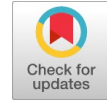


Automatic Recognition of Medicinal Plants: Based on Multispectral and Texture Features using Hidden Deep Learning Model



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Abstract: Identification of medicinal plants automatically in the environments is necessary to know about their existence around us. Recently, there are many techniques followed to recognize plants automatically such as through leaves and flowers with their shape and texture. Leaf-based plant species identification systems are widely used nowadays. This proposed research work uses a deep learning approach using Convolutional Neural Networks (CNN) to recognize medicinal plants through leaves with high accuracy. For this research, leaf images are collected from nature and used as the experimental dataset. The authors have collected leaf items from 5 different medicinal plants. After the collection of images and have to pre-process them which plays an important role in the classification steps. Deep learning model and algorithm are used for classification purposes among them, VGG16 worked pretty well and got an accuracy level of 95.48%. In real life, this paper can well affect the medical sector and learn more about medicinal plants.

Keywords: Deep Learning, Transfer Learning, Convolutional Neural Networks, VGG19.

I. INTRODUCTION

Medicinal (Herbal) plants play an important role in providing fundamental health care services to the people. They act as vital therapeutic agents and the main raw materials for manufacturing primitive and modern drugs. Around 25% of the prescribed drugs even anti-cancer drugs are also extracted from plants [1]. It is reported that about five thousand cryptogams and phanerogams grow in Bangladesh

and between them, around one thousand have medicinal properties [2][3]. They construct significant items of medicines or therapeutic agents of various traditional systems of medicine, especially Unani, Ayurvedic, and Homeopathic drugs. Medicinal plants applied by Herbalists are found to aid scientists as they researched them and found most of them relevant [4]. The extinction of these plants is very common nowadays due to the lack of knowledge about the plants. If we don't save these plants now, we will have to count many losses. Image classification is one of the most important phases for herbal plant detection from leaves. Machine learning largely depends on this feature identification. So, the authors have used the image classification feature of machine learning to recognize the plant leaves [5]. According to World Health Organization (WHO), the United States uses plants to make 25% of its modern drugs [6]. Bangladesh is a developing country; most of the population lives in rural areas, and many use herbal medicine given by Herbalists [7]. The knowledge of Herbalists about herbal medicine usually passes through family tradition. So, very few people know about these herbal plants. These herbal medicines are very helpful to cure diseases also there is a nominal side effect of it [8][9]. But now their existence is at a risk. To save the herbal plants and provide basic knowledge about them. So in this paper, the authors have worked with five herbal plant leaves, which are: "Bashok", "Joba", "Nim", "Thankuni", and "Tulshi".

A. Objective

The authors have targeted Bangladeshi herbal plants for this research. So, the objective of this research is the following:

- To identify the herbal plants automatically by capturing the leaf image.
- Providing information about these plants so the user can easily recognize and learn about them.
- To separate dangerous plants from useful plants so that one doesn't use the wrong plant and get sick.
- Providing a whole database of Bangladeshi herbal plants.
- Providing knowledge of using and cultivating herbal/medicinal plants to save their extinction and for better human health.

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Automatic Recognition of Medicinal Plants: Based on Multispectral and Texture Features using Hidden Deep Learning Model

II. RELATED WORKS

Major headings should be typeset in boldface with the first letter of important words capitalized. Many research works have been done in these few years, this section gives an overview of some existing papers and their applications. Sofiene Mouine [10] pro-pounded a leaf-based plant identification android application that has been developed where an image is captured by an Android phone and stored in a server.

Another server is used for the identification process where a large-scale match-ing algorithm was implemented. The suggested image is provided by an offline database. A KNN classifier is used to build a list of species. They used 6698 images from 122 different species as the training dataset. Tejas D. Dahigaonkar et al. researched [11] the Identification of Ayurvedic Medicinal Plants by Image Processing of leaf samples and developed a system with 32 species of medicinal plants. This system focused on green leaf items which are classified by the SVM classifier. And they have achieved an accuracy of 96.6677%. T. Sathwik et al. [12] developed a plant identification system by analyzing the leaf sample's texture features from the Gray Level Co-occurrence Matrix. They used the least dissimilarity method for classification. The system achieved an accuracy of 95%. Thi Lan Le [13] propounded a fully automatic leaf-based plant identification system for Vietnamese medicinal plants. In this system, 3 datasets are being used. The first dataset consists of 1905 leaf items belonging to 32 species, 2nd dataset consists of 8775 leaf items belonging to 126 species, and the last dataset consists of 1312 leaf items belonging to 55 species. This dataset is divided into 2 parts for training and testing. They apply four steps with these datasets to get the expected result: petiole detection, leaf orientation normalization, modified KDES, and SVM-based classification. In their android application, a large plant database also adds to the search for Vietnamese medicinal plants. the database is stored on an online server. Adams Begue [14] work with 24 different plant species and proposed an Automatic Recognition of Medicinal Plants application using Machine Learning Techniques. They have used many machine learning techniques and they have obtained 90.1% accuracy with a random forest classifier

using a 10-fold cross-validation technique. They also used KNN, NB, SVM, and other neural networks. With RF out of 720 leaves, 649 leaves were classified correctly. KNN classifier performed the lowest accuracy with this dataset.

As we can see, many works have been done before on the Automatic detection of medicinal plants using leaves in many countries. But in Bangladesh, we can't find similar work or research yet.

A. Research Summary

For this research, the authors have collected around 2839 images of 5 different leaf items. The dataset is divided into training, validation, and test sets. The collected image is being pre-processed. Processed images are trained and tested. Then the new model is connected to an android device by creating a local server. Captured image from the android device is being sent through an API call and request for response. The server then predicts the image and sends the result back to the android device as output.

A big challenge of this research is in the collection of the dataset and applying different methods. It was not easy to capture images through a mobile phone. Many herbal medicine companies in Bangladesh were requested for a dataset but a great matter of sorrow is that no one respond. Another major problem of this research is managing a high-configuration computer.

III. METHODS AND PROCEDURES

The authors use a deep CNN to fit the dataset that completes the architecture and the model's features described in the following section. This research concentrates on classifying images of 5 leaf items containing 2839 pictures. Also, 1592 images are applied for training and 1137 for validation, and 10 for testing. The models applied are pre-trained on the large scale of the dataset which is called ImageNet. Many deep models tasted on our dataset which are VGG16, VGG19, Inception-V3, Xception, MobileNet, DenseNet121, and ResNet50 [15][16][17].

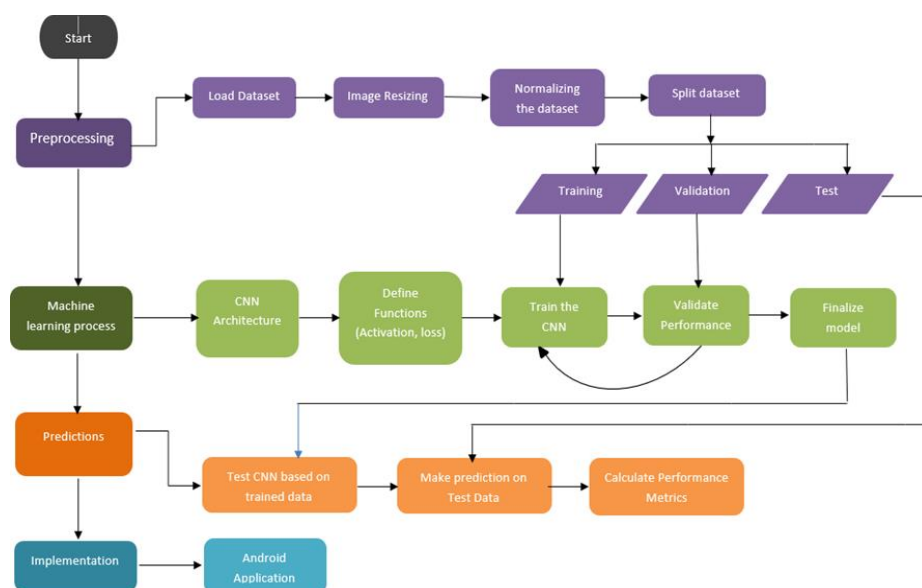


Fig. 1: Process Flowchart

The dataset was in two different ways capturing images with an android phone and collecting images from the internet. The standard image format (jpg). The dataset consists of 2850 images used for this research where 32% of the data is Tulshi, 25% is Nim, 23% is Joba, 11% is Thankuni and 9% is Bashok. A few of these images are collected from the internet and others are captured using an android device camera. Collected images from different angles and positions so that model can learn properly about each class. There are 656 images of Joba collected in this dataset and these images

are from various places in Bangladesh and a few from the internet.

Table I: Statistics of the Dataset

Class Name	Class Label	Total Data	Train Data	Validation Data	Test Data
Bashok	0	241	187	32	22
Joba	1	656	220	408	28
Nim	2	714	347	336	31
Thankuni	3	323	256	53	14
Tulshi	4	916	593	308	15



Fig. 2: Data Sample

From the total dataset, 56% of data is used for training and 39% data for validation, and 5% data for testing. Splitting the dataset gives more accuracy than using the whole dataset for training.

A. Data Preprocessing

Data preprocessing is an important part of the deep learning program. It plays an important role to transform raw data for the machine learning algorithm. The pixel format of every digital image is in the range of 0 ~ 255. 0 is black and 255 is white. Colorful images have three maps which are red, green, and blue. Still, the range is 0 ~ 255. Rescale 1/255 transforms every pixel value from the range [0, 255] to [0, 1]. Datasets are used to train the model. The model sees the dataset and learns from it. So, splitting the dataset is important. Datasets can be divided into 3 sets. Train, validation, and test set.



Automatic Recognition of Medicinal Plants: Based on Multispectral and Texture Features using Hidden Deep Learning Model

IV. EXPERIMENTS AND RESULTS

Applied a few models for research to measure which one gives me better performance on the dataset. The applied variations are VGG16, VGG19, Inception V3, Xception, MobileNet, ResNet, and DenseNet121. Here is the model trained by ImageNet, for each model, and plot the training accuracy and validation accuracy. Also, worked with 5 classes of datasets it didn't take too long. In this part, the authors have created a Numpy Array file for training the dataset. In this file, images will be converted into an array file and stored there.

A. Impact of Initial Training Data with VGG16 and VGG19

VGG16 is CNN (convolutional neural network model), this model is proposed by Simonyan [18] and 92.7% accuracy is achieved by this model in the top-5 test in ImageNet. Over 14 million images belong to 1000 classes in ImageNet. This model is submitted to ILSVRC-2014. NVIDIA Titan Black GPU is used to Train VGG16 and it took weeks to train. VGG19 is a type of VGG neural network Architecture which was proposed by Wang [19]. The main difference between VGG16 and VGG19 is VGG16 is consist of 16 layers of Neural Network and the VGG19 is consist of 19 layers of Neural Network. And these two are different in size.

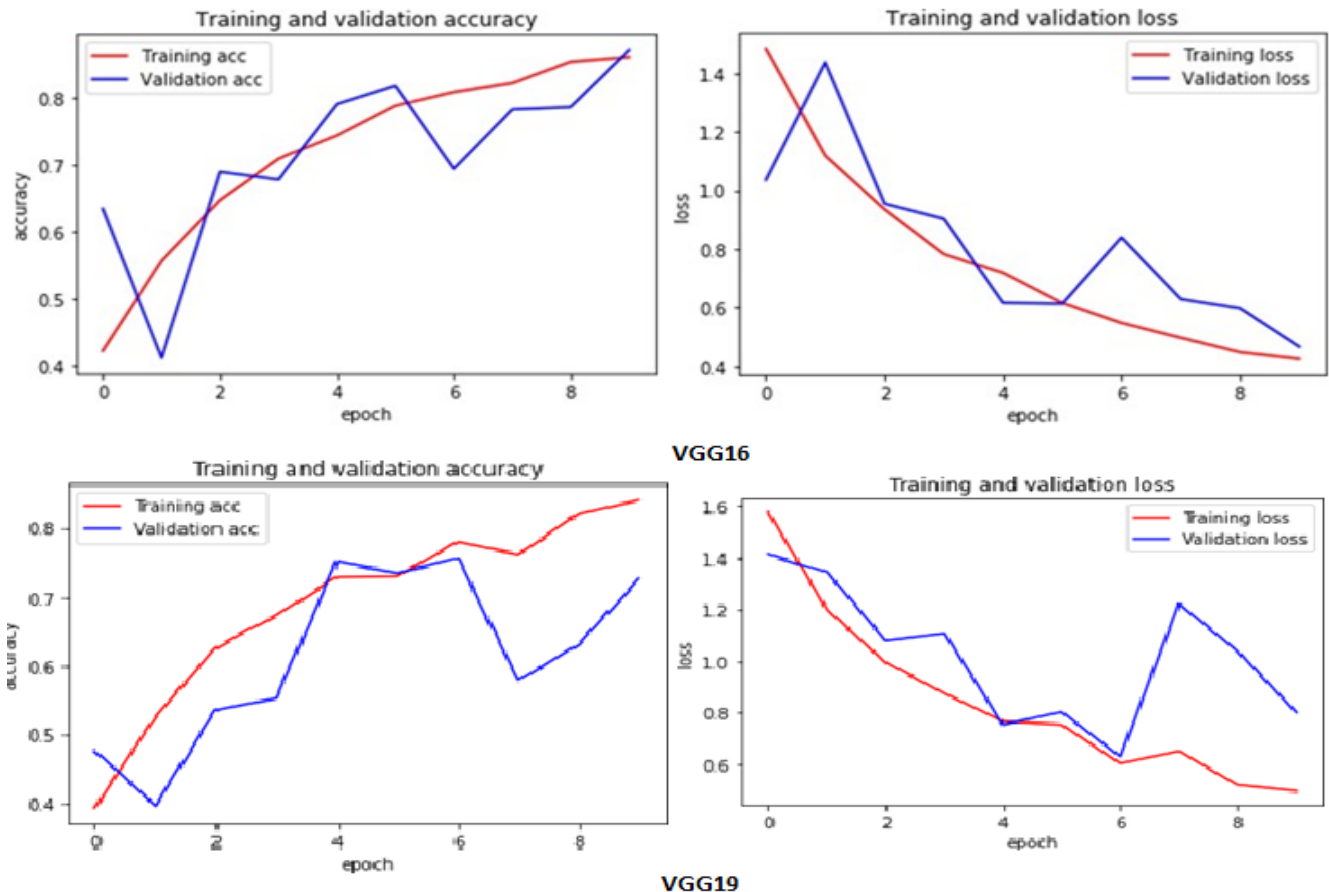


Fig. 3: Validation Accuracy and Loss on VGG16 and VGG19

Figure 3 is a loss curve of VGG16 which shows that both curve loss is decreasing in the same manner with a minimal gap at the end. So, this situation is in the middle of underfitting and overfitting. So it can be said that this model is near to a good fit. It also shows the VGG19 model that the validation curve has a high loss with great distance. It shows a lot of noise also. So the model can be said to be under-fitted for this kind of dataset.

B. Training data with Inception-V3 and Xception

Inception-v3 is a convolutional neural network consisting of 48 deep layers [19][20]. It is the third edition of Google's Inception convolutional neural network. During ImageNet Recognition Challenge it was first Introduced. The image input size of this network is 299x299. It has 2x Conv. Layers of 64, 128, 256, 512, and 1024 channels respectively consist of a 3x3 kernel with the same padding. It uses 2x2 pooling with the same padding. Then pass the image through three dense layers where the first 2 consist of 4096 units and the last SoftMax layer of 10 units. Xception is a convolutional neural network that is an Extreme version of Inception. In 2017 CVPR published it. Its performance is recorded better than inception-v3. The Xception has 36 Conv. Layers. These 36 convolutional layers are divided into 14 modules that have linear residual connections around them except for the First and the last one [21].

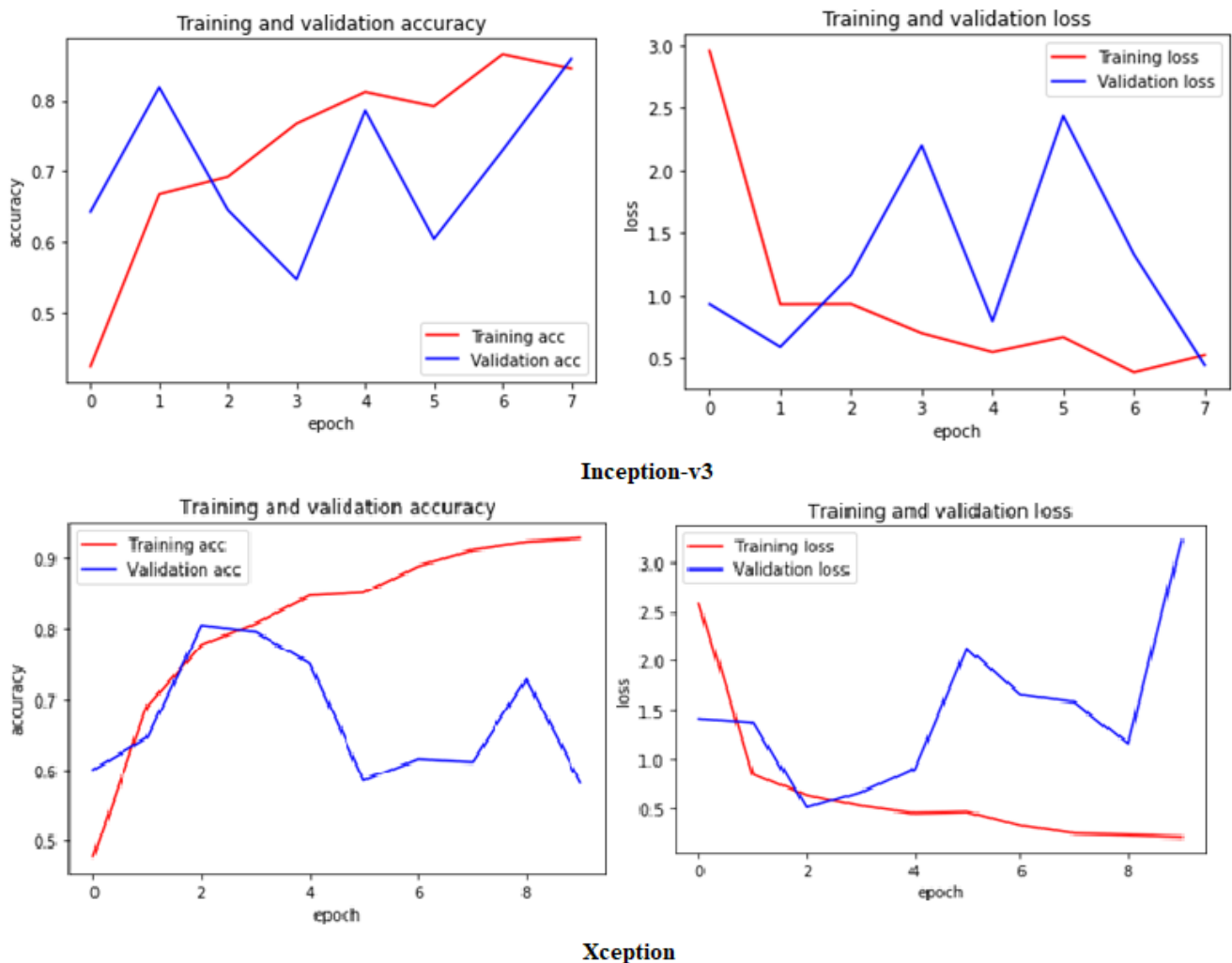


Fig. 4: Validation Accuracy and Loss on Inception-V3 and Xception

Figure 4 shows the loss curve of Inception-v3, which shows a high noise rate. So, this model is under-fitted. It also shows the loss curve of Xception where it shows that the validation loss curve is increased at a high loss so which means it is under-fitted.

C. Training data with MobileNet, DenseNet121, and ResNet50

MobileNet is a model architecture of CNN for image classification and mobile Vision. MobileNet consists of 30 layers with a convolutional layer with a stride size of 2, a depth-wise layer, a point-wise layer that doubles the channel, a depth-wise layer with a stride size of 2, and again point-wise layer with a double size of channels. DenseNet is one of the discoveries in neural networks. It was developed specifically to improve the vanishing gradient in high-level neural networks [22]. DenseNet121 consist of (6+12+24+16) x 2 = 12, 1 Dense blocks and layers. Where there are convolutional and pooling layers, (6, 12, 24) transition layers, and 1x1 and 3x3 conv Dense blocks. ResNet50 is a convolutional neural network that is 50 layers deep [23]. Res-Net50 consists of a convolution with a kernel size of 7x7 and 64 different kernels. It has a stride of size 2 in 1 layer. Max pooling also has stride 2. The next is 1x1, 64 kernels, and 3x3, 64 kernels. And these are used 3 times so a total of 9 layers. Next, is 1x1, 128 kernels 2 times, and 1x1, 512 kernels repeated 4 times so it is a total of 12 layers. After that comes 1x1 256 kernels, 3x3, 256 kernels, and 1x1 1024 kernels all repeated 6 times so a total of 18 layers [24]. It is an under-fitted model too. The loss curve of DenseNet121 where the curves have no match or similarity of loss. Validation loss is high and it clearly shows unrepresentative data for this model. So, the data didn't suit this model. The loss curve of ResNet50 where both curves are decreasing the loss but there has much noise and the loss rate is high. So, this model is under-fitted for this dataset.

D. Learning Curve Analysis

Learning curves are a very useful diagnostic tool in machine learning. The model's performance can be evaluated from these learning curves [25]. In model training, there are a few situations, such as whether a model can be underfitting or overfitting, as well as whether the training and validation datasets are suitably representative.

Automatic Recognition of Medicinal Plants: Based on Multispectral and Texture Features using Hidden Deep Learning Model

E. Comparison Among Models

Table II: Models Comparison

Model Name	Total Parameters	Trainable Parameters	Size (MB)	Train Accuracy	Train Loss	Validation Accuracy	Validate on Loss	Train Time (MIN)
VGG16	2,514,205	2,514,205	9.60	95.48%	0.3286	84.79%	0.5733	49.0863
VGG19	2,513,950	2,513,950	9.61	92.53%	0.2835	71.98%	0.8139	41.3410
Inception-V3	5,125,405	5,125,405	19.57	95.41%	0.1290	84.92%	0.4435	23.2024
Xception	10,040,605	10,040,605	38.32	93.25%	0.2736	58.22%	3.3598	28.146
MobileNet	5,023,005	5,023,005	19.15	88.38%	0.2564	78.97%	0.9175	04.55125
DenseNet121	5,023,005	5,023,005	19.18	93.20%	0.2315	57.89%	2.2011	4.10847
ResNet50	5,023,005	5,023,005	11.38	34.73%	1.7149	35.86%	1.5331	5.71938

F. Feature Extraction Algorithms Used

Besides, we applied other image classification technics earlier to perform a simple image classification task using computer vision and machine learning algorithms [26]. After extracting and saving global features and labels from the training dataset, we created a machine-learning model with the help of computer vision. Then for training, the model took the help of Scikit-learn. We chose LR(Logistic Regression), LDA (Linear Discriminant Analysis), KNN (K-Nearest Neighbors), RF(Random Forests) NB(Gaussian Naïve Bayes), and SVM(Support vector Machines) as machine learning models for my dataset. And compared to them, the best result was 91.55% from Random Forest.

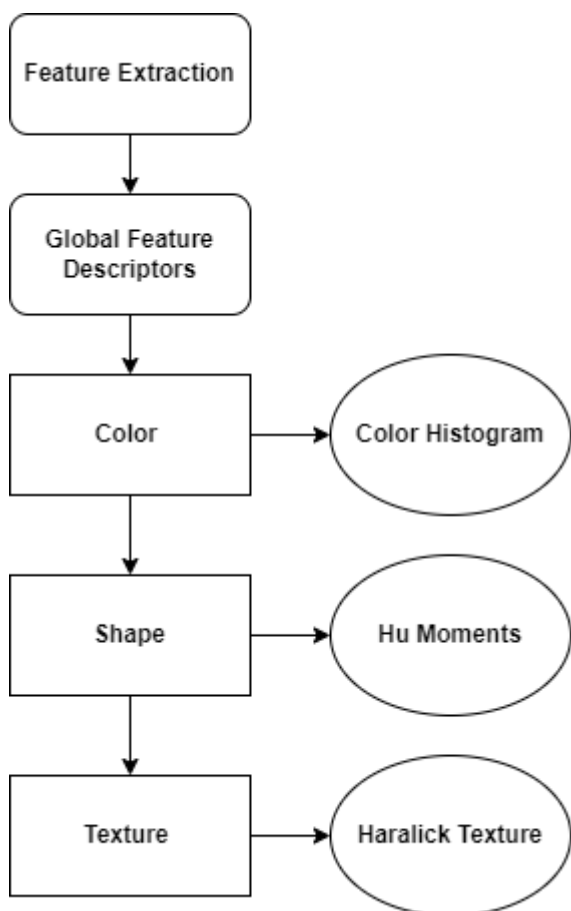


Fig. 5: Feature Extraction by Algorithms

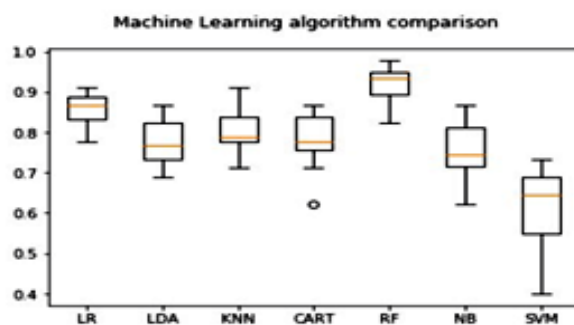


Fig. 6: Boxplot of Traditional Machine Learning Algorithms

Comparing the Deep learning models and other machine learning models the best result was from VGG16 which is 95.48%.

V. CONCLUSION AND FUTURE WORK

This research, applied a convolutional neural network to Bangladeshi medicinal plants to make an automatic herbal plant detection system. Applied many deep learning models using transfer learning. We have classified only five plant leaf items and collected as much data. In the future work with a vast amount of datasets to get more accuracy.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	On request, the data used to back up the study's conclusions can be provided by the corresponding author.
Authors Contributions	Writing the initial draft, as well as writing the review and revising. For instance: Formal analysis, editing, reviewing, and supervision of writing. The manuscript's published form was approved by all authors after they had read it.

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