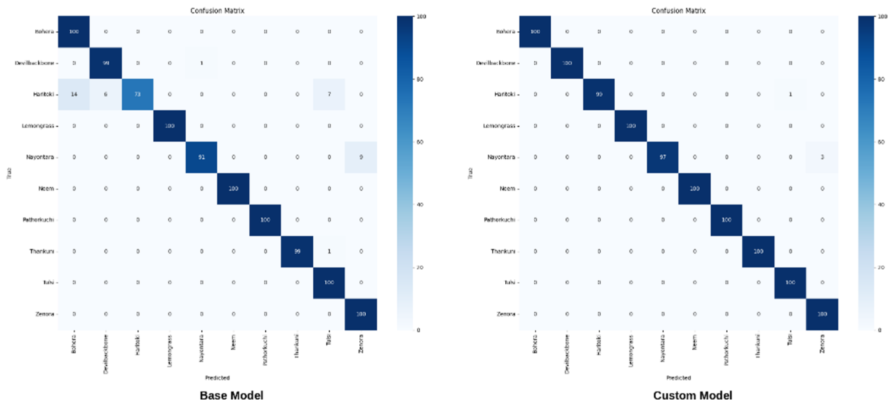

Fig. 6. Confusion matrix of the base model and custom model on Dataset 3

The accuracy and loss curves of the two models, which are the baseline EfficientNetV2-B1 and the proposed model, show that both models show good performance, but the proposed model has a better learning performance. In the case of the baseline, the training accuracy was gradually rising, whereas the validation accuracy was fluctuating. Conversely, the convergence and both training and validation accuracy of the proposed model converged at a faster rate and with higher values that are close to each other. Its loss curves decreased rapidly in early epochs, indicating more efficient learning and improved generalisation. In general, the accuracy and loss curves prove that the proposed model not only can perform better but also learn more strongly and stably in comparison to the baseline.

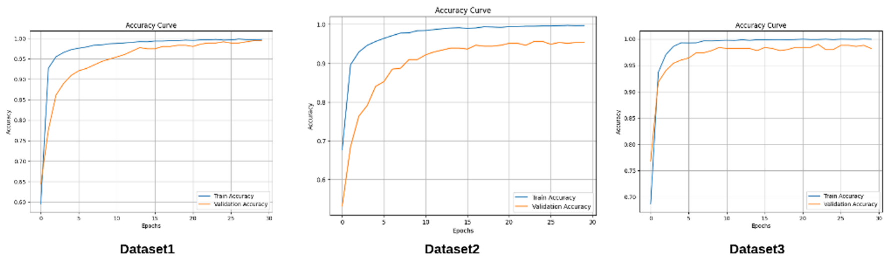

Fig. 7. Training accuracy of the base model.

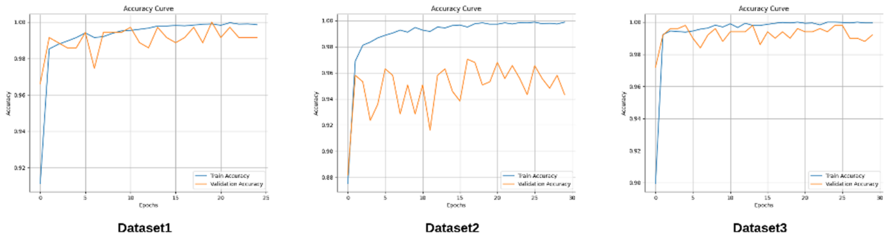

Fig. 8. Training accuracy of the proposed custom model

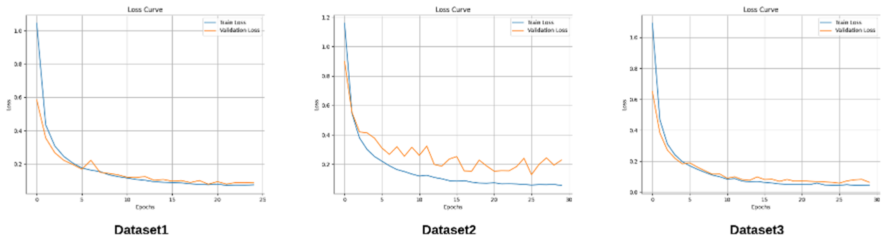

Fig. 9. Loss curves of the proposed custom model

Table 4. Comparison of the Proposed Model with Existing Work (Training and Testing Accuracy)

Model/Author	Dataset	Train Accuracy	Testing Accuracy
No existing work	Dataset 1	-	-
Proposed Model		99.9%	99.57%
Islam et al. [23]	Dataset 2	98.46%, 92.93%	80.69%, 90.09%
Proposed Model		98.2%	97.52%
Uddin et al. [8]	Dataset 3	98%, 99%	Not mentioned
Proposed Model		99.9%	99.60%

Table 4 shows a performance comparison between the baseline model EfficientNetV2-B1 and the proposed model in three datasets. The findings are a clear indication that the proposed model is always better than EfficientNetV2-B1 with respect to accuracy, test accuracy, and F1 scores. As an example, the proposed model has obtained a higher accuracy of 99.9%, 98.2%, and 99.9% in the three datasets compared to EfficientNetV2-B1, which has a higher accuracy of 98.3%, 95.5%, and 96.2%, respectively. Likewise, test accuracy is also high with the proposed model, with 99.57%, 97.52%, and 99.60% compared to 98.30%, 95.05%, and 96.20% of the baseline. Dataset 1 and Dataset 3 were set on a plain white backdrop, and Dataset 2 has real-life, complex backdrops. Therefore, the accuracy of Dataset 2 is slightly lower as compared to that of Dataset 1 and 3. Moreover, the F1-score analysis shows the strength of the suggested model with almost perfect numbers (macro and weighted F1 of 1.0 on two datasets and greater than 0.97 on the other dataset), which demonstrates that the model has better class-wise balance in its predictive ability. Fig. 7. Training accuracy of the base model. Fig. 8. Training accuracy of the proposed custom model. Fig. 9. Loss curves of the proposed custom model. In contrast, EfficientNetV2-B1 has lower F1 scores between the values of 0.95-0.98. These findings confirm the success of the proposed model in providing better accuracy and balanced classification in various datasets, thus making it better than the baseline model. The model strongly generalizes and prevents overfitting.

The proposed model is much improved in contrast to the current work. A training accuracy of 98.46% and a testing accuracy of approximately 90.09% were reported by Islam et al on Dataset 2. Conversely, our formulated model attained 98.2% training accuracy and 97.52% testing accuracy, which is a definite increase in the test data. In the same way, the Dataset 3 model by Uddin et al. demonstrated the training accuracies of 98 to 99 percent in two custom CNN models with no testing accuracy reported, whereas our proposed model had a training accuracy of 99.9 percent and a testing accuracy of 99.60 percent.

5 Conclusion

This research shows deep learning and transfer learning approaches for automatic identification and classification of Bangladeshi medicinal plants. Conventional approaches like SVM, KNN, and Random Forest have limitations in their success due to the anatomical similarity of plant leaves and the absence of a widely available dataset adapted to Bangladeshi species. We proposed a customized state-of-the-art CNN architecture and transfer learning models to achieve a more vigorous outcome to overcome these challenges.

The proposed customized model is built upon the EfficientNetV2-B1 backbone and further enhanced using a Squeeze-and-Excitation (SE) attention mechanism. It integrates a 30% dropout rate and L2 regularization that reduce overfitting and improve generalization. A small rise in complexity with 7.86M parameters compared to the base EfficientNetV2-B1 model, which has 7.09M parameters, achieves significantly better performance. On Dataset 1, Dataset 2, and Dataset 3, the baseline model consequently gains 98.30%, 95.05%, and 96.20%, while our customized proposed model achieves 99.57%, 97.52%, and 99.60% test accuracy on the same datasets. These results, obtained across three distinct medicinal plant datasets, illustrate the superiority of our approach.

Based on these consistent improvements, this study demonstrates the effectiveness of the customized architecture that holds promise for future applications in healthcare and biodiversity research.

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