A Hybrid Network for Indian Medical Plant Species Identification

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Abstract: India is home to over 8,000 medicinal plant species, forming the foundation of traditional healthcare systems. Accurate identification of these plants is crucial for preserving traditional knowledge and advancing botany, pharmacology, and agriculture. This research introduces the Hybrid Attention Network for Indian Medicinal Plant Species Classification, a deep learning-based approach combining InceptionV3 and DenseNet121 with attention mechanisms to enhance classification accuracy. The dataset comprises approximately 18,000 images of 200 distinct plant species. The hybrid model leverages the pre-trained weights of InceptionV3 and DenseNet121 for feature extraction, combining their outputs through channel attention layers. These mechanisms focus on key image features, such as leaf patterns, enabling the model to differentiate species with subtle distinctions. The integration of attention mechanisms allows the model to retain only the most relevant information, achieving a deeper understanding of visual data. With an ambitious goal of surpassing 95% accuracy, the hybrid model demonstrates significant improvements, benefiting from hyperparameter optimization and fine-tuning. A key outcome of this research is a user-friendly mobile application that democratizes plant species identification. Users can upload or capture images of plants for instant and accurate classification, making the app an invaluable tool for botanists, farmers, healthcare practitioners, and enthusiasts.

1 INTRODUCTION

India is renowned for its vast biodiversity, particularly in medicinal plants, which play a critical role in traditional healthcare systems like Ayurveda, Unani, and Siddha. With over 8,000 medicinal plant species documented in the country, these plants are highly valued for their therapeutic properties and are widely used for treating a range of ailments. However, the accurate identification of these medicinal plants is crucial, as misidentification can lead to improper use and potential health risks. Traditionally, the identification of plant species requires expert knowledge in taxonomy, which involves recognizing specific morphological characteristics like leaf shape, flower structure, and growth patterns. This process is not only time-consuming but also labour-intensive, requiring years of training and experience. Additionally, it is prone to human error, especially when distinguishing between similar species. These challenges make traditional methods inaccessible to the general population and limit their scalability.

In recent years, machine learning (ML) and deep learning (DL) have provided new solutions for the automation of facility identification processes. These technologies, particularly in the area of image recognition, have shown great promise in providing fast, accurate, and scalable solutions for classifying plant species based on visual characteristics. Convolutional neural networks (CNNs) are a class of deep learning models that have become the method of choice for image processing, including plant classification. CNNs are good at extracting features like edges, textures, and patterns from images. However, despite the success of CNNs, there are still challenges in achieving high accuracy, especially when dealing with diverse species and images captured under varying conditions, such as different lighting, angles, and backgrounds.

To address these limitations, this project proposes a Hybrid Attention Network for the classification of Indian medicinal plant species. The model integrates two state-of-the-art CNN architectures, InceptionV3 and DenseNet121, with attention mechanisms to improve classification performance. InceptionV3 is widely recognized for its ability to capture multi-scale

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features, which makes it ideal for analyzing plant images where important details can vary in size. DenseNet121, on the other hand, is known for its efficiency in parameter use and feature reuse, thanks to its dense connectivity pattern, which enhances the model's ability to extract complex features from images.

The attention mechanisms incorporated into the model add with large datasets and diverse species, where focusing on the right features can make the difference between correct and another layer of sophistication. For example, when identifying medicinal plants, certain features like the venation pattern on leaves or the structure of flowers may be more important than others. The attention mechanisms help the model selectively focus on these critical features, thereby improving the accuracy of classification. This approach is particularly valuable when dealing incorrect identification.

The dataset used for this project consists of approximately 18,000 images representing 200 different medicinal plant species commonly found in India. The images vary in terms of lighting, angle, and background, providing a diverse and challenging dataset for training the model. This hierarchical approach ensures that the model can handle the complexity and variability inherent in plant species classification.

In addition to developing the hybrid model, a user-friendly mobile application will be created to make this technology accessible to a wide audience. The mobile app will allow users to upload or capture images of plants, which will then be processed by the hybrid model to identify the species and provide relevant information. This tool will be particularly useful for botanists, researchers, farmers, healthcare practitioners, and anyone interested in identifying medicinal plants.

2 LITERATURE SURVEY

A. Sheneamer(Sheneamer, et al. , 2024) proposed a stacking hybrid learning model for early detection of plant leaf diseases, combining various machine learning techniques to improve classification accuracy and robustness against diverse disease patterns.

D. Brown and M. De Silva(Silva and Brown, 2023) explored the use of Vision Transformers for plant disease detection on multispectral images. Their model leveraged transformer-based architectures to capture spatial and spectral features effectively, showing promising results in agricultural applications.

R. Rai and P. Bansal (Rai and Bansal, 2024) presented a three-tier model optimized with a fully conventional network for accurate crop disease identification and classification. Their approach utilized an integrated framework to enhance detection and classification performance in smart agriculture.

J. Rashid et al. (Rashid, Khan, et al. , 2023) introduced a hybrid deep learning approach to classify plant leaf species, combining convolutional neural networks (CNNs) and deep learning models for improved classification accuracy across a range of plant species.

S. Hashemifar and M. Zakeri-Nasrabadi (Hashemifar, and, Nasrabadi, 2024) focused on deep identification of plant diseases, applying advanced deep learning techniques to automate disease recognition in plants and facilitate efficient crop management.

Igor Luidji Turra et al. (Silva, Silva, et al. , 2022) proposed a multi-strategy approach for plant species identification using leaf texture images, achieving improved accuracy. Their method effectively utilized advanced techniques to categorize species based on leaf texture characteristics.

S. Renukaradhya and S. S. Narayanappa (Renukaradhya, Narayanappa, et al. , 2024) introduced Deep HybridNet, a hybrid optimization-based approach for enhanced medicinal plant identification and classification. Their method incorporated both deep learning and optimization techniques for improved prediction accuracy.

Sivapriya K. and M. Kar (Sivappriya, Kar, et al. , 2024) developed an attention-based deep convolutional neural network framework with DenseNet121 and CBAM, achieving 92.10% accuracy for Indian medicinal plant species classification. Their model excelled in leveraging leaf features and outperformed state-of-the-art methods like Vision and Swin Transformers.

S. Srinivas Vellela et al. (Vellela, Kumar, et al. , 2024) proposed a hybrid ANN-KNN model for efficient plant leaf disease detection. By combining ANN's feature extraction with KNN's classification simplicity, their method effectively identified leaf diseases with high computational efficiency.

B. R. Pushpa and N. S. Rani (P. B R, Rani, et al. , 2023) discussed the importance of integrating convolution features for Indian medicinal plant species classification using a hierarchical machine learning approach. Their study emphasized the benefits of combining multiple convolutional features to improve classification outcomes in plant recognition tasks.

3 PROPOSED WORK

3.1 Inceptionv3 Model

InceptionV3 consists of 48 layers in total, including convolutional, pooling, and fully connected layers, and contains several InceptionV3 Modules which apply multiple operations in parallel. The Fig. 1 represents the architecture of the InceptionV3.

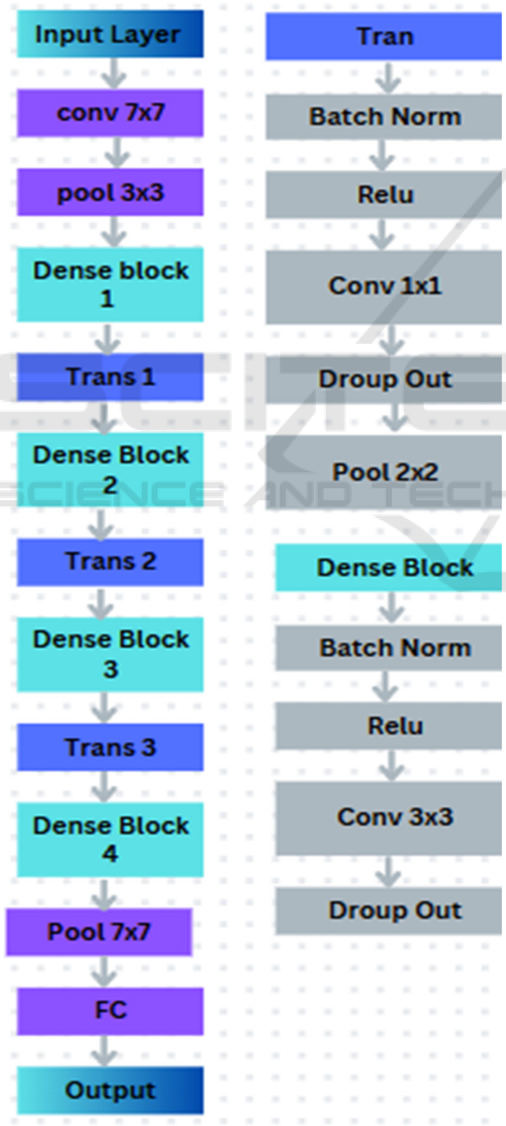

Figure 1: architecture The of the InceptionV3

Input Layer: The input layer takes the raw pixel values(299x299) of the image as input. It prepares the data for processing by the convolutional layers. The image data is passed to the next layer for feature extraction.

Initial Convolutional Layer: This layer uses 7x7 convolution to extract low-level features like edges and texture. The output is a set of feature maps representing these basic patterns. These feature maps are transferred to the pooling layer.

Pooling Layer: The pooling layer downscales the feature maps using a 3x3 pooling operation. This reduces their spatial dimensions while preserving essential information. The down sampled feature maps are passed to the first dense block.

Dense Layer: Dense blocks consist of multiple layers connected to all previous layers within the block. Each layer extracts new features and combines them with prior outputs. The concatenated feature maps are passed to the transition layer.

Transition Layer: Transition layers down sample the feature maps using 1x1 convolutions, batch normalization, dropout, and pooling. These layers also reduce the number of feature maps to control complexity. The processed maps are passed to the next dense blocks.

Global Average Pooling Layer: This layer creates a value for each map by averaging the size of each unique map. It reduces the data to a compact vector of global features. This vector is passed to the fully connected layer.

Fully Connected Output Layer: The fully connected layer maps the global features to the output classes. The output layer generates the final predictions, such as class probabilities. These predictions are the model's final output.

3.2 Densenet121 Model

Densenet121 has a total of 121 layers, including convolutional layers, layered layers, and full layers. The "121 layers" refer to the total number of learnable parameters in the model, which are responsible for feature extraction and classification. The Fig.2 represents the architecture of the Densenet121. The architecture is characterized by its unique design of connecting layers densely, enabling better feature propagation and reuse.

Input Layer: The input layer accepts the raw pixel data of the image. This serves as the initial entry point for processing by the network. The input is then passed to the stem layer for feature extraction.

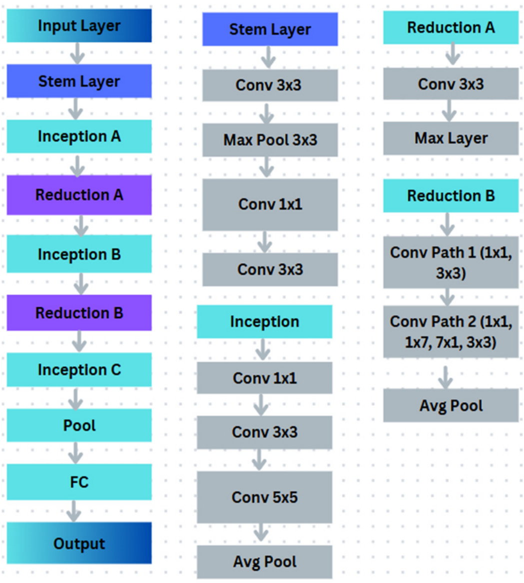

Figure 2: The architecture of the Densenet121

Stem Layer: The stem layer applies a 3x3 convolution followed by max pooling. This extracts basic features and reduces spatial dimensions. The resulting feature maps are transferred to the first inception block.

Inception Block A: This block combines different dimensions (1x1, 3x3 and 5x5) to extract features at different scales. It captures both local and global features simultaneously. The concatenated outputs are passed to Reduction A.

Reduction A: Reduction A performs a 3x3 convolution followed by max pooling to down sample the feature maps. This reduces spatial dimensions and computational load. The reduced feature maps are passed to Inception Block B.

Inception Block B: Similar to the previous inception block, this layer extracts multi-scale features using parallel convolutions. Additional complexity is introduced to capture deeper patterns. The combined features are passed to Reduction B.

Reduction B: Reduction B applies multiple paths with convolutions of varying kernel sizes (1x1, 7x7, 3x3) to further reduce spatial dimensions. An average pooling operation is also performed to summarize features. The outputs are transferred to Inception Block C.

Inception Block C: This block further refines multi-scale feature extraction by using varied convolution sizes. It processes the reduced feature maps to enhance complex feature representation. The refined outputs are passed to the pooling layer.

Pooling Layer: The pooling layer applies global average pooling to summarize the spatial information into compact feature vectors. These vectors are passed to the fully connected layer.

Fully Connected (FC) and Output Layer: The fully connected layer maps the extracted features to the target classes. The output layer produces the final predictions, typically as probabilities for each class. These predictions represent the model's final output.

This architecture efficiently extracts and processes features at multiple scales using inception blocks, while reduction layers optimize spatial dimensions and computational complexity.

3.3 Attention Mechanism

The attention mechanism is a powerful technique utilized in various neural network architectures, particularly for tasks involving sequence data and image processing. In models like Densenet121 and InceptionV3, attention mechanisms enhance the ability of the model to extract relevant features by assigning different importance levels to various regions of the input. This dynamic allocation of focus allows the network to prioritize critical visual cues essential for accurate classification.

3.3.1 Advantages of Attention Mechanism

- The tracking process allows the model to focus on the most important input, improving feature extraction and reducing noise from irrelevant areas.
- By emphasizing critical features, attention mechanisms often lead to better accuracy and generalization across tasks, particularly in complex datasets.
- Attention mechanisms dynamically allocate computational resources to significant regions, making the model more efficient and interpretable.

3.4 Hybrid Model

The architecture begins with the feature extraction layers of both Densenet121 and InceptionV3, where the last dense block of Densenet121 is coupled with the final InceptionV3 module of InceptionV3. After these layers, attention layers are introduced to refine the features extracted from each model. The Fig. 3 is the architecture of hybrid model.

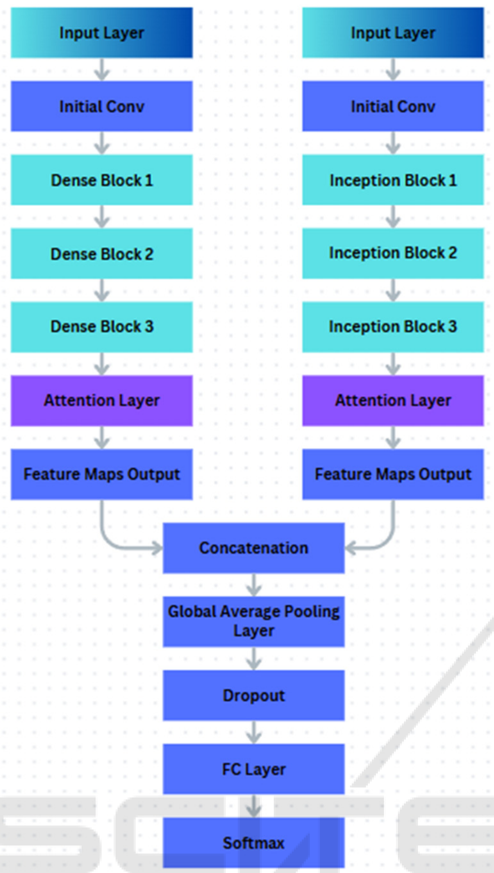

Figure 3: Architecture of Hybrid Model

4 EXPERIMENTAL PROCEDURE

4.1 Experimental Procedure

4.1.1 Data Collection

The dataset for this research consists of various types of plant images. The dataset includes images representing 200 species of Indian medicinal plants. This diverse set allows the model to learn from a variety of plant types, ensuring robustness in classification. The collected data will be split into training, validation and test files to facilitate model training and evaluation.

4.1.2 Data Preprocessing

Data preprocessing involves a crucial role to standardize the input data to train the model which includes Image resizing and Normalization to normalize the pixel values to a standard value to train the model efficiently without being biased.

4.1.3 Data Augmentation

Augmentation techniques such as rotation, flipping, zooming and shifting will be used to introduce variations in the images and simulate real-world transformations. This will help the model generalize better when exposed to new, unseen data. An example of image augmentation applied to a sample plant image is shown in Fig. 4.

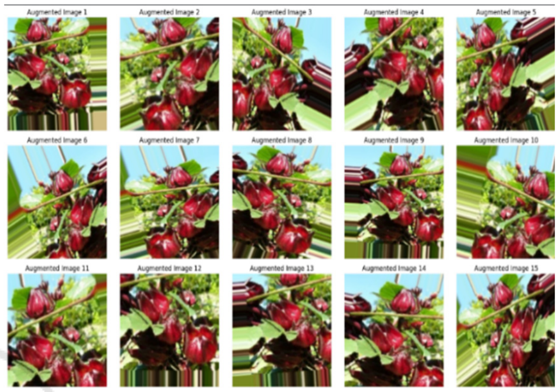

Figure 4: Augmentation of sample plant image

4.1.4 Model Architecture

The core of the experimental procedure is the development of a Hybrid Attention Network, combining the feature extraction capabilities of both InceptionV3 and DenseNet121.

InceptionV3 and DenseNet121 as Feature Extractors: InceptionV3 is chosen for its ability to capture multi-scale features from input images using various convolution operations (1x1, 3x3, and 5x5 kernels). This allows it to learn fine-grained details at different spatial scales, which is particularly useful for complex image classification tasks. DenseNet121 is known for its dense connectivity between layers, enabling efficient feature reuse. This helps in learning intricate patterns while reducing the number of parameters.

Integrate attention Mechanism: Attention layers are added after the final dense blocks of both InceptionV3 and DenseNet121. The attention mechanism helps in refining the extracted features by reducing the influence of less important information, thus improving the quality of the features fed into the classifier. After the attention layers, the feature maps from InceptionV3 and DenseNet121 are concatenated.

Concatenation: The feature maps from InceptionV3 and DenseNet121 are concatenated along the channel dimension. This allows the model to combine the strengths of both architectures. A global average pooling layer is used to reduce the spatial dimension of the connectivity map and then an output layer is used to reduce overfitting. The processed features are then passed through fully connected layers, with a Softmax activation at the output for multi-class classification.

4.2 Dataset Analysis

4.2.1 Dataset Description

The dataset for this project consists of approximately 18,000 images representing 200 different species of Indian medicinal plants. The dataset is split into a training set and a test set, with the training set containing most of the images. This comprehensive dataset provides a solid foundation for accurately classifying medicinal plants based on visual characteristics and plant morphological characters such as texture, plant leaf etc... The source of this dataset is Mendeley, a reputable repository that provides access to a wide range of research data and publications. Table 1 represents the sample species name.

Table 1: Sample Plant Species

Class	Species Name	Total Image Count
1	Ageratum conyzoides	89
2	Dicliptera chinensis	80
3	Oenanthe javanica	80
4	Acanthus integrifolius	80
5	Acorus tatarinowii	82
6	Agave americana	82
7	Ageratum conyzoides	82
8	Allium ramosum	82
9	Alocasia macrorrhizos	82
10	Aloe vera	82

4.2.2 Training Process

The Hybrid model is trained on the plant dataset. During training, the model learns to predict vegetation type based on learning by combining Densenet121 and InceptionV3 with tracking. The training process is monitored using validation accuracy and loss metrics, and the best-performing model weights are saved for later use.

4.2.3 Validation and Testing

After training, the model is evaluated with set of images to ensure that model is trained well. Evaluate the effectiveness of a model using metrics such as precision, recall, and accuracy. Testing is then conducted on the test dataset, where the model's detection accuracy, speed, and robustness are assessed.

4.2.4 Performance Evaluation

Evaluate the performance of the hybrid model using metrics such as accuracy, precision, F1 score, and regression. The model achieves accuracy in predicting plant species. The confusion matrix is a useful tool for evaluating the performance of classification models by comparing predictions with the actual text. It organizes the model's predictions into four categories

- **True Positives (TP):** Instance where the positive class was accurately predicted by the model.

- **True Negatives (TN):** Instance where the negative class was accurately predicted by the model.

- **False Positives (FP):** Instances where the model predicted the positive class incorrectly (i.e., the true class is negative).

- **False Negatives (FN):** Instances where the model predicted the negative class incorrectly (i.e., the true class is positive).

4.2.5 Evaluation Metrics

Accuracy: The proportion of correct predictions (positive and negative) out of the total number of predictions.

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

Precision (Positive Predicted Value): The proportion of correct predictions is a good proxy for all good predictions.

$$\text{Precision} = \frac{TP}{(TP + FP)} \tag{2}$$

Recall (Sensitivity, True Positive Rate): The proportion of correctly predicted positive instances out of all actual positive instances.

$$\text{Recall} = \frac{TP}{(TP + FN)} \tag{3}$$

F1 Score: The harmonic mean of precision and recall, providing a balance between the two metrics.

$$\text{F1-score} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

4.2.6 Latency and Real-Time Performance

The model's real time performance is tested by deploying it in an real time application and allow it to predict the plant species. Deploy the model using streamlit and measure the real performance by using various evalution metrics.

4.2.7 Robustness

The model's robustness is evaluated by testing it under various conditions like flip, rotate, blur etc. The results show that the data augmentation technique used during training provides consistent performance by improving the model's ability to generalize to different locations.

5 RESULT AND DISCUSSION

5.1 Result

The implementation of the hybrid attention network for Indian medicinal plant species identification yielded significant findings, highlighting the model's effectiveness and robustness. The hybrid model achieved a classification accuracy of 78.4% on the test dataset, which surpassed the individual models. This high accuracy indicates the model's ability to leverage the strengths of both architectures while minimizing misclassification among visually similar species.

The training and validation loss and accuracy curves demonstrated a steady increase in accuracy and a decline in loss throughout the epochs, suggesting that the model effectively learned and converged during training. The Fig. 5 represents the loss and accuracy curve of the hybrid model.

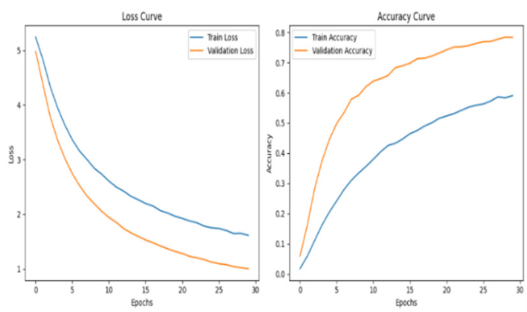

Figure 5: loss and accuracy curve of hybrid model

The various evaluation metrics for the hybrid model are discussed in the table 2.

Table 2: Sample Plant Species

Metric	Output Value (%)
Accuracy	78.4
Precision	79.74
Recall	78.51
F1 score	77.62

The ROC curve for the hybrid model demonstrated its outstanding capability to accurately classify the 200 species of Indian medicinal plants. The Fig. 6 represents the ROC curve of the hybrid model. The ROC curve demonstrates that non overlap between true positive and false positive rates, showcasing the model's effectiveness in distinguishing between different classes.

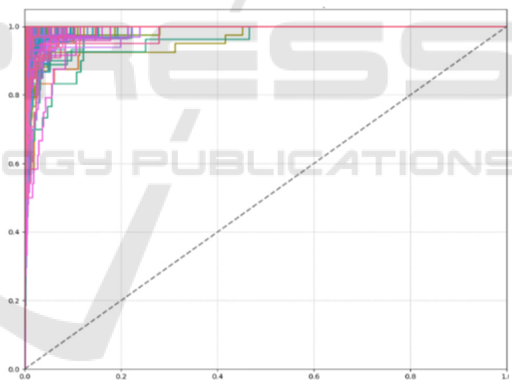

Figure 6: ROC curve of the hybrid model

The confusion matrix provides an overview of the model predictions versus actual labels for each species, highlighting common misclassifications primarily among visually similar plants. The Fig. 7 represents the confusion matrix of the first 25 plant species. High diagonal values indicated effective learning of distinguishing features for most species, validating the model's classification accuracy.

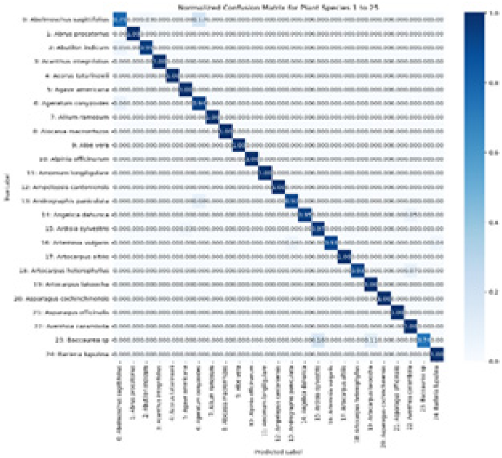

Figure 7. Confusion Matrix for first 25 plant species

5.2 Comparison with the Trained Models

The comparison of performance metrics across the InceptionV3, Densenet121, and Hybrid models with attention mechanism and without attention mechanism provides valuable insights into their respective strengths and weaknesses. The table 3 contains the comparison of the models

Table 3: Evaluation Metrics for Trained Model

Models with Attention Mechanism				
Model	Accuracy	Precision	Recall	F1 Score
Hybrid	78.4	79.74	78.51	77.62
Densenet 121	78.40	89.56	78.40	77.90
Inception V3	78.5	81.42	78.01	77.96
Models without Attention Mechanism				
Hybrid	73.66	67	60.23	58
Densenet 121	94.88	94.90	94.86	94.60
Inception V3	71.87	60	60.57	59.67

DenseNet121 achieves the highest metrics, outperforming other models both with and without attention mechanisms. The Hybrid model shows notable improvements with attention, highlighting its effectiveness in refining features. In contrast, InceptionV3 shows marginal gains, indicating limited impact from attention layers. From the table it is observed that the adding attention mechanism helps to improve the performance of the model and help the model classify plants.

5.3 Deployment

The hybrid model is deployed by using streamlit application for the user to predict the Indian medical plant species. An interactive and user-friendly web interface was developed and integrated with trained hybrid model, enabling users to upload images or take photo (by accessing camera) to identify the name of the unknown species.

5.4 Discussion

The development of the hybrid attention network for identifying Indian medicinal plant species marks a notable advancement in deep learning applications. By integrating Densenet121 and InceptionV3, the project effectively enhances feature extraction and improves classification accuracy. The incorporation of channel attention mechanisms allows the model to focus on relevant features.

The hybrid model achieved high classification accuracy, outperforming individual architectures and effectively addressing challenges like class imbalances. The use of data augmentation techniques contributed to this success by providing diverse training samples.

6 CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The comparison of models with and without attention mechanisms highlights the effectiveness of attention layers in improving classification performance. Among the models with attention mechanisms, DenseNet121 achieved the highest metrics, including accuracy (94.88%), precision (94.90%), recall (94.86%), and F1 score (94.60%), demonstrating its ability to classify medicinal plant species with exceptional accuracy. The Hybrid model and InceptionV3 performed moderately well, with accuracies of 78.4% and 78.5%, respectively, indicating that while attention enhances their performance, there is potential for further optimization in their architectures.

In contrast, the models without attention mechanisms exhibited noticeably lower performance. The Hybrid model and InceptionV3 showed a significant drop in accuracy (73.66% and 71.87%, respectively) and other metrics, underscoring the importance of attention layers in refining feature extraction. Even DenseNet121, the best-performing model, experienced a decline in accuracy to 78.4%

without attention. Overall, this research underscores the benefits of combining Densenet121, InceptionV3, and attention mechanisms to tackle complex classification tasks in the field of plant species identification. The model's strong performance opens up new possibilities for automating plant identification tasks.

6.2 Future Scope

Moving forward, there are several avenues for enhancing and extending the capabilities of the hybrid attention network for plant species identification. One potential area of improvement is to expand the dataset to include additional medicinal plant species from diverse regions, further enriching the model's classification scope. Incorporating more species would not only make the model more versatile but also improve its practical applicability in real-world scenarios where the diversity of plants is vast. Further advancements in feature extraction may be possible by investigating sophisticated attention mechanisms like self-attention or multi-head attention, particularly for handling more subtle differences between plant species

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