Recognition of Jute Diseases by Leaf Image Classification using Convolutional Neural Network

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Abstract— **As Convolutional Neural Network (CNN) is achieving the state-of-the-art in the field of image classification, this research work focuses on the finding prominent accuracy of the jute leaf image diseases using deep learning approach. Acquiring the better performance in disease identification is the main purpose of this paper. Among different types of jute leaf diseases, Chlorosis and Yellow Mosaic have been selected to recognize the diseased leaves from the healthy leaves. As per our knowledge, no other method for leaf disease detection of Jute plant has been proposed for the first time. Using a dataset of 600 images, proposed model is aimed to classify two common jute leaf diseases. CNN achieves an overall accuracy of 96% without applying any image preprocessing and feature extraction method. The results suggest that proposed deep learning model provides an improved solution in disease control for jute leaf diseases with high accuracy.**

Keywords—Jute leaf disease classification, Machine learning, Image Augmentation, Disease Prediction, CNN.

I. Introduction

Jute (scientific name: Corchorus olitorius and Corchorus capsularis) is an important fiber-yielding plant of Bangladesh. Jute has been considered as one of the most important cash crop as it plays a crucial part in the economy of the country and also very popular in the name of golden fiber [1]. According to the scenario of Jute cultivation in the world, Bangladesh is ranked second among them in respect of production. In 2010-2011, 8.4 million bales of jutes were produced in Bangladesh from 1.75 million acres of land (BBS, 2011). Jute fiber is manufactured mainly from commercially significant species, specifically White jute.

Jute leaves also contain nutritional value and they use as thickeners in soups, sauces, and stews. Jute leaves is known assaluyot or ewedu in some part of the world. In some places, cultivators grow jute for just only its fresh leaves [1]. It is possible to found some specialty stores where they stock jute leaf in fresh, frozen, or dried form depending on their location and size. In the West African region, it is one of the most popular vegetable. Due to growing recognition of natural products, the demand of jute leaf as medicinal plant is increasing day by day in both developed and developing countries. In accordance with some reports, jute leaves contains as many as 16 active nutrients compounds [2]. Table I shows all those nutrients values after boiled the leaves.

TABLE I. Nutritional values of jute leaves as saluyot [2]

Nutrients	Boiled	Nutrients	Boiled
Moisure (%)	80.4-84.1	Food Energy (cal.)	43-58
Protein (gr.)	4.5-5.6	Fiber (gr.)	1.7-2.0
Carbohydrate	7.6-12.4	Ash(gr.)	2.4
Calcium (mg)	266-366	Phosphorus (mg)	97-122
Iron(mg)	11.6	Sodium (mg)	12
Potassium(mg)	444	Vitamin A	6,390
Thiamine (mg)	15	Riboflavin (mg)	28
Niacin (mg)	1.5	Ascorbic acid mg	95

Jute plants can be affected by various kinds of diseases. Leaf mosaic has been informed to be the most marring disease among them. In 1917, Finlow was the first to report this disease. In the foremost jute growing countries of the world, the leaf mosaic of jute has extensive spread occurrence, namely Bangladesh, Burma, India, etc. Among the limiting factors of jute cultivation, leaf mosaic being considered the most influencing one. Leaf mosaic can be recognized by few symptoms like small yellow patches on the lamina during the beginning stage of infection which stepwise enhanced in size to form green and chlorotic integrated streaks indicating the presence of a yellow mosaic [1]. From the survey, it has also been observed that infection due to these diseases diminish plant height to the extent of 20% as a result it affects the yield of the most important cash crops [1].

Image processing algorithms and techniques has been playing an important role in agricultural industries for the recent years, especially in the area of leaf disease detection. This research is focused to recognize jute leaf disease using CNN (Convolutional Neural Network). CNN is one of the deep feed-forward artificial neural networks which have the features like local connection, augmentation and pooling operation that make it possible to effectively shorten the network complexity.

The aim of this study is as follows:

a) The proposed CNN method classify two types of jute leaf diseases which classify the jute images with minimal error rate.

b) Detection of jute leaf disease through automatic method will be beneficial for farmers to reduce an arduous work of monitoring in a big farms.

The paper is organized as follows. Section II discusses about the literature review. Dataset, the proposed machine learning classifier, the feature selection methods and the evaluation of classification performance are described in section III. Section IV specifies the classification performance assessments and classifications results. Finally, the conclusion of our work is given in section V.

II. Literature Review

Though very few numbers of researches have been conducted on recognizing leaf diseases in various species apart from jute leaf using the techniques of image processing. In the paper by Zarreen and her co-authors have discussed about the detection of jute stem disease using image processing and machine learning. They have used the color co-occurrence technique and Multi-SVM (Support Vector Machine) classifier for extracting the features for texture analysis. An android app has been developed to provide the result of the users. They have tested the accuracy in two different cases, case I: without hue based segmentation with an accuracy of 60% and case II: with hue based segmentation with an accuracy of 86% [3]. Xiao Sun and his co-authors proposes about recognition of tea leaf disease using image processing and CNN. For the research purpose, they have used BP (Back Propagation) and SVM (Support Vector Machine) classifier to improvise the tea leaf disease recognition efficiency. By using CNN, they have observed an accuracy of 93.75%, whereas the accuracy of SVM and BP neural network is 89.36% and 87.69% respectively [4]. S. Sladojevic and his co-authors have discussed about recognition of 13 different plant diseases by leaf image classification except jute leaf using deep Neural Networks. They have developed a framework to recognition plant diseases by leaf image using CNN. The results of their experiment show that their developed model achieved an accuracy between 91% and 98% [5]. Arivazhagan and his co-authors have offered the detection of unhealthy region and classification of plant leaf diseases using texture features. They have used HSI (hue, saturation, intensity) color model and color, co-occurrence matrix, and SVM (Support Vector Machine) to detect plant leaf diseases. They have also proposed an algorithm, which can successfully detect and classify the examined diseases with an accuracy of 94% [6]. In the paper by Amar Kumar Deya et al. have presented about leaf rot disease detection of betel vine using digital image processing system. Precision of their proposed method is high, but the recall value is low in some cases it is only 50% [7]. Dastogeer et al. have considered about leaf disease detection using light microscopy and PCR (Polymerase Chain Reaction) where they have used PCR methodology to detection of the causal agent of leaf mosaic of jute and they have observed on 1% agarose gels for the sample corresponding to infected plants, using primers [8].

Many researchers have already accomplished to classify different types of plant leaf images (e.g. Tea leaf [4], Betel Vine [7]) through machine learning approach excluding jute leaf image. So, it is necessary to classify Jute diseases by leaf image that will help the farmer to take precautions for infected leaves maintaining the standard level of nutrition (TABLE I) on both vegetables and medicine.

III. Materials and Methods

A. Dataset

Our research used two types of Jute leaf disease dataset which contains 600 images with 350 instances are disease effected image and 250 instances for healthy images.

B. Image Augmentation

In machine learning, deep networks need large amount of training data to achieve good performance. When we train a machine learning model, what we truly do is optimizing its parameters with the end goal that it can delineate specific input (for example, an image) to some output (a tag). Our main objective of fine tuning is to find out that part where our model's loss is low, which occurs when our parameters are optimized in the correct way. Accordingly, we need an ever-increasing number of data. For getting more information, we simply need to make minor modification to our current dataset. Minor changes, in case of images can be generated through augmentation techniques, such as rotation, flips, translation, crop, scale and, etc. For the purpose of the study, we have used flip, rotation and scaling techniques [9].

In flip technique, an image can be flipped horizontally and vertically. A vertical flip is proportionate to flipping a picture by 180 degrees and after that flipping it in horizontal way.

Sometimes, image rotating may cause change of image dimension when rotating the image. 90 degrees, 180 degrees or any kind of rotation will not hamper the image dimension if the image size is square. If it's a rectangle, 180 degrees rotation will not destroy size of image. Moreover, black backgrounds will be visible if the rotating factor is 0.5 positive and negative both.

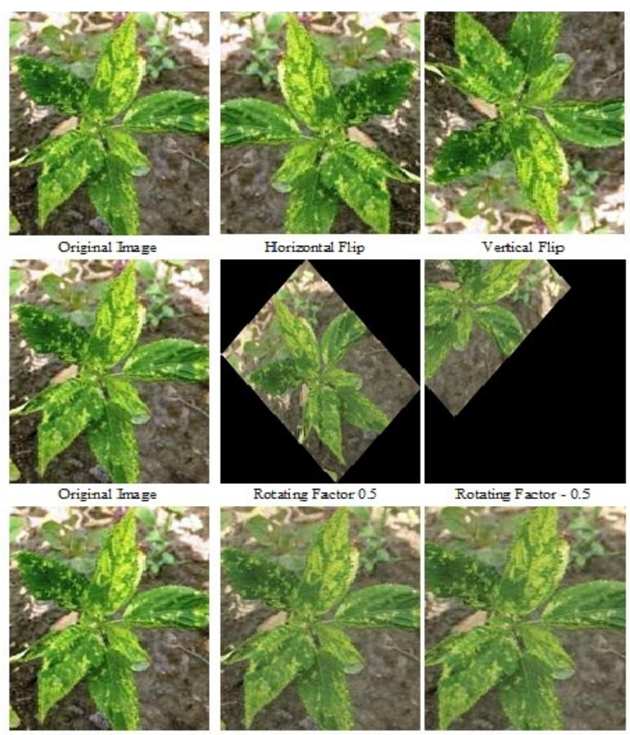

Fig. 1. Flipped, Rotation and Scaled augmentation technique applied in jute leaf image

There are two types of image scaling techniques e.g., outward or inward. Generated image size will be larger than the original image size in case of outward scaling. Inward scaling decreases the image size by guessing the pixel values beyond the boundary. Most scaling techniques cut out a portion from the new image, with size equal to the original image [9]. Outward scaling is used in this work. Fig. 1 shows an example for jute images that are being scaled.

C. CNN Model for Disease Detection

CNN is one of the most efficient deep learning neural network algorithms in the field of computer vision. CNN outperforms in the field of image recognition, image classification, and image segmentation and so on. The main aim of CNN is to process different types of data such as 1D for signal or time series data, 2D for images or audio signals and 3D for video or depth images [10]. As, it has been achieving the state-of-the-art for image classification, we have used traditional CNN to classify our jute leaf image dataset. CNN comprises of two different major parts: feature extraction and classification [11]. Feature extraction part performs in convolution and pooling layers where classification part performs in fully connected layers.

A chain of convolution, pooling operations and fully connected layers are performed during the image classification problem. Input images are passed through the convolutional layer to extract features [12]. The main reason behind using CNN is to reduce the image dimension without losing features when extracting.

Convolutional Layer: An input image size of X×Y is convolved with a kernel (filter), where the size of the filter will be a×a in the convolutional layer. Each pixel of input image is considered as an input matrix convolved with the kernel and generate output image features. convolution operation [17]. The output of the M^{th} convolution layer with Bias B, referred as $\mathrm{output}_i^{(m)}$, comprises of feature maps. The following eq. 1 is used for convolutional operations in our model

$$\mathrm{output}_i^{(m)} = \sum_{j=1}^{a_i^{(m-1)}} K_{i,j}^{(m-1)} * \mathrm{output}_j^{(m)} + B_i^{(m)} \qquad (1)$$

ReLU: Neural Network (NN) can be applied if nonlinearity is found in the dataset. Because of having some drawbacks of Sigmoid function, ReLU is more reliable for non-linear operation [12]. After applying the convolution layer on our jute leaf image dataset, the activation function rectified linear units (ReLUs) in eq. 3 can be employed for nonlinear transformation of the outputs of the $\mathrm{output}_i^{(m)}$ in eq.2.

$$Y_i^{(m)} = Y(\mathrm{output}_i^{(m)}) \qquad (2)$$

$$Y_i^{(m)} = \max(0, Y_i^{(m)}) \qquad (3)$$

In this pixel wise operation, all negative pixel values are replaced with 0 in feature map which reduce the dimensionality of the feature vector [12].

Pooling Layer: The main purpose of the pooling layer is to reduce the complexity of the next layers. There are three types of pooling: max pooling, sum pooling and average pooling or average pooling. Although pooling has no effect on the number of filters [13]. Every image contains a large number of features which is generated in the convolutional layer. These features can cause overfitting problem during training phase. To avoid overfitting problem, maximum pooling is applied by choosing the largest value of the feature map. It also reduces the training time [11]. Max pooling helps in automatic feature extraction technique for our dataset.

Fully Connected Layer: To classify the features the output of the max pooling is fed into the classifier which is called Fully Connected Layer (FC Layer). Not only classifying the features but also FC layers learn non-linear combination of these features [11] [12]. A number of fully connected layers are needed to cover the CNN architecture. High level features of convolutional layer flatten the image into the column vector. This flattened column vector is fed to the feed-forward neural network [14].

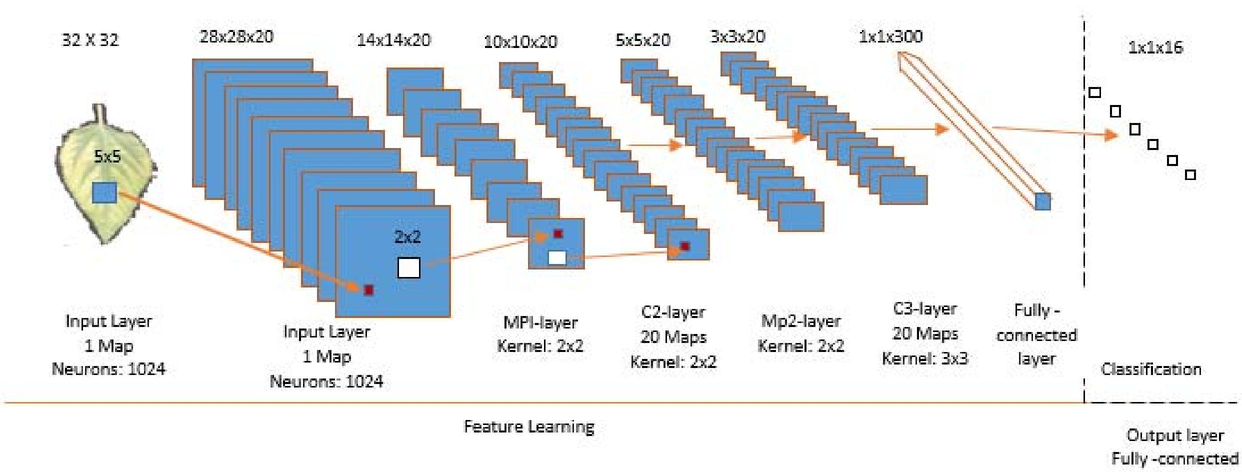

Fig. 2. Proposed Architecture of DCNN

In our dataset every image having a width and height of 32×32 pixels and a depth of 3 (because of RGB channel) [13][14]. Feature vector can be generated by one or more convolutional layer consecutively. A number of kernels are used in every convolution layer. These kernels are convolved with the input image and the depth of the yielded feature maps $K_{i,j}^{(m-1)}$ is proportionate to the number of filters covered in the

Softmax: Softmax function classify the object within the value of 0 and 1 using probability [14]. A softmax activation function is used in the output layer by the following equation:

$$y_i^{(m)} = f\left(z_i^{(m)}\right), \qquad \text{where } z_i^{(m)} = \sum_{i=1}^{d_i^{(m-1)}} w_{i,j}^{(m-1)} y_i^{(m-1)} \qquad (4)$$

where $w_{i,j}^{(m)}$ Are the weights which is updated by the fully connected layer to perform classification of three types of jute diseases and transfer function is *f* which shows the nonlinearity [17].

The training of the CNN is started after getting the output signals. Stochastic gradient descent algorithm is performed while training [15]. The algorithm evaluated the gradients using a single arbitrarily selected example from the training set. Table II shows the parameters of CNN during training phase. Here, a convolution layer represented by "Conv". Every hidden layer consists of Convolutional layer, ReLU and Pooling layer where "Conv" symbolizes Convolutional layer.

TABLE II. CNN TRAINING PARAMETERS

Type of Layer	Description	Output
Input Layer	Input Image	32 X 32X 3 images
Hidden Layer 1	Conv1+Relu+Pool1	14 x14 x 20 2 × 2 kernel with stride of 2
Hidden Layer 2	Conv2+Relu+Pool2	20 feature maps 2 × 2 kernel with stride of 2
Hidden Layer 3	Conv3+Relu+Fully Connected Layer	1 x 1 x 300 2 × 2 kernel
Classification Layer	Softmax	1 Fully Connected Layers

To classify 3 types of jute leaf diseases such as Chlorosis, Yellow Mosaic and healthy, we input images which width and length is 32 and 32 respectively. We applied 3 hidden layers consecutively one after one in this CNN model.

While training, each image of the training data has been resized to fixed 32 ×32 pixel ratio.

Moreover, we have fixed 0.001 as our learning rate in these 3 layered CNN architectures and 99 iterations are considered here to train the CNN model.

IV. CLASSIFICATION PERFORMANCE ASSESSMENT

A deep learning based CNN and three conventional supervised machine learning techniques Random Forest (RF), K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) have been implemented to recognize jute disease based on the leaf. The assessment of the recognition model by the five evaluation metrics [16, 18]. The evaluation metrics are expressed as below:

- Accuracy = (TP + TN) / (TP + FN + FP +TN)
- Sensitivity = TP / (TP + FN)
- Specificity = TN / (TP + FP)
- Precision = TP / (TP + FP)
- G-mean = √ (Sensitivity × Specificity)

Here, TP = True Positive, TN = True Negative, FP = False Positive and FP = False Negative.

V. RESULT ANALYSIS AND DISCUSSION

Python Keras libraries executes to recognize associated tasks. The model has been trained and tested by 80% and 20% images. Table III displays the confusion matrix of CNN and machine learning techniques.

Table IV tabulates the classification results of CNN and machine learning techniques which has been calculated from the confusion matrixes of Table III. Table IV indicates that CNN predicts the highest total of TP of 113 and TN of 233 and the lowest total of FP of 7 and FN of 7 which gives the best results.

TABLE III. CONFUSION MATRIX OF CNN AND MACHINE LEARNING TECHNIQUES

		Chlorosis	Yellow Mosaic	Healthy
CNN	Chlorosis	**38**	2	0
	Yellow Mosaic	2	**27**	1
	Healthy	1	1	**48**
RF	Chlorosis	**30**	6	4
	Yellow Mosaic	9	**18**	3
	Healthy	5	9	**36**
KNN	Chlorosis	**31**	3	6
	Yellow Mosaic	5	**23**	2
	Healthy	3	7	**40**
SVM	Chlorosis	**34**	1	5
	Yellow Mosaic	4	**25**	1
	Healthy	6	3	**41**

TABLE IV. CLASSIFICATION RESULTS OF CNN AND MACHINE LEARNING TECHNIQUES

	TP	FP	FN	TN
CNN	113	7	7	233
RF	84	36	36	204
KNN	94	26	26	214
SVM	100	20	20	220

The classification performance of CNN and machine learning techniques which are measured by the evaluation metrics is displayed in Table V. CNN achieves the best accuracy of 96% where RF, KNN and SVM achieve 80%, 86% and 89% respectively. The highest sensitivity, specificity, precision and g-mean of 94%, 97%, 94% and 95% are also succeeded by CNN.

TABLE V. CLASSIFICATION PERFORMANCE OF CNN AND MACHINE LEARNING TECHNIQUES

	CNN	RF	KNN	SVM
Accuracy	.96	.80	.86	.89
Sensitivity	.94	.70	.78	.83
Specificity	.97	.85	.89	.92
Precision	.94	.70	.78	.83
G-Mean	.95	.77	.83	.87

From the graphs in Fig. 3 and Fig. 4, the maximum validation accuracy of 96% and the minimum validation loss of 4% are accomplished by the CNN during the training accuracy and traiming loss. The validation accuracy increase from the lower to the higher and validation loss decrease from the higher to lower by the icrease of epoch numbers.

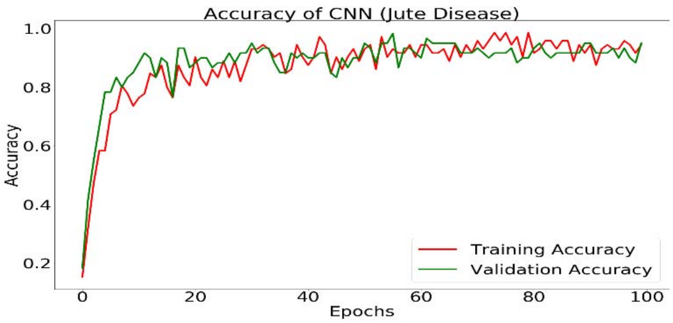

Fig. 3. Training Accuracy vs Validation Accuracy of CNN

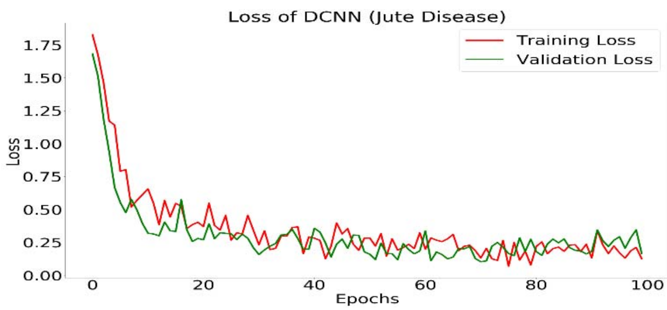

Fig. 4. Training Loss vs Validation Loss of CNN

VI. CONCLUSION

In this paper, CNN is considered for detection and classification of jute leaf diseases. For comparison-based investigation, Random Forest (RF), K-nearest neighbors (KNN) and Support vector Machine (SVM) are implemented for the classification of the jute leaf diseases. Sequence of operations were occurred through training of these networks using various learning parameters and a number of epochs. In observation, the experiments on the given datasets (image size of 32×32 pixels) showed large improvement in accuracy of disease classification and recognition. The development of an application using CNN can help the farmers for taking precaution after cultivating.

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