Medicinal Plant Species Detection using Deep Learning

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***Abstract*— In the present era, the world is trending towards Automated Systems without human intervention with rapid development in Technology. One such area is medicinal plant species detection, where an expert identifies the medicinal leaf based on their botanical knowledge. We propose a deep learning model to detect the medicinal plant species based on its leaf image and advanced computer vision. This paper compares the Convolutional Neural Networks (CNN) variants viz., MobileNet, ResNet50, Inception v3, Xception, and DenseNet121 for Indian origin medicinal plant species detection. We have evaluated CNN variants to classify the medicinal leaf images and observed that the Inception v3 model outperforms all other conventional methods. Our proposed architecture adopts the Inception v3 model and the stochastic gradient descent technique during the training process for optimizing and achieving better results. Our experimental results show that the Inception v3 model achieved 95% accuracy in the Indian origin medicinal plant species classification**

Keywords*— *Medicinal Plant Species Detection; Inception v3; Convolution Neural Networks; stochastic gradient descent technique; Deep Learning.

I. INTRODUCTION

The plants serve the entire humankind with food, clothing, shelter, and medicine from time immemorial. As per statistics of WHO, it is estimated that 80% of people in Asia and Africa depend on herbal medicines obtained from plant extracts. Many health ailments like fever, headache, and diarrhea were treated using various herbal medicines prepared from the leaf, stem, bark, and root extracts of the plant. The medicinal plants and their uses need to be preserved for future generations in digital form. Ancient India has widely practiced Herbal medicine made out of plant extracts to cure various health ailments as it is non-toxic and has no side effects. However, many of these medicinal plants are in the wild forests. Only an expert can identify such plants with features like leaf shape, color, size, texture and give us some visual judgment to classify them as medicinal plants. There are efforts to develop Automated Systems [1] for automatic plant species detection without the involvement of experts, and great methods have come to the general use case. Leaf recognition [2] in plant species detection is another critical area where a progressive study is done.

The primary problem is to identify medicinal plants found rarely in the wild forests. The medicinal plant identification [3] poses a significant problem for researchers in Botany, Chemistry, and related fields. Hence, much expertise is needed to identify the medicinal plants based on the features of the plant leaf size, shape, color, and texture as the purpose is to offer treatment for many ailments. Computer vision methods help to recognize leaf images accurately and efficiently. Plant identification applications are based on features such as plant leaves, roots, flowers, and bark. Depending on the soil, water, climatic conditions, and natural vegetation, there are various medicinal plants available worldwide. Hence there is no one unique system possible to identify all types of medicinal plants. Plant leaf detection is a research problem in the domain of computer vision. With advancements in technology, medicinal plant leaf detection could be solved with the help of machine learning. Our effort is to build a system that classifies the leaf image as a medicinal or non-medicinal plant species.

There are many existing schemes for medicinal leaf detection using Artificial Neural Networks (ANN) [4], Convolutional Neural Networks (CNN) [5], etc. The existing computational models for leaf recognition have some challenging issues. One of these is the extraction of plant features and their representation to classify plant species accurately. Experts generally focus on leaf shape to classify the species and develop algorithms among all the existing methods. With advances in deep learning, computer vision frameworks, plant leaf classification have become an active area of research. CNN is a class of deep neural networks built to solve problems related to visual imagery. The existing framework mainly comprises preprocessing, feature extraction, selection, and classification. In recent years, the CNN architectures has had tremendous success; it has played a role in understanding the various features of images. We apply CNN models, such as Inception v3, ResNet50, DenseNet121 etc to enhance the accuracy rate of the dataset.

This paper proposes deep neural network architecture to classify Indian medicinal plant species. Some of the leaf species are shown in Fig. 1. The significant contributions of our paper are as follows:

- Evaluation of different CNN variants for the problem of medicinal leaf identification.
- Inception v3 architecture, a variant of Convolutional Neural Networks to classify the medicinal leaf of Indian origin.
- Using stochastic gradient descent technique for optimizing and achieving better results.

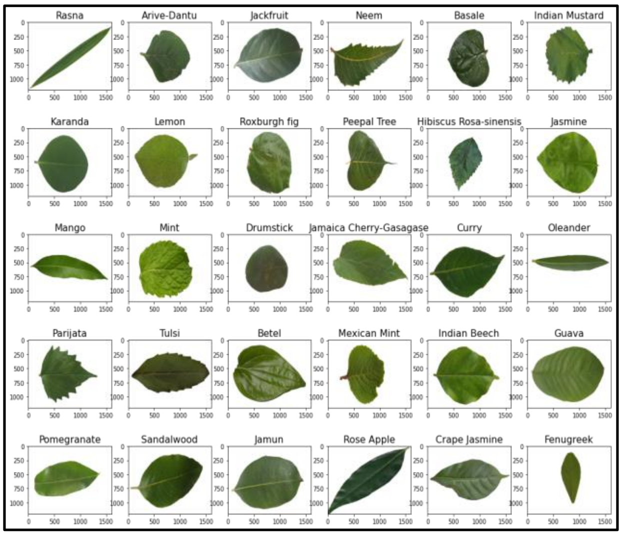

Fig. 1. Figure showing the images of the Indian origin leaf species

The rest of the paper is organized as follows. The literature survey is presented in the second section of the paper. The third section details on the learning model and optimization techniques used to perform leaf classification. We present the performance evaluation of our model with the existing models and compare the results with a detailed discussion in the Fourth section. The Fifth section presents the Conclusion.

II. RELATED WORK

In this Section, we present the existing medicinal plant detection schemes using deep learning. Various technologies were used world-wide to identify medicinal plants grown in their geography. Hence, these models require a fixed dataset to train their model. As the medicinal plants differ with respect to their territory, food habits and climatic conditions the medicinal plants and their availability and uses also vary. Now, we present the various learning models in literature to identify medicinal plant species.

The authors in [6] developed a computer aided system using Probabilistic Neural Networks to identify medicinal plants in Indonesia. This system employs a simple PNN method with the PDR classifier combination to improve the plant identification accuracy. The system used three-leaf features to identify the medicinal plants, i.e., Morphology, Shape, and Texture. This system was tested to identify 30 species of medicinal plants in Indonesia. Hence the dataset is limited to only medicinal plants of Indonesia.

An extension of this work is developed as an android application for mobile phones as “MedLeaf" [7] to identify the medicinal plants for any given image of a leaf. This system extracts leaf textures using Local Binary Pattern, and to classify the image, they used Probabilistic Neural Network. Combining these two methods resulted in an accuracy of 56.33% in identifying the 30 species of medicinal plants of Indonesia.

Many plant identification methods use the leaf shape as one of the features, but very few methods exist for leaf recognition based on the texture and age of the leaf. Local Binary Pattern (LBP) [8] is simple in computation to identify a leaf based on its texture. Several LBS classification schemes exist for various biometric applications. One of the variants of LBS is Modified LBS (MLBS) [9] when the leaf samples are represented in symbolic form rather than the traditional representation. This improves the performance in terms of the accuracy of the classification algorithm. One of the observations is that there are variations in the leaf texture based on its age, and hence 100% precision and recall could not be achieved for such species. This study is limited to one texture feature while other features like flower, fruit, or bark remain untapped. This research germinated the idea for multi-stage classifiers for better performance.

The authors in [10] have explored multi-feature sets in the identification of medicinal plant leaves. In standard plant identification, leaf shape, color, texture, vein, etc., form the feature set for the training process. Sometimes, the leaf matches precisely like the training phase image, but they may not be similar. Hence, it is essential to compute the accuracy of the system. In the case of medicinal plant identification, accuracy is a very crucial factor to be considered. In general, the images are categorized based on a shape like oval, rectangular, oblong, etc. However, none of the works have categorized this shape feature. The work in [11] is a unique Shape Descriptor Algorithm for Medicinal Plant Identification (SDAMPI) with Abridged Image Database, which categorizes the shape of the leaf. Also, the leaf description, which is pixel information, is difficult to identify shape. So, the SDAMPI algorithm maintains the leaf shapes in Freeman chain code representation for its line and shape description. It gives ease of use and simplicity in the storage of the shape information. The five features viz. vein, shape, base, apices, and margin serve as the classifier input. These features are extracted from the collected leaf images and merge with the descriptors stored in the database to form a plant species description. If a match is found in the database, the corresponding description is presented; else, this forms a new entry in the descriptor database. Rather than the existing pixel representation, it is compared with chain codes for simplicity in computation and accuracy.

The authors in [4] have created a customized Artificial Neural Network (ANN) for the Philippines herbal plant identification. Their image processing techniques have extracted leaf features of the herbal plant with 50 images per plant, and a feature dataset of 600 images was used to train the ANN. This study is restricted only to 12 plants, and thus the image dataset size is limited.

One of the deep learning solutions for plant leaf recognition is using CNN. The authors in [5] have used the Vietnamese plants' dataset for training this network. There are many CNN architectures like VGG16, Resnet50, Inception v3, DenseNet121, Xception, and MobileNet. They have evaluated the accuracy of all these models as part of their work. The dataset is VNPlant-200, where the model trains 200 species of Vietnamese plant leaf details. The larger the dataset better will be the accuracy of the model.

The accuracy and success rate of machine learning algorithms depend significantly on the quality of the training data and the size of the dataset. In image recognition systems, image quality also plays a vital role in improving the system's accuracy. Such systems heavily rely on the training image data that is supplied as input. The training dataset is not typical for every region on the earth due to the natural diversity. There are various plants, leaves, flowers, and fruits grown in a particular soil for its geographical location. Hence it is impossible to obtain a dataset. The authors in [12] have developed a system without any of the existing datasets. The system is built on principles of deep learning, transfer learning, and crowdsourcing to perform plant organ detection, plant image collection, data validation, and plant identification. The plant organ detection is done using OrganNet and the plant identification with the VnPlantNet by applying transfer learning methods on GoogLeNet architecture. By Crowdsourcing, the dataset is built by collecting the leaf images from the web for plant organ detection. GoogLeNet has a more profound and broader architecture than CNN and hence is efficient in Image recognition. This system served from image collection through filtering the images with VNPlantNet to identify the 100 species of Vietnamese medicinal plants.

The research work done so far in medicinal leaf identification is outlined giving their detailed methodology. Some of the works are designed only for a specific dataset based on the medicinal plants available in their geography. Hence we have ventured our proposal to detect medicinal plants of Indian origin using CNN variants. In terms of the deep neural networks, the models viz., ResNet50, Inception v3, Xception, and DenseNet121, which we have adopted, have proved to be the best match for this problem. The details of the training model are presented in Section III, and the performance of the model on the dataset outperforms the existing model.

III. PROPOSAL

Before This section presents the detailed methodology and the algorithm used to classify the medicinal plant species. In this section, we have used Indian medicinal plants dataset to identify their leaves using the proposed deep learning architecture along with advanced computer vision. The dataset specifications are given as follows.

The foremost requirement is the Indian medicinal plants and their features maintained in the dataset [13]. The data set comprises thirty species of medicinal plant images, where each species has 60-100 images of high quality. The Dataset consists of 1822 images, with each image having 3x 256 x 256 pixels. Each species has leaves of varied age and health. The images are selected based on the leaf-like, fully mature leaves with varied texture, color, and size for improving accuracy. This dataset is built for the research community to facilitate accurate predictions. The digitization of medicinal plants led to many Artificial Intelligence tools to help automatic leaf detection in the wild. Here advanced computer vision techniques help in eliminating the lighting effects and color variations in the images.

We apply the CNN architecture models and advanced computer vision solutions to classify images of Indian origin medicinal plants. The block diagram of the medicinal leaf detection by applying the Convolutional Neural Networks (CNN) model is shown in Fig. 2. The system needs to undergo training and testing phases in sequence. The images in the dataset are split into two parts for the training phase and testing phase. Initially, the dataset was low, so we augmented the dataset size. We augment the training dataset and define the loss function. We have used the Stochastic Gradient Descent (SGD) optimizer [14] to randomly select samples instead of the whole dataset for each iteration during training. This optimizer allows us to pick up random samples out of the more extensive dataset. SGD uses a batch size of one to perform each iteration which reduces the cost of computation of the model. That will reduce the cost of training the model. The training samples are loaded into the model where the training activity takes place. This training algorithm which we use, learns the image features, and the remaining test samples can be used to test the system. Based on the test sample given, the system will classify the test image to its corresponding image label.

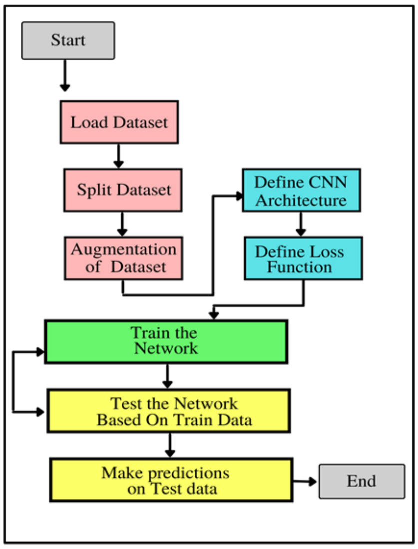

Fig. 2 Block diagram of the Classification process

We need to train the system with the dataset using our proposed Deep Learning (DL) model, as shown in Fig. 3. Deep Learning emerged to be the fastest training model with voluminous training data.

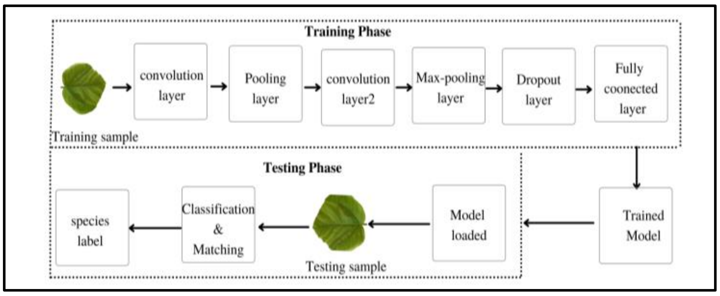

Fig. 3. Schematic diagram of the Deep Learning Model

We chose to use the Convolutional Neural Networks (CNN) to give better results than the conventional methods. CNN's architecture with an input layer, multiple alternating convolution layers, aggregated or sub-layer, and nonlinear layers. Our proposal deals with the classification of the images to fall into one of the trained classes based on the medicinal features exhibited by the input test sample.

Our research problem deals with computer vision and recognition. In this domain, the ImageNet Large Scale Visual Recognition Challenge is an annual competition held for Models using the Imagenet dataset subsets. Among the top-performing models are GoogLeNet, AlexNet,VGG, PNASNet-5 and ResNet in previous years. In order to choose a training model with better accuracy, we have compared five deep neural network architectures viz., ResNet50, Inception v3, Xception, MobileNet and DenseNet121. The details about each of the training models is analyzed further in Section 4.2 for experimentation. We chose the Inception v3 model for this problem. Hence the details about the same are mentioned.

The Inception family consists of four architectures. The first one was Googlenet released in 2015, also termed as

Inception v1 with addition of the batch normalization feature, Inception v2 was released. Meanwhile, Inception v3 contains features such as convolution factorization and better optimization. And the last architecture from inception family the Inception v4, which is the latest architecture it includes features such as more Inception modules and simplified architecture. Our research problem deals with classification of medicinal plant species so we have used the Inception v3 model. This model uses Convolution Factorization, a technique that involves reducing the number of parameters without reducing network efficiency. This was done by adding a 1 x 1 convolutional layer before 3 x 3 and 5 x 5 convolutions, making the architecture more cost-effective than the existing one that leads to lower chances of overfitting. Another essential feature to focus in Inceptionv3 architecture is the availability of an auxiliary classifier as a regularizer that helps in obtaining deeper networks. Inception v3 also contains features such as efficient grid size reduction, which helps in developing less expensive networks. An overview of the CNN architecture is shown in Fig. 4 with the input image and alternating convolutional layers, pooling, and max pooling alternating layers to obtain a set of images. These images are now classified into the respective medicinal class trained by the system to obtain the leaf labels.

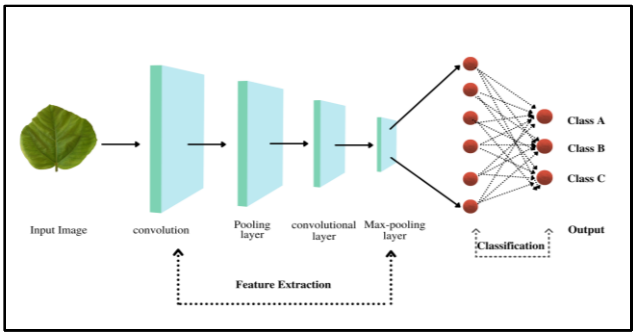

Fig. 4. CNN architecture

IV. Performance Evaluation

Now, we present our experimental setup and the performance of the CNN models to validate our proposal. The results are analyzed for the accuracy of the model. First, we start with the specification of the dataset, the hardware specifications and then present the models used to compare the results obtained in various models.

4.1 The Data set

The 'Medicinal leaf dataset' consists of 1822 images of Indian medicinal plants categorized in 30 species, where each species has 60-100 different images. The dataset was split into a training set and test set with a ratio of 70:30, respectively. Each image consists of 3 x 256 x 256 pixels which were randomly augmented and picked according to its test and train ratio during the preprocessing.

4.2 Experimental Setup

Our approach included using randomly initialized weights trained on the Google Colab [15] with 12 GB of RAM and a Tesla K80 GPU. To avoid overfitting, we adopted Keras open-source data enhancement technique to increase the size of the data, which helped us preprocess the training data. The entire source code is hosted on GitHub which can be accessed using this link [16] for further details.

4.3 Result Analysis

We present the details about the various learning models to compare our Inception v3 model. First model is the Resnet50 which uses Batch normalization at its base to improve the performance of the network. It works on identity connection which provides solutions for vanishing gradient problems. A residual learning framework is used to ease the training of networks that are substantially deeper than those used previously. ResNet50 which was released in 2015 holds the ability for developing extremely deep networks which can be trained using standard SGD and reasonable initialization function. To achieve this, it relies on microarchitecture called a residual module. It contains 50 different layers consisting of 48 Convolutional layers, 1 Max pool layer, and a Global Average pooling layer.

The DenseNet121 is another CNN architecture which comprises five convolutional layers. These layers are interconnected in a feed-forward manner in which the first layer is connected to the remaining 4 subsequent layers. Similar arrangement is followed by each subsequent layer with L (L+1)/2 direct connections. We deployed Densenet121 in order to train the model on a dataset of Indian Medicinal plant species and our observations lead us to the understanding of how complex CNN layers work.

One more CNN architecture is the Xception, which is an extension implementation of Inception architecture which consists of depth wise separable modules instead of Inception modules. There are 36 convolutional layers in a base exception model. In general trends Exception outperforms Inception v3 model on large datasets, due to efficient use of model parameters.

Another model is the MobileNet developed to support the mobile environment and it was the first mobile based Computer Vision model developed in Tensorflow. It uses depth wise separable convolutions that reduces the number of parameters in comparison to other convolutional networks. The final output leads to a simple lightweight neural network supported in a mobile device. We have trained the models viz Resnet50, Xception, DenseNet 121, MobileNet, and Inception v3 models with our dataset with the following specifications. The random weights were applied with the same configured weights by 30 neuron fully connected layers. The Stochastic gradient descent technique with learning rate or =0.05, momentum (p) = 0.9 was applied during the training stage of four deep learning CNN architectures. We have provided 150 epochs of training to achieve a satisfying validation accuracy.

Table I: Obtained accuracies of different CNN Architectures

Model	Accuracy	Image Size
ResNet50	90.68	256 x 256
DenseNet121	91.94	256 x 256
Inception v3	95.16	256 x 256
Xception	91.40	299 x 299
MobileNet	85.48	224 x 224

The results are present in Table 1 shows that Inception v3 achieved 95% and outperformed other models. All the results which were obtained are compared in Table I for the varied size of the images. Our results demonstrate that the Deep Learning neural networks outperform traditional approaches on manual classification. Since our research focuses explicitly on Indian medicinal plant species, the proposed approach provides a method to identify these species in the wild.

The graph in Fig. 5 shows the accuracy achieved for various CNN architectures. The MobileNet model has an accuracy of 85.48%, ResNet50 has 90.6%, Xception has 91.4%, DenseNet has 91.9%, while the Inception v3 has 95.16% accuracy in classifying our medicinal plant images. It is evident from the graph that the Inception v3 model outperforms other models in terms of accuracy.

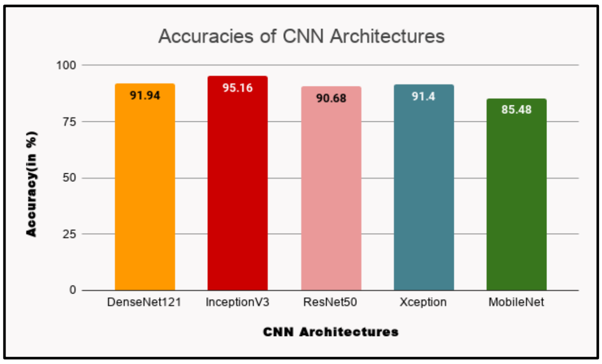

Fig.5 Graph showing the accuracy of the various CNN architectures

We partition the entire dataset in the ratio of 70:30 for the training and testing phase, respectively. We utilize the same training dataset in training the Resnet50, Xception, DenseNet121, MobileNet, and Inception v3 models. In order to compare the performance of these models, we compute the validation accuracy and validation loss graphs. The part of data held back during testing is known as the validation dataset. We compute the validation accuracy to validate the performance of the classifiers. So, the validation dataset is used to compute the validation accuracy. For the proposed model, we compute the training accuracy and validation accuracy for the dataset. Here training accuracy is the number of correct classifications achieved among all the classified images. We computed the training, validation accuracy and training, validation loss for the Inception v3 model.

We plotted the graph in Fig. 6 with the number of Epoch (samples of the dataset used for training) on the X-axis and Accuracy on the Y-Axis. We have observed that the red line showing the training accuracy in the first graph increases with the number of epochs in the model. The blue line shows the validation accuracy without deviation from the training accuracy. There is no constant drop in validation accuracy in the path of the generated accuracy; it is increasing gradually. However, the difference between the training accuracy and the validation accuracy is negligible. This means that the model is a good fit and not in an under fit situation and does not give a poor performance.

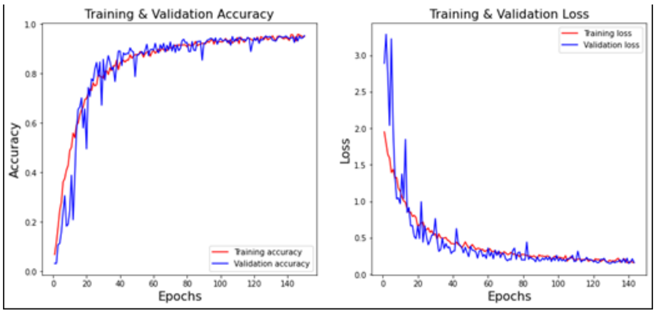

Fig.6. Graph showing the Training Accuracy and the Validation Accuracy for the Inception v3 model

In ideal cases, the Training Loss and Validation Loss for a good fit model are high at the beginning of the training activity. It gradually decreases as more training samples are added and finally flattens without change, indicating that different training samples to the model are of no use. Also, the gap between these two curves is considerably small. At the same time, the validation loss is slightly more significant than the training loss. These are the ideal characteristics for the training or validation loss graph. Here the model is neither undertrained nor over trained, so there is a constant loss value over the entire graph. We can see that loss has gradually decreased with the training, which means that the model is not overfitting. The Loss graph in Figure 6 shows the curve near equals to best fit for the Inception v3 model. In the training phase, the accuracy and loss graph is a smooth red line; this is a good observation as the model is applied on 70% of the dataset. During the test phase, the samples are randomly applied on the model, not from the training model, and the test samples are new for the model; hence there is a spike in the blue line.

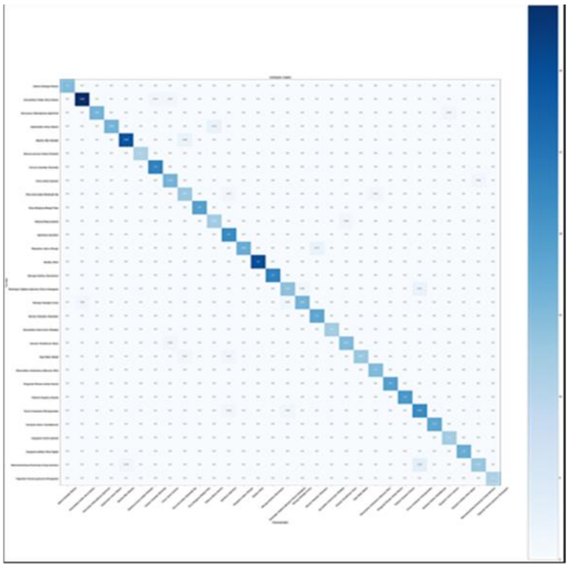

Fig. 7. Confusion matrix for Inception v3 classification model for 30 classes

In Fig.7, the confusion matrix for the Inception v3 model has been generated. Each cell of the matrix contains the successful images classified under each class of the species. In total, we have 30 class labels of medicinal plants, and each species has 60-100 images. Each row and column of the matrix represents the class label. The corresponding cell represents the number of images correctly predicted under this class label. Since the Inception v3 model is trained on a dataset of 30 classes, it can be seen as a confusion matrix for all the 30 classes, and the performance of the model on those classes is generated. The predicted values by the model can be seen along the diagonal in the matrix, and also, the diagonal follows a uniform path, as shown in Fig. 7. It can be observed that the model is neither an under fit nor over fit in this case. The expected performance of this model is acceptable and falls under the category of best fit.

V. CONCLUSION

We proposed Indian origin medicinal plant species detection using advanced computer vision and deep learning architectures. Our proposed architecture uses a stochastic gradient descent optimizer to randomly choose the training samples to improve the learning model efficiency. The dataset has 30 species of medicinal plants of Indian Origin, where for each species, the dataset comprises 60-100 high-quality images intending to improve the accuracy of the learning model. We have conducted experiments in Google Colab for medicinal plant species detection and evaluated the performance of MobileNet, ResNet50, Xception, DenseNet121, and Inception v3 models by various metrics like Training accuracy, Validation Accuracy, and Validation Loss and confusion matrix. The MobileNet model has an accuracy of 85.48%, ResNet50 has 90.6%, Xception has 91.4%, and DenseNet121 has 91.9%, while the Inception v3 has 95.16% accuracy in classifying our medicinal plant images. The validation accuracy and loss curves exhibit the best fit for the given dataset with a minimal gap between the training and validation graphs. Thus giving the ideal results for the Inception v3 model. It is evident from these results that the Inception v3 model outperforms other models in terms of accuracy on the Indian medicinal plant species dataset.

REFERENCES

[1] VijayaLakshmi, Balasubramanian, and Vasudev Mohan. "Kernel-based PSO and FRVM: An automatic plant leaf type detection using texture, shape, and color features." Computers and Electronics in Agriculture 125 (2016): 99-112.

[2] Su, Jianyu, Meihua Wang, Zhenxin Wu, and Qingliang Chen. "Fast Plant Leaf Recognition Using Improved Multiscale Triangle Representation and KNN for Optimization." IEEE Access 8 (2020): 208753-208766.

[3] Sabarinathan, C., Abhisekh Hota, Ashish Raj, Vivek Kumar Dubey, and V. Ethirajulu. "Medicinal plant leaf recognition and show medicinal uses using convolutional neural network." Int. J. Glob. Eng 1, no. 3 (2018): 120-127.

[4] De Luna, Robert G., Renann G. Baldovino, Ezekiel A. Cotoco, Anton Louise P. De Ocampo, Ira C. Valenzuela, Alvin B. Culaba, and Elmer P. Dadios Gokongwei. "Identification of philippine herbal medicine plant leaf using artificial neural network." In 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), pp. 1-8. IEEE, 2017.

[5] Quoc, Trung Nguyen, and Vinh Truong Hoang. "Medicinal Plant identification in the wild by using CNN." In 2020 International Conference on Information and Communication Technology Convergence (ICTC), pp. 25-29. IEEE, 2020.

[6] Herdiyeni, Yeni, Elvira Nurfadhilah, Ervizal AM Zuhud, Ellyn K. Damayanti, Kohei Arai, and Hiroshi Okumura. "A computer-aided system for tropical leaf medicinal plant identification." International Journal on Advanced Science, Engineering and Information Technology 3, no. 1 (2013): 23-27.

[7] Prasvita, Desta Sandya, and Yeni Herdiyeni. "MedLeaf: Mobile application for medicinal plant identification based on leaf image" International Journal on Advanced Science, Engineering and Information Technology 3, no. 2 (2013): 5-8.

[8] T.Ojala, Matti Pietikäinen, Multiresolution Gray-scale, and rotation invariant texture classification with local binary patterns, IEEE Trans.Pattern Anal. Mach. Intell.24 (2002)971–987.

[9] Naresh, Y. G., and H. S. Nagendraswamy. "Classification of medicinal plants: an approach using modified LBP with symbolic representation." Neurocomputing 173 (2016): 1789-1797.

[10] J. G. Thanikkal, A. Kumar Dubey, and M. T. Thomas, "Whether color, shape, and texture of leaves are the key features for image processing based plant recognition? An analysis!" in Proc. Recent Develop. Control, Autom. Power Eng. (RDCAPE), Oct. 2017, pp. 404–409.

[11] Thanikkal, Jibi G., Ashwani Kumar Dubey, and M. T. Thomas. "Unique Shape Descriptor Algorithm for Medicinal Plant Identification (SDAMPI) With Abridged Image Database." IEEE Sensors Journal 20, no. 21 (2020): 13103-13109.

[12] Nguyen, Thi Thanh-Nhan, Thi-Lan Le, Hai Vu, and Van-Sam Hoang. "Towards an Automatic Plant Identification System without Dedicated Dataset." International Journal of Machine Learning and Computing 9, no. 1 (2019): 26-34.

[13] S, Roopashree; J, Anitha (2020), "Medicinal Leaf Dataset", Mendeley Data, V1, doi: 10.17632/nnytj2v3n5.1.

[14] Diederik P. Kingma and Jimmy Ba. Adam: A Method for Stochastic Optimization. arXiv:1412.6980 [cs], January 2017. arXiv: 1412.6980.

[15] Google colab https://colab.research.google.com

[16] https://github.com/ShubhamGupta19/Indian-Origin-Medicinal-Plant-Species-Detection-using-Deep-Learning