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CNN-based Leaf Image Classification for Bangladeshi Medicinal Plant Recognition

Raisa Akter
Dept. of Computer Science and Engineering
Manarat International University
Savar, Dhaka, Bangladesh
raisa.alam.miu@gmail.com

Md Imran Hosen
Dept. of Computer Science and Engineering
Manarat International University
Savar, Dhaka, Bangladesh
imranhosen@manarat.ac.bd

2020 Emerging Technology in Computing, Communication and Electronics (ETCCE) | 978-0-7381-2401-8/20/$31.00 ©2020 IEEE | DOI: 10.1109/ETCCE51779.2020.9350900

Abstract— Classifying plant species has taken much attention in the research area to help people recognizing plants easily. In recent years, the convolutional neural networks (CNN) have achieved tremendous computer vision results, especially in image classification. Usually, humans find it difficult to recognize proper medicinal plants. It requires the intuition of an expert botanist, which is a time consuming manual task. In this research, we proposed an automated system for the medicinal plant classification, which will help people identify useful plant species quickly. A new dataset of 10 medicinal plants of Bangladesh is introduced, collected from different regions across the country, and some state-of-the images collected from different sources. After that, a three-layer convolutional neural network is employed to extract the high-level features for the classification trained with the data augmentation technique. The training process was done on 34123 images, and the experimental result on another 3570 images proved that this method is quite feasible and effective, which gave by a 71.3% accuracy rate.

Keywords— Computer Vision, Image Recognition, Leaf Classification, Convolutional Neural Network.

I. INTRODUCTION

There are almost 374,000 plant species around the world [1]. Among all the plants, some used in medicine, which provides many drugs from the ancient time to the present. Within the context of Bangladesh, there are about 449 enlisted medicinal plants [2]. Among them, a lot of traditional and modern medicine exists which can be derived from these plants. Considering this huge number, the medicinal plant classification is a fairly difficult task and lengthy process even for experienced botanists. Because it relies much on the inherited knowledge of an expert botanist. Also, the plants are hard to recognize because of their almost similar shape and color. So, it is important to study and classify plants correctly for further use. As manually identifying these plants requires a lot of time, an automation process is needed to automate this plant classification system so that the people with no botanical knowledge can identify plant easily.

Our objective of this research is to make the process of plant classification easy for a human. In this regards, we propose an approach for classification of Bangladeshi medicinal plants. This method offers an alternative solution to the traditional way of identifying medicinal plant images by the botanist and reduces time, the manpower and associated costs for the whole process. To the best of our knowledge, there is no availability of medicinal plant dataset in Bangladesh for research. In this paper, we introduce an image dataset of 10 classes of Bangladeshi medicinal plants which were taken in different conditions. Also, a three-layer convolutional neural network is applied to classify the plants. In CNN, there are feature maps which capture the result of the filters to an input image. That feature map is then passed to a fully connected layer to perform the classification. For performing the classification with convolutional neural network, it requires a huge amount of training data. Data augmentation is a technique used for enlarging the data. It was first introduced in 2001 [3]. This technique increases the multiplicity of data for training model without collecting new data. It is more effective for reducing overfitting and improving generalization [4].

Today, the applications of computer vision are trying to make it easier to identify plants for humans. Plants can be classified using its bark, roots, seeds, flower and leaves [5], [6]. According to Anant at el. [7] the plant leaves contain essential feature and also it is two dimensional. So it is easy to study the shape of leaves than the flower or morph of plants because of their three-dimensional structure. Previously, the plants were identified using many features of leaves including leaf margin, veins, etc. with standard classifiers such as support vector machine, KNN and random forest. But there are limitations in these approaches. Firstly, the images must be spotless without having any natural background that makes it difficult to classify in real-world situations. Secondly, the hand-crafted features are easily affected by the noise and the change of conditions such as light, rotation, etc. Thirdly, all these techniques were applied to a limited number of images with a limited number of features. These techniques can't extract the high-level feature on itself. To extract high-level features or key features, CNN is far better than other methods [8].

There were many approaches which used CNN for plant classification. In most cases, they applied their method on a dataset which was clicked on a lab environment or in a plain background. For which we add a novelty to our practice by using a dataset which contains both single and multiple leaf images also in the natural environment.

The rest of the paper is organized as follows: Section II discusses the related works which have been done previously. Section III introduces the dataset and the data augmentation

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techniques used in this paper. In Section IV, the proposed model architecture is analyzed. Section V mentions the experimental result and discusses this result. Finally, Section VI concludes the paper while mentioning the future direction of our work.

II. Related works

In the past decades, there were various works on plant classification, some of were based on low-level feature extraction such as color, texture and leaf vein extraction, etc. [9], [10], [11]. Also in 2013, R.Janani et al. [12] used a small dataset of 63 medicinal leaf images of 6 classes and implemented an ANN classifier. They used a minimum of eight input features and got 94.4% correct identification accuracy of leaves. In 2014, Mohd Shamrie Sainin et al. [13] proposed a framework for identifying the tropical medicinal plants in Malaysia, which was based on the extracted pattern from the leaf. They used an ensemble classifier and got almost 65% accuracy from five species of plants. In 2017, a new dataset on medicinal plants of Mauritius was introduced. They applied different algorithms on this dataset. They found the best accuracy from random forest classifier, which was 90.1% [14]. Also in 2017, Adil Salman et al. [15] studied different features related to leaf shape, size. They selected convex area, filled area and perimeter e.t.c for identifying the leaves of twenty-two class. They achieved an accuracy of 85% to 87%. In 2016, Codizar [16] proposed a desktop application LeaVes which aims to classify a plant species by leaf images alone. They used the handcrafted image featuring and different machine learning algorithm: centroid-radii model, moment-invariant model, canny edge detection, morphological operations, image difference, artificial neural networks as classifiers to achieve 95% accuracy.

These approaches classified medicinal leaf images based on a limited number of hand-crafted features. Later, some researchers used deep learning techniques to automate the feature extraction procedure. In this regard, important work was done by Chaoyun Zhang et al. [17]. They achieved 94.6% accuracy using the combination of CNN and data augmentation together for plant identification. They used the Flavia dataset for classifying the plants.

In 2016, Hulya Yalcin et al. [18] applied a pre-trained convolutional neural network to classify sixteen kinds of agricultural plants. They also evaluate performance with SVM classifier, and their experiment indicates that their CNN model gives a higher performance which is 97.47%. S.H Lee et al. [19] published a paper in which the use of deep learning to harvest discriminatory features from leaf images by learning and applied them as classifiers for plant identification was investigated. Their result showed that learning the features using CNN can provide better feature representation of leaf images as compared to using hand-designed features. M.M Ghazia et al. [20] and Aydin et al. [21] applied transfer learning to identify plant species using deep convolutional neural network on different dataset and got the accuracy of about 78.44%. Sue Han Lee et al. [22] developed a convolutional neural network architecture for the LifeCLEF dataset challenge, which was the competition of identifying 1000 species of images of plants. They got about 68.9% accuracy after applying augmentation techniques. Recently in 2019, a new dataset on medicinal plants images in the natural scene has been introduced. The dataset consists of a total of 10279 images of 10 plant species. The authors got 93.6% accuracy by using the VGG16 model to extract the features from the images and then applied the LightGBM classification method [23]. Also in 2018 and 2019, Bhanuprakash Dudi et al. [24] and Jing et al. [25] have researched on plant classification where they extracted features using CNN and classified the plants applying various machine learning algorithms such as ANN, SVM, KNN and Naive Bayes. They achieved 98% accuracy on grayscale images. We were inspired by the work [17] where data augmentation was used first in plant classification.

III. Data collection and augmentation

A new Bangladeshi medicinal plant dataset is introduced which contains 37,693 images of 10 different medicinal plants with one default class. The following plants are selected for classification: '*Calotropis procera*', '*Aloe indica*', '*Phyllanthus emblica*', '*Justicia adhatoda*', '*Andrographis paniculata*', '*Catharanthus roseus*', '*Azadirachta indica*', '*Moringa oleifera*', '*Centella asiatica*', '*Ocimum tenuiflorum*'. The total number of raw images of plant classes is 1671. Among them, 39% of the images were collected from different sources, and the other 61% images were clicked in different conditions using the mobile phone. As convolutional neural network requires a large number of training images, the augmentation technique can bring massive effect in this small amount of images. So we applied augmentation techniques such as flipping and different rotation angles. After that, the number of images becomes 37,693. The number of images per class is given in Fig. 1.

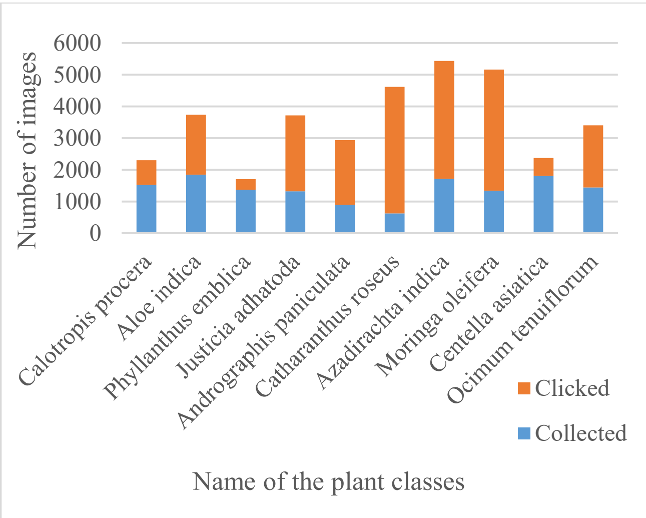

Figure 1: Bangladeshi medicinal plant dataset: 35393 images of 10 classes and one default class. The number of images in each class is between 1708 and 5439. The blue region indicates the number of images collected from different sources, and the red region is the clicked images from different location in Bangladesh.

In the table below the detailed information about the dataset is given:

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TABLE I:
SUMMARY OF THE BANGLADESHI MEDICINAL PLANT DATASET

Class label	Total Image		After Augmentation	Percentage (%) of total dataset
	Collected from Bangladesh	Collected from other sources		
0	37	73	2310	6.53
1	90	88	3738	10.56
2	11	55	1708	4.83
3	114	63	3697	10.45
4	97	43	2940	8.31
5	190	30	4620	13.05
6	177	82	5439	15.37
7	182	64	5166	14.6
8	27	86	2373	6.7
9	93	69	3402	9.6

In Fig. 2, the sample image from each class is shown, and in Fig. 3, the augmentation effect is described for a particular image.

Figure 2: Sample images from Bangladeshi medicinal plant dataset. The image labels represent the scientific name of that plant class.

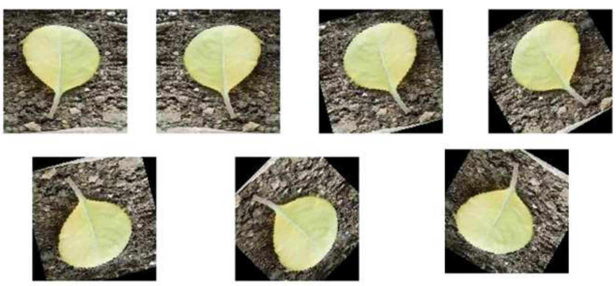

Figure 3: Rotation and flipping effect on an image. The leftmost image is the actual image, and the other images are augmented image.

The drive link of the dataset is given below where the train and test data were separated into two folders.

https://mega.nz/file/0vxkHIwA#c3Lhm73Szv1Ii-PxuINz6wgjwwgdvqpfevo6z-0J53M

IV. NETWORK ARCHITECTURE

In this work, we build a small convolutional neural network from scratch to classify the exact classes. Technically in a convolutional neural network, every input images are passed through a series of convolutional layers with different kernels. Then the convolution operation has been done by element-wise matrix-multiplication and sums the result which turns into a feature map. Here we applied 128 different types of weight filter to produce the feature map. As we used different filters, it will make different types of feature maps. So we stack all the feature maps and pass these through an activation function for summing this up and also for having non-linearity effects. Fig. 4 describes the basic feature extraction procedure of CNN architecture.

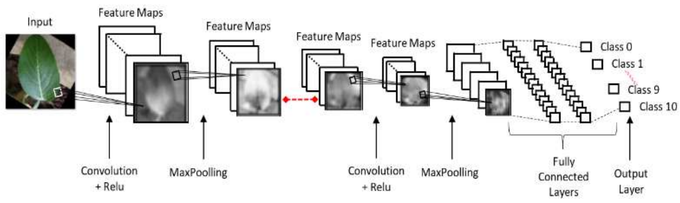

Figure 4: Feature extraction procedure of our proposed architecture. Here the feature map obtained from the first convolutional layer and the third convolutional layer is demonstrated. Then the MaxPooling operation is done to reduce the number of parameters.

The proposed CNN architecture as illustrated in Fig. 5 is consist of several layers, in which convolutional, Gaussian noise, Batch normalization, Max Pooling and Dropout are placed sequentially. This pattern was repeated three times. Then, a large dense layer was placed at the output end of the network in an attempt to better translate the large number of feature maps to class values. The input image was 128 x 128 with 3 channels and which was then fed with a CNN of 128 different kernels each having 3x3 filter size and also an activation function (ReLU) was added for non-linearity effect [26] which is defined as below:

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x > 0 \end{cases} \qquad (1)$$

As the size of the dataset is comparatively small, it may represent a harder mapping problem to learn for the neural network. So to make this smoother, one way is to add noise to inputs during training. For this reason, we added Gaussian noise to make the inputs different every time and network will less able to memorize during training. We also added batch normalization which standardizes each layer input for every mini-batch. The batch normalization also stabilizes the learning process.
After that, a pooling layer with filters of size 2x2 was applied to reduce the total amount of parameters in the network. The pooling layer uses the MAX operation on every depth slices of the input and resizes. Lastly, a dropout rate is added. Hence, the network becomes less sensitive to the specific weights of neurons. This dropout technique results in a better-

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generalized network and is less likely to overfit during training.

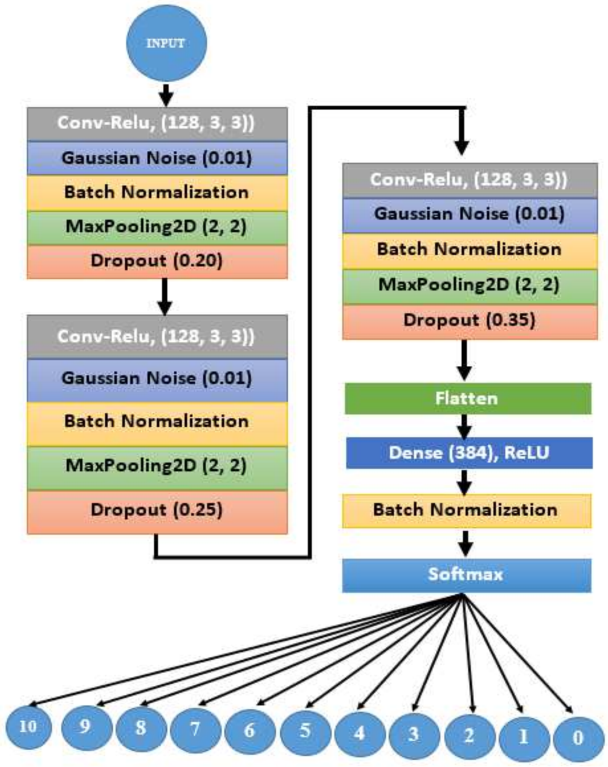

Figure 5: Network Structure of Proposed Model. Starting with an input layer, followed by a CNN layer, Gaussian noise and batch normalization layer. Then a MaxPooling layer to reduce the total parameter number and finally a dropout layer to disable a certain amount of neurons. This pattern is repeated three times. Lastly, a fully-connected layer is added before the Softmax output function.

This pattern is repeated three times with gradually increasing dropout rate. In the end, a fully-connected layer is added and a softmax output function is used to turn the outputs into probability-like values and allow one class of the 11 to be selected as the model's output prediction. We added an extra input and output class called 'none' class to classify that the input images belong to that 10 plant classes or not.

TABLE II:
SUMMARY OF PROPOSED NETWORK ARCHITECTURE

Layer Type	Kernel Size	Number of parameters	stride	shape
Input image	-	-	-	(128,128,3)
Conv	(3,3)	3584	1	(None,128,128,128)
Max Pooling	(2,2)	-	-	(None,128,128,3)
Conv	(3,3)	147584	1	(None,64,64, 128)
Max Pooling	(2,2)	-	-	(None, 32, 32, 128)
Conv	(3,3)	147584	1	(None, 32, 32, 128)
Max Pooling	(2,2)	-	-	(None, 16, 16, 128)
Dense	-	12583296	-	(None, 384)
Softmax classifier	-	4235	-	(None, 11)

*None is the number of pictures determined at model training
*Conv: Convolutional

To learn the weights, we chose to use the efficient Stochastic Gradient Descent (SGD) optimizer with a momentum of 0.9. As a loss function, the categorical cross-entropy loss [27] was used which is defined as:

$$\mathrm{CE} = -\sum_{c=1}^{M}\left(y_{i,c}\log(p_{i,c})\right) \qquad (2)$$

The function calculates a separate loss for each class label per observation and sums the result. Here M is the total number of classes, y_i is the binary indicator (0 or 1) if class label c is the correct classification for observation i^{th} and p_i is the predicted probability observation i^{th} is of class c.

V. EXPERIMENTAL RESULT

In the experiment, the images were divided into two parts: the training and the test image dataset. To use the dataset, we first need to process the images because machines can't take the images as they are. So the data were preprocessed to become suitable for upcoming training steps. In the preprocessing techniques, first we resized the images into 128*128 dimension to establish a fixed size. Then the images are converted into numpy array. After that, each image was normalized by dividing each value of data by 255 which is maximum observation and scaled the data into [0, 1].

After preprocessing the data, they were sent to the convolutional neural network for feature extraction.

As we said, we used double augmentation technique at preprocessing, in the training period the other augmentation method such as width shift, height shift, zoom range etc. was applied. The mentioned model was trained using multiple learning rates through the epochs, firstly 0.01 for 10 epoch, then 0.001 for 165 epoch and lastly 0.0001 for 125 epoch. It was trained with 300 epochs and a small batch size of 64. The entire training phase finished in approximately 7.5 hours, where each epoch took almost 87 seconds. In the training period, the weights were optimized through backpropagation. Backpropagation is a process where the weights of the layers were correctly tuned with respect to the optimization function while carrying out forward and backward passes.

The graphic representations of the network performance are shown in Fig. 6.

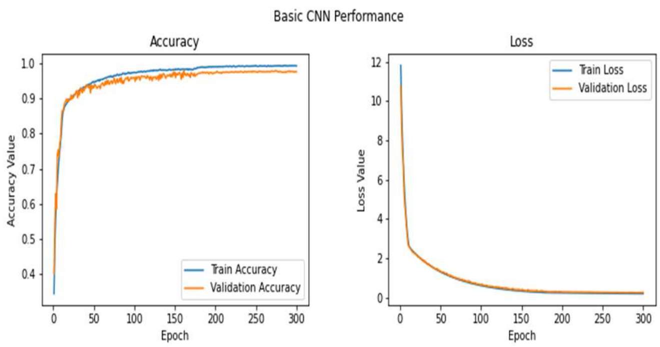

Figure 6: Performance of the proposed model with training and validation accuracy (in the left) and training as well as validation loss (in the right) plots.

From Fig. 6, it has been seen that the validation accuracy is above 95%. In the rightmost loss curve, in the initial training period the validation loss was almost 11, and in the end the loss was about 0.3.

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The confusion matrix is given in Table III. From the table, we can see that 2,550 images were accurately classified where 1,020 images were misclassified.

TABLE III:
CONFUSION MATRIX ON TEST IMAGES WHICH INDICATES THE NUMBER OF ACCURATELY CLASSIFIED AND MISCLASSIFIED IMAGES

Confusion Matrix											
Name of the plants	*Calotropis procera*	*Aloe indica*	*Phyllanthus emblica*	*Justicia adhatoda*	*Andrographis paniculata*	*Catharanthus roseus*	*Azadirachta indica*	*Moringa oleifera*	*Centella asiatica*	*Ocimum tenuiflorum*	None
Calotropis procera	202	0	0	0	0	2	17	0	0	10	0
Aloe indica	27	279	0	3	4	23	7	0	0	34	1
Phyllanthus emblica	0	0	40	21	0	0	0	0	0	0	0
Justicia adhatoda	21	0	23	244	4	0	38	3	17	12	16
Andrographis paniculata	8	1	0	14	234	27	7	0	0	1	2
Catharanthus roseus	2	0	0	0	0	406	13	0	0	9	32
Azadirachta indica	0	18	1	0	0	45	414	24	22	8	14
Moringa oleifera	3	3	16	1	10	0	41	396	21	13	0
Centella asiatica	0	0	21	44	0	14	21	27	83	42	0
Ocimum tenuiflorum	12	1	1	21	5	6	2	27	49	199	13
None	1	0	0	1	0	5	18	1	0	53	49

Table. IV shows the precision, recall and f1 scores of our proposed method on the test images. The proposed model got the accuracy of 71.3%, where the macro average decreased, but the weighted average increased.

TABLE IV:
PRECISION, RECALL AND F1 SCORE OF PROPOSED MODEL

Class label	**Precision**	**Recall**	**F-1 Score**	**No. of test images**
0	0.7318840	0.8744588	0.7968441	231
1	0.9238410	0.7380952	0.8205882	378
2	0.3921568	0.6557377	0.4907975	61
3	0.6991404	0.6455026	0.6712517	378
4	0.9105058	0.7959183	0.8493647	294
5	0.7689393	0.8787878	0.8202020	462
6	0.7162629	0.7582417	0.7366548	546
7	0.8284518	0.7857142	0.8065173	504
8	0.4322916	0.3293650	0.3738738	252
9	0.5223097	0.5922619	0.5550906	336
10	0.3858267	0.3828125	0.3843137	128
Accuracy		0.71316526611		3570
Macro average	0.6646	0.6760814	0.6641362	3570
Weighted average	0.7204	0.7131652	0.7129380	3570

We compared our approach with the other general methodology. Table V summarizes the total experiment, which shows that the classifiers didn't perform well on our dataset.

TABLE V:
PERFORMANCE OF DIFFERENT MACHINE LEARNING CLASSIFIERS.

Sl. No	Classifier	Accuracy (%)
1	SVM	20.36
2	K- Nearest Neighbour	28.44
3	Random Forest	47.25

We also experimented with different CNN architecture and got the most accuracy in the three-layer convolutional neural network. The performance of the different number of convolutional layer is given in Table VI.

TABLE VI:
PERFORMANCE OF DIFFERENT CNN ARCHITECTURE.

CNN	Accuracy (%)	Precision	Recall	F-1 Score
2 layer	62.80	0.608	0.624	0.583
3 layer	66.92	0.630	0.651	0.623
4 layer	69.33	0.657	0.675	0.646
3 layer (with dropout + gaussian noise + batch normalization)	71.3	0.664	0.676	0.664

The training was performed on a Google Colab environment featuring a GPU service, 25 GB RAM. The learning model

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was developed in Keras, a Python library for deep learning, using Tensorflow backend and trained over GPU.

VI. CONCLUSION

In this work, we introduced an attention architecture for the task of extracting features for plant classification and identified medicinal plants from leaf images. We collected a dataset of Bangladeshi medicinal plants, preprocessed them, and classified the plant species using a deep learning technique. In our paper, we described the methodology of the architecture. We analyzed the results based on both training and testing sets, and our result is quite impressive, which correctly identifies 71.3 % of leaves. Besides, the results of the proposed architecture are promising and comparable to other existing methodology through in our dataset, we have both single and compound leaf images.

In the future, we will focus on exploring the CNN model for better performance in both single and compound images as well as we will extend our dataset. Finally, we aim to build a mobile application based on this model by which people can be able to identify medicinal plants more easily.

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