Classification of Succulent Plant Using Convolutional Neural Network

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Abstract. Machine learning methods such as deep neural networks have remarkably improved plant species classification in recent years. It is very challenging task to classify plant species based on their categories. In this work, deep learning approach is explained to identify and classify succulent plant species using VGG19, three layers CNN and five layers CNN network on our dataset. The proposed architecture achieved a significant result from VGG19 and three layers CNN model. In succulent plant image dataset, there are 10 different classes of succulent and non-succulent plants. The dataset consists of 3632 succulent plant images and 200 non-succulent plant images. The model achieved 99.77% accuracy which performs better than VGG19 and three layers CNN model.

Keywords: Succulent plant · Convolutional Neural Network · Augmentation · Adam optimizer

1 Introduction

Plants are very useful for us in many ways they give us oxygen through photosynthesis process. They also provide us with food and many other things. Plant reducing causes certain levels of pollutants, such as benzene and nitrogen dioxide and keep the air temperature down not just that reduce noise from a busy road. There are many types of plants but we chose succulent plant because it looks very beautiful, grow slowly so space is usually not a problem, medically uses, and purifies air rapidly, and also removes formaldehyde. Most plants release oxygen during the day and at night they release carbon dioxide but succulent plant keep releasing oxygen all night [1]. A research of NASA found that succulent plant like snake plant and aloe vera are capable of removing 87% of volatile organic compounds (VOC) [1]. In the library and study environment, they are extra helpful because VOC element like benzene and formaldehyde are found in books and ink [1]. Succulent plant-like aloes have many medical uses. They use as a laxative, to treat joint pain, skin inflammation, conjunctivitis, hypertension, stress, etc. [2]. They offer us a positive example by saving water and prospering in troublesome conditions,

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advising us that we are more grounded than we understand and even the most exhausting circumstances are not the stopping point [3].

Succulent plants have a worldwide conveyance and they normally come from the dry areas. It may store water in different structures, for example, leaves stems and roots [4]. It has a reputation for being easy to grow. In Africa, Cotyledon Orbiculata is known as "kanniedood", which means "cannot die" [5]. There are more than 30 botanical families of succulent plant from small and large trees [6]. Three types of succulent plants are used for trading, those are Cacti, Aloe and Euphorbia [7]. Because of their capacity to endure dry season conditions and the coming of reasonable warming required to develop these plants outside their regular range, succulent plants are especially supported as house plants [7]. They are popular for house gardening and prized by many plant gatherers because of their irregularity in nature. Identifying a succulent plant is very challenging for non-expert because there are many species that look similar [8]. There are some identification techniques like Visual Identification, Chemical Identification, and Genetic Identification. For Visual Identification plant's characteristics such as size, color, presence of spines, flower or leaf shape are used [7]. Characteristics of a flower is very important because sometimes using other features we can classify to genus or family level. Analyzing the Chemical synthesis of a plant it is possible to classify the plant as mass level. For Genetic Identification DNA pattern is used and it is possible to classify plant to species level [7].

Nowadays, computer vision based techniques like CNN has been playing an important role to classify plant like objects. The point of this research is the proposed CNN technique to identify and classify the succulent plant. This paper is composed as follows: Sect. 2, discusses some previous work-related to plant classification. In Sect. 3, dataset and method have been discussed. Section 4 contains result and discussion of result. Finally, Sect. 5 is the conclusion of the work.

2 Literature Review

There are many researchers work to classify plant through leaf image and flower image and some researchers classify leaf disease but there is no one work with succulent plant image to classify and identify. Belal A.M. Ashqar et al. present plant seedlings classification approach with a dataset. Convolutional Neural Network (CNN) algorithms, a deep learning technique extensively applied to image recognition [9]. Nowadays many researchers using CNN [12] as a classifier and their accuracy is good. N. Valliammal et al. classify plant through leaf image recognition. They converted images from RGB to gray then preprocess the images. For feature extraction, they use border tracing algorithm and for image segmentation, use Preferential Image Segmentation (PIS) method [10]. Shanwen et al. and his co-authors proposed a semi-supervised locally linear embedding (SALLE) to classify plant based on leaf image. They used Manifold learning method for feature extraction and selection & LLE method for avoiding the local minima problems. Used KNN as a classifier and achieve 90% accuracy [11]. K-Nearest Neighbors (KNN) is another popular classification technique. Researchers have used KNN to classify plant type [14], to identify the plant leaves [15]. M.E. Nilsback et al. develop a visual vocabulary as object classifier that explicitly represents the various aspects like color, shape, and texture that distinguish one flower from another [13]. Enes Yigit et al. used support vector machine (SVM) to design an automatic identifier for the plant leaves and gain 94.2% accuracy [15]. Another author used WPROP method and PROP density estimator method and gain 96.69% and 96.82% accuracy [16]. Guillaume Cerutti et al. used some image processing technique like image segmentation, contour detection, image rotation to differentiate among different parts of a tree. To differentiate between foreground and Background used Naive Distance-based Classification for classification purposes [17]. Anxiung et al. worked with flower image and to characterize the color features from flower image they proposed color histogram of ROI and two features sets like Centroid-Contour-Distance (CCD) and Angle Code Histogram (ACH) to characterize the shape features of a flower [18]. Marco Seeland et al. investigates from detection, extraction, fusion, pooling, encoding of local features for quantifying shape and color information of flower images. Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG) methods, Opponent SIFT and C-SIFT, SVM, MKL also used and gained 94% accuracy [19]. M. Turkoglu et al. extracted features from leaves. Color features, vein feature, Fourier Description, Gray-Level Co-occurrence Matrix are calculated by Extreme Learning Machine (ELM) classifier and achieve 99.10% accuracy on Flavia leaf dataset [20]. Another author has discussed many types of research Like ResNet, AlexNet, VGG 16, VGG 19, DenseNet, SqueezeNet, MXNet [21].

Numerous specialists have just achieved to group various kinds of plant leaf pictures through AI approach. Thus, it is important to classify the succulent plant by image dataset.

3 Methodology

In this paper, our methodology contains few stages of workflow such as data collection, data processing, divide the dataset in train set and test set, evaluation of data, identification, classification and accuracy. Figure 1 is showing our workflow diagram.

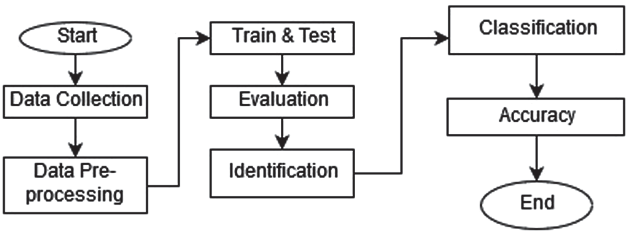

Fig. 1. Workflow diagram

3.1 Dataset

We have made a dataset of succulent plant. We have collected all data from different nurseries from inside and outside Dhaka city. Our data set contains 10 different classes of succulent plant those are Acanthocereus tetragonus, Euphorbia lacteal, Euphorbia trigona, Haworthiopsis limifolia, Hoya Kerrii, Sansevieria trifasciata, Gymnocalycium mihanovichii, Huernia macrocarpa, Mammillaria compressa and others. Our dataset contains 3632 images total. We took 2776 images in the training set and 856 images in the test set. Figure 2 shows different types of data with class name.

Fig. 2. Images of succulent plant and non-succulent plant

3.2 Data Preprocessing

After collecting all the data, we divided our dataset into 10 different classes. 9 classes contain succulent plant and one class contains non-succulent plant. After resizing all images into 240 × 240 pixels with 72dpi in RGB color mode, all the image data are fed to our model. To reduce unnecessary objects from the background, image cropping is done on our images. Adobe Photoshop tools are used for pre-processing our data.

Data augmentation technique is employed to avoid overfitting and expand the dataset artificially. It increases the value of base data by including data got from inside and outside sources within a venture. It helps to get better result by increasing data of the dataset. Figure 3 shows an example of a succulent plant that are augmented.

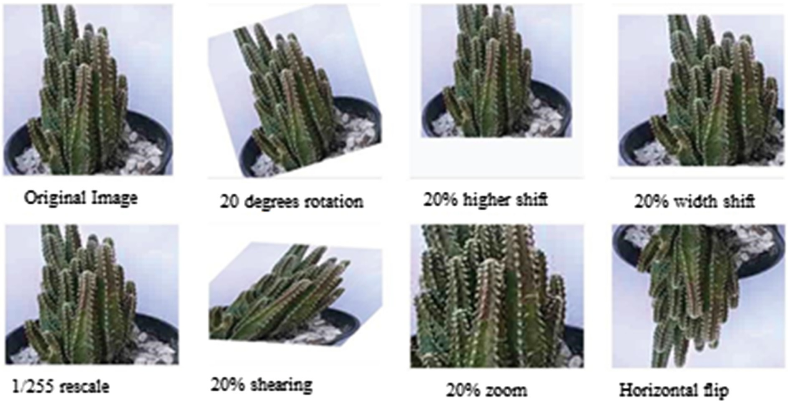

Fig. 3. Augmented image data of succulent plant.

3.3 Proposed Architecture

In the computer vision field, CNN is one of the most productive deep learning algorithms. CNN mostly used for image recognition, image classification, etc. We have proposed a CNN model to classify our succulent plant dataset. CNN contains two diverse significant parts: feature extraction and classification. In convolutional layers feature extraction performs and in the fully connected layer classification performs. There are five convolutional layers, four pooling layers and one fully connected layer in our proposed architecture. Our first convolutional layer is input layer and its padding is same, the filter size is 32 with 3 × 3 kernel and its input size is 240 × 240 with RGB color mode. In this layer, ReLU activation function is used and max-pooling layer with pool size 2 and stride 2 is used to reduce the parameter with 25% dropout. Filter size of the second convolutional layer is 64 filter size with 3 × 3 kernel with same padding and strides 1. To increase the stability of the convolutional network batch normalization is used in this layer. Our third convolutional layer is 64 filter size with 3 × 3 kernel and its padding are same and strides 1 with batch normalization and the result go through next max-pooling layer and dropout layer. The output of the third layer is the input of the fourth layer. Our fourth convolutional layer is 64 filter size with 3 × 3 kernel, same padding with 1 × 1 strides and the output goes through batch normalization, ReLU, max-pooling layer and dropout layer as like the previous layer. Filter size of our fifth convolutional layer is 256 with 3 × 3 kernel, same padding with 1 × 1 strides. The output goes through batch normalization and ReLU and max-pooling layer as like a previous layer than goes through another 25% dropout layer. After all, five-layers, there is a fully connected layer or dance layer. Our fully connected layer has 512 hidden nodes with batch normalization, ReLU and activation with a 50% drop out with softmax activation (Fig. 4).

3.4 Performance of Proposed Architecture

For training the model, we input our training data and test data into the model. We have used 76% of data for training the model and rest of the data is used for testing purpose.

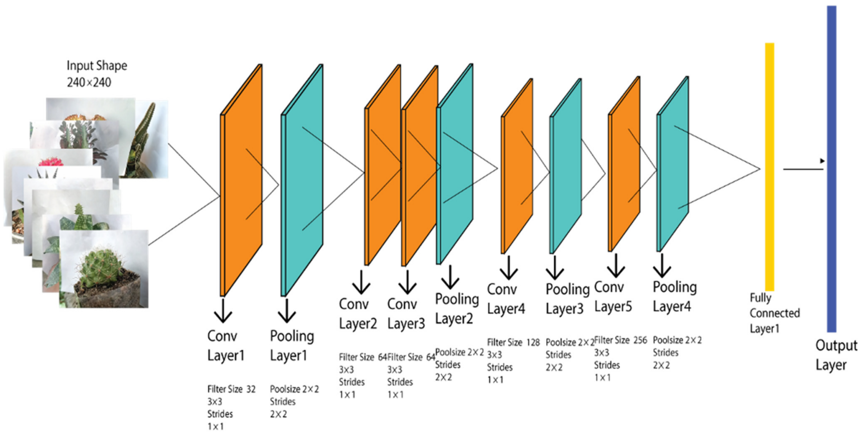

Fig. 4. The architecture of the proposed CNN model.

Fixed sized of 240 × 240 image is the input of the model and applied 5 convolutional layers, four max-pooling layers respectively and a fully connected layer in the network. While training all images from training set the image data is also used to fix 240 × 240 pixel ratio into the first layers. While training, the model pooling layers help to gradually reduce the spatial size of the representation for minimizing the number of parameters of the network. Adam Optimizer is used to compile our model. We fixed value of learning rate 0.000001, our proposed method uses Adam optimizer. From test set and train set we get some data in the validation set. We have run 40 epochs in our model. We used the same dataset in other two model which are VGG19 and another CNN and this CNN network were based on four convolutional layers, three max-pooling layers and one fully connected layer. Table 1 shows the accuracy of the different model which was applied to our dataset.

Table 1. Accuracy comparison of three models

Model	Accuracy
VGG19	95.86%
Three layers CNN	97.66%
Proposed CNN model	99.77%

4 Experimental Result and Analysis

We separated our dataset into two sets like the training set and test set. There are 76% data of our dataset in the training set and the rest of the data is in the test set. From test set and training set, some images are taken and made the validation set of data for validation purposes. An error of the training set of data is called training loss. After running the validation set of data through the trained network, we get some error. This error is called validation loss. Train error and validation error drop with the increasing epochs. With the drop of train loss and validation loss, train accuracy and validation accuracy increase rapidly. In Fig. 5 training loss vs validation loss and training accuracy vs validation accuracy can be noticed.

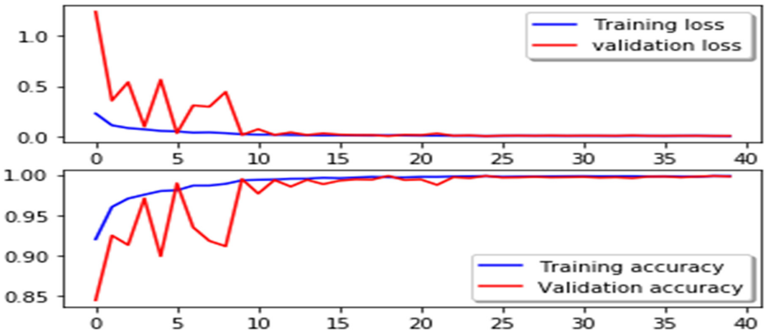

Fig. 5. Training loss vs validation loss, training accuracy vs validation accuracy.

A survey of prediction results on a classification problem is called a confusion matrix. The number of correct and incorrect prognostications are reviewed by each class with count values and broken down. After completing our work, we get our confusion matrix in Fig. 6.

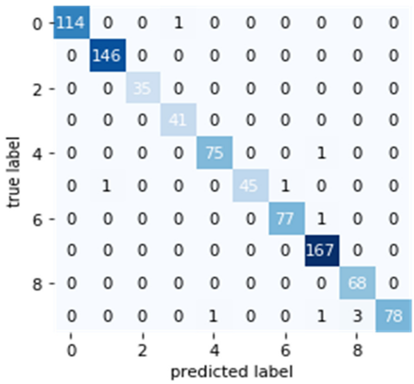

Fig. 6. Confusion Matrix

We have used the average accuracy performance metric based on the confusion matrix. Confusion Matrix has four components True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). From our confusion matrix (Fig. 6), we have calculated our total TP = 846, TN = 7693, FP = 10, FN = 10 values.

Accuracy can be measured from TP, FP, TN and FN values. Table 2 is showing the classification performance of the proposed architecture based on the confusion matrix.

Table 2. Classification performance of the proposed architecture.

Measure	Value	Derivation
Accuracy	0.9977	ACC = (TP + TN)/(TP + TN + FP + FN)
Precision	0.9883	PPV = TP/(TP + FP)
Recall	0.9883	RC = TP/(TP + FN)
Specification	0.9987	SPC = TN/(FP + TN)
Negative predictive value	0.9987	NPV = TN/(TN + FN)
False positive rate	0.0013	FPR = FP/(FP + TN)
False discovery rate	0.0117	FDR = FP/(FP + TP)

In Table 3, we compare our model accuracy with some similar work and can see our result is better than other methodologies.

Table 3. Comparison result with existing models.

Author name	Category	Algorithm	Accuracy
Ashqar, B.A.M., AbuNasser, B.S., Abu-Naser, S.S (2019)	Plant seedlings classification	CNN	99.48%
Zhang, S., Chau, K.W. (2009)	Plant leaf classification	SALLE, K-NN	90%
Siraj, F., Salahuddin, M.A., Yusof, S.A.M. (2010)	Digital image classification for Malaysian blooming flower	CNN	67%
Yigit, E., Sabanci, K., Toktas, A., Kayabasi, A. (2019)	Plant leaf identification	SVM	94.2%
Proposed architecture	Classification of succulent plant	CNN	99.77%

5 Conclusion and Future Work

In this paper, we proposed a deep learning approach to classify 10 different classes of succulent plants through the CNN model. Five convolutional layers, four max-pooling layers are considered for building our network model. Dropout layer is imposed in each fully connected layer for reducing the overfitting in the system. Rotation, Shifting, Scaling, Shearing and Flipping data augmentation approaches are employed for augmenting the dataset. After successful completion of 40 epochs, the model achieves 99.77% accuracy with the dataset. In this study, we consider total 9 classes of succulent plants which is insufficient to optimize the model or make difficulty to other unknown succulent species. Therefore, our future aim is to augment number of succulent plant classes for better optimization and make an android app which will help the user to identify succulent plant.

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