International Journal of Modern Agriculture, Volume 9, No.3, 2020
ISSN: 2305-7246

Grapes Leaf Disease Detection Using Convolutional Neural Network

Gopal Ghosh[1], Sujata Chakravarty[2]
[1,2]Centurion University of Technology & Management, Bhubaneswar, Odisha, India
Email:[1]Gopalghosh268@gmail.com, [2]sujata.chakravarty@cutm.ac.in

Abstract

Grapes production is the most vital grown Fruit crop in India. Due to leaf diseases the productivity is decreased by various types of diseases on fruit. It is mainly caused by fungi, bacteria etc. It reduces the limit fruit production and to control the increased disease without accurate disease diagnosis, and proper action to control at appropriate time. Image Processing is one of the essential techniques for leaf disease detection. In this paper is to vary in leaf detection of grapes using CNN Classification technique. To start with first the diseased region is founded by using segmentation. Then both colour and texture features are extracted and resized in pixel and intended. Then finally used the classification technique to detect the disease leaf. The system can successfully classify the disease with accuracy of 98%.

Keywords: Image Processing; Augmenting; Pre-processing; Classification; Conventional neural network (CNN).

Introduction

Grape is a very commercial fruit crop of India and ranks as the seventh-largest producer of grapes in the world [1]. Maharashtra Comes first rank in terms of production of grapes as it accounts for more than 81.22% of the total production of India is the major exporter of fresh grapes in the world [2]. Fresh Grapes are widely consumed and made raisins in India [3]. Fragmented Grapes are widely used for production of drinks like wine and brandy [4]. However, grape leaves diseases have hindered the development of the grape industry and caused significant economic losses [5]. Hence, the diagnosis and identification of leaf diseases have received extensive attention from orchard workers and experts on disease and pest control [6].

Diseases present in plants are the genesis of crop losses over the world [7]. Grape plants are highly vulnerable towards diseases like black rot, Esca, Leaf Blight, Healthy insect pests like beetle, thrips, wasps etc [8]. And disorders like berry drop, berry cracking. Pest can be controlled using sprays [9]. But in case of diseases, timely detection and treatment efforts need to be taken so that appropriate control measures can be taken to have a healthy grape yield. [10].

Related work

To reduce the diseases from plant researchers made tremendous efforts to identify Leaf diseases [11]. With continuous development of machine learning algorithms, they have widely utilized to identify plant infected and diseases [12]. In (Hamuda et al, 2017). proposed an automatic crop detection algorithm [13]. This algorithm is used to detect cauliflowers disease from live video streams under natural light in different weather conditions, and the detection results compared with ground-truth data that were obtained via manual annotation [14]. This algorithm organised a sensitivity of 98.91% and a very precision of 99.04%. In another article, leaf features of plant are divided into 2 categories which are general visual features and domain related visual features [15]. The normal visual features are dwell of texture, colour and shape. These features were known as common features on images and no alliance with other type and content of images [16]. Visual features that are Domain-related mixed with morphology character of a leaf are shape, width and vein. Also domain related visual features are necessary for feature extraction process .Local descriptors and Global features are 2 groups, which are derived from common features as explained by Shabanzade et al. (2011)[17]. Generally the global features are properties that describe a leaf shape, such as width, leaf area and length. Local descriptors explain leaf details such as correlation, homogeneity, contrast and texture [18]. The skeleton, colour and shape are most important features for plant classification. In their publications Valliammal and Geeta Lakshmi had declared that leaf image could be classified on the basis of colour, shape, texture or combination of all properties [19]. Were Zhang (2008) added some features such as surface perimeter, surface area and variance of green, red and blue channels that belongs to colour features and some texture features like texture entropy, texture energy and texture contrast [20]. In (Ji et al., 2019), Ji et al. proposed a united convolutional neural Networks model architecture based on its integrated method. The proposed CNNs architecture, namely, United Model was designed to classify common grape leaf diseases [21]. United Model was able to extract complementary discriminative features owing to the combination of multiple CNNs. And the experimental results had shown that United Model realized the best performance on various evaluation metrics and achieved an average test accuracy of 98.57%[22]. According to studies, CNNs have obtained best results in plant disease recognition. However, CNNs is very rarely used in the field of grape leaf disease detection [23]. In addition, most application image identification algorithms are based on popular transfer learning techniques, and few Improvements have been made to the algorithms [24]. Hence, an image identification is based on CNN Model for grape leaf diseases is proposed in this paper.

Methodology

There are four important stages that are proposed in this model: Data acquisition, Image processing and Image segmentation, Feature extraction and the last Classification as shown in [Figure-1].

Algorithm

STEP I: After retrieving images from the dataset, each image data augmentation. The diseased leaves are transformed (including 90 degrees, 45 degrees, 180 degrees, and 270 degrees) by flipping, horizontal and vertical operations and save into train dataset.

STEP II: After retrieving images from train dataset, each image through following pre-processing process like (Resize image size to 256*256, converting image to Smoothing image using Gaussian filter)**.**

STEP III: Extraction of features in leaf image using several feature extraction methods such as: colour based features RGB (red mean, green mean, blue mean), texture based features (contrast, correlation, inverse difference moments).

STEP IV: Converting the labels to categories for model compatibility depending on the images to their respective class (one healthy class, three diseases class) with values from 0 to 4.

STEP V: Modelling the classifier by using Training dataset 80% of the data. By the help of Neural Network Techniques.

STEP VI: Validating the model Using Testing dataset (rest of the 20% data) and Comparison of result.

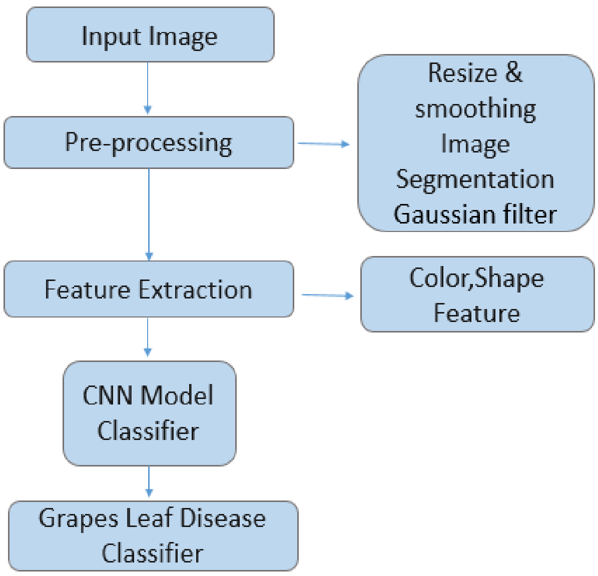

Figure 1: Flow Diagram of the Model

Convolution Neural Network (CNN)

CNN is that only the layer that is fully connected. CNN model includes three parts: Where the first part is the "pre-network module",and its first deep separable convolutional layer is filtered with 64 kernels of size 3 × 3. Then, 3 × 3 max-pooling layer is added after the first deep sap rate convolutional layer. The next step deep separable convolutional layer contains 64 convolution kernels of size 3 × 3, which is followed by a 3 × 3 max-pooling layer and a batch normalization layer. Than Next, there is an Inception structure, which is followed by another max-pooling layer. The second module, "cascade dense Inception module". Which is composed of four Inception structures with in dense connections. The application of dense connectivity strategy improves there usage efficiency of feature maps and promotes the fusion of multi-dimensional features among the Inception structures, enhancing the diagnostic performance for grape leaves disease. The last module is composed of two max-pooling layers, an Inception layer, and a 7-way Softmax layer given in [figure-2].

A Convolutional Neural Network (CNN) has four layers, Convolutional Layer (CONV), Rectified Linear Unit Layer (ReLu), Pooling Layer (POOL), Fully-Connected Layer (FC).

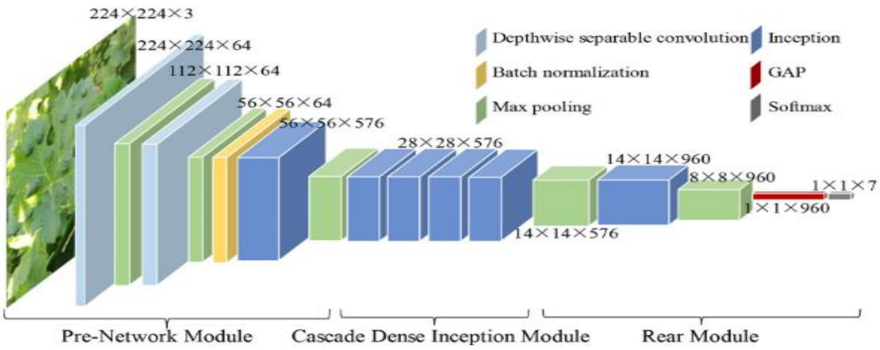

Fig 2. CNN Model

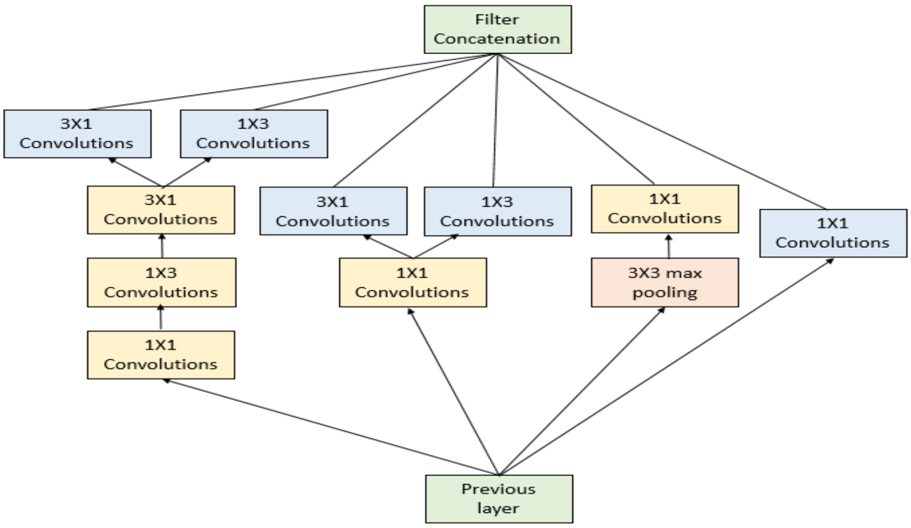

Figure 3: CNN Model

Convolutional Layer

In Convolution it is first layer which it is used to extract the features of an input image. It established the connection between pixels by learning image features using small small squares from an input data. The Layer contains N no of filters which are very small in size (for example [3x3]). These 3x3 filters are convoluted with in the input image matrix by sliding its filter slide through width and height of the image. Firstly, the feature matrix and it is multiplied pixel by pixel with in the selected square from the image. Then the values are added and finally it divided by the total no of pixels (in example it is 9 due to 3x3 filter size).

The obtains value is inserted in a new matrix. This process helps to reduce the image without loss or other any feature.

Rectified Linear Unit Layer

In ReLu layer the pixels are not necessary. Pixels are deactivated only the important pixels which are kept. From Convolutional layer we get positive as well as negative pixel values. The positive pixels are important for finding of features and the negative values are of less importance. The ReLu layer either converts the pixels into 0 or 1. it is converted to 0 If the value of pixel is negative then and for any value greater than 0 it retains the same value.

Pooling Layer

In pooling layer it does a simple job of down sampling or compressing the dimensions of Pixel of input image. A long step is selected as which can be 2x2 or 5x5 etc. After selection a long step it is applied to the dimension matrix obtained from the Convolution Layer. The Maximum value is taken from each long step and stored in a new matrix. Depending on the long Pooling is of two types Max and Min Pooling. When the long step is large such Pooling is known as Max Pooling where as small step is known as Minimum Pooling. For example, if the input is [64*64*12] and if a stride of 2x2 is applied then after down sampling the output will be [32*32*12]

Fully-Connected Layer

In Fully Connected Layer has neurons that all are fully connected to all the neurons of the previous layer. Multiple Fully Connected layers are stacked as per the architecture used. It is often the last layer which is used in CNN which is responsible to predict the output or the label of the input classes. Different activation functions are used like softmax which is used to classify multiple-class problems. Hence, it is an output dimension of [1x1xM] where M is the no of classes or labels that is used for classification.

Data Set

The images of Grapes leaf disease have been collected from Plant Village repository. The collected dataset has almost 5,769 images that belongs to 4 various classes in [figure-3]. It include images of all types of leaf diseases that occurs in Grapes plant. Each and every downloaded images are in the RGB colour space and were saved in JPG format. The details of dataset provided in [figure-4] (Table-1)

Table1: Dataset

Label	Category	Number	Training samples	Test samples
1	Black rot	3637	3007	630
2	Esca_(Black Measles)	3669	3009	660
3	Leaf blight_(Isariopsis_Leaf_Spot)	3638	3008	630
4	Health	2254	1614	640
Total		13,198	10,638	2,560

Figure 4:(a) Esca_ (Black Measles); (b)Black rot; (c) Leaf blight_ (Isariopsis_Leaf_Spot); (d) Healthy;

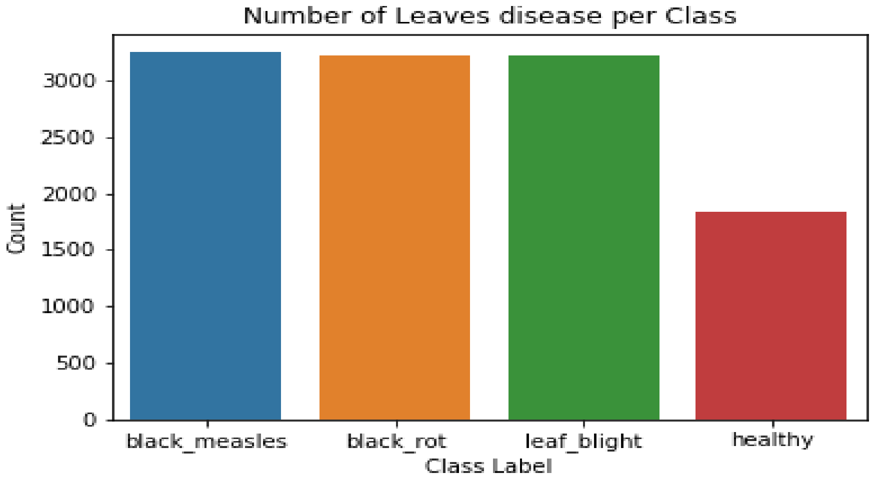

Figure 5: Leaf per Class

Data Argumentation

The overfitting problem in the training set data using CNN can be overcome via data augmentation. Digital image processing technologies are used for data augmentation operations. Which include interference of image brightness, contrast, and sharpness. The relative positions of the camera, and the diseased leaves are imitated via rotation transformations (including 90 degrees, 45 degrees, 180 degrees, and 270 degrees) and flipping via horizontal and vertical symmetry operations. Gaussian filter, interference of contrast, and sharpness are used to simulate the effects of equipment factors shown in [figure-5]. The brightness values of each image are randomly adjusted by increasing or decreasing the RGB values of the pixels.

Figure 6: Data Argumentation

International Journal of Modern Agriculture, Volume 9, No.3, 2020
ISSN: 2305-7246

Pre-processing

Image dataset obtained consists of variable dimensions of images. The images are broken into multiple images of dimensions 256*256 resolution so that the training process of the model should be increased and beneficial for the computation. The importance of normalizing either input or output variables lean or needed to increase the training process speed. It is done by improving the numerical conditions of the normalization problems. Normalization also helps to get all pixels values of images in a particular range by using the standard deviation and mean value. Smoothing of images by using Gaussian Filter. It is a linear filter. It's usually used to reduce noise or to blur the image. It is also used for edge detection. The Gaussian filter is helpful to blur, reduce contrast and edges. Adaptive image thresholding using thresholding method. Image thresholding is a simple, effective way of partitioning an image into a background and foreground. This image analysis method is a type of image segmentation that segregate objects by transforming grayscale images into binary images. Closing of holes using Morphological Transformation. Were morphological transformations are some simple operations based on the image shape. It is normally performed on binary images. It needs two inputs, one is our original image, and the second one is called a kernel or structuring element which decides the nature of operation shown in [figure-6].

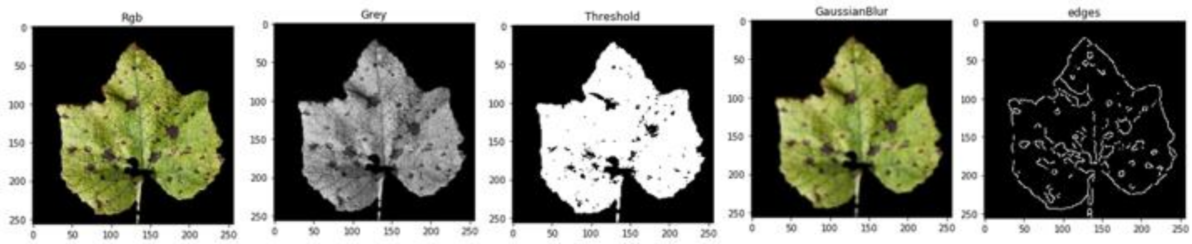

Figure 7: Data Pre processing

Feature Extraction

Image processing, algorithms are used to detect various desired shapes (Features) of digital Image. In this method various features of plant leafs were used like: shape features, colour Features, texture features. Shape feature include features like Surface area, Surface Perimeter, Disfigurement. Shape features are essential as they provide different methods to define an image, using its most essential characters and dimension the amount of data stored. It is common to use colour features for image classification. Colour features can be extracted by using red, green and blue channels of image respectively. Texture feature might be useful to depict certain repeated patterns and arrangement regularity in specific part of images, could be used to describe the characteristics of images, and could provide characteristics metrics such as contrast, correlation and homogeneity. Where texture features can be extracted by using mahouts method. Feature extraction is particularly important in the area of optical character recognition or classification.

Result

As we have undergone for the classification of the spectral images, we need to compare the results of the different classifiers. Hence an assessment criterion has to be used in order to evaluate the degree of extent, how much a classifier has performed better in identifying the classification result and the original features. For this we have taken 4types of grapes patches from the dataset and passed their data to the classifiers and assigned them the classes 0,1,2,3 where 0 stands for Esca_ (Black Measles)and class 1 stands for Black rot and class 2 stands for Leaf blight_ (Isariopsis_Leaf_Spot) class 3 stands for Healthy;

Some commonly used assessment indicators are confusion matrix, overall accuracy etc.

Confusion Matrix

The confusion matrix is also known as the error matrix, the main job of the confusion matrix is to compare whether the classification result is matching with the ground truth or not.

$$X = \begin{matrix} x11 & x12 & \cdots & x1c \\ x21 & x22 & \cdots & x2c \\ \vdots & \vdots & \ddots & \vdots \\ xc1 & xc2 & \cdots & xcc \end{matrix} \quad (1)$$

Here the c stands for a number of categories and X_{ij} (i, j=1,2...c) is the number of samples and X_{ii} on the diagonals represents the same sample points that were divided correctly.

Performance of each grape leaves disease has evaluated by Precision, Recall and F1 Score. Confusion matrix, is best for expressing accuracy, is expressed by matrix in (n rows and n columns). Each column stands for number of instances in a ground truth class while each row stands for number of instances in a predicted class to see confusing two classes. Precision, Recall and F1 Score are derived as number of false positive (FP), true positive (TP), false negative (FN), and true negative (TN) results.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Overall Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Overall Accuracy

The overall accuracy refers to the ratio of the samples points which were predicted correct over the original set of samples. Confusion matrix and Overall Accuracy.

Table 2: overall accuracy

Class	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
0: Esca	99	98	98	98.33
1: Black rot	98	99	99	98.66
2: Leaf Blight	99	98	97	98
3: Healthy	97	99	99	99.33

Result and Discussion

To analyse the performance of the models based on the input extracted feature set, Overall accuracy has been considered and listed in. Best classification accuracy of 98% is achieved by the CNN model.

The model is evaluated using 7429 augmented images and run for 10 epochs. The performance of the classifier evaluated in terms of sensitivity, specificity and overall accuracy as shown in [table-3] is calculated using sklearn.metrics. Presenting the model coefficient and model loss. Is a frequently used performance criterion to evaluate success in Fruits images. Calculated model accuracy and model loss is shown in [figure-7].

Figure 7: Loss

Accuracy	98.55%
Loss	4.86%

Table3

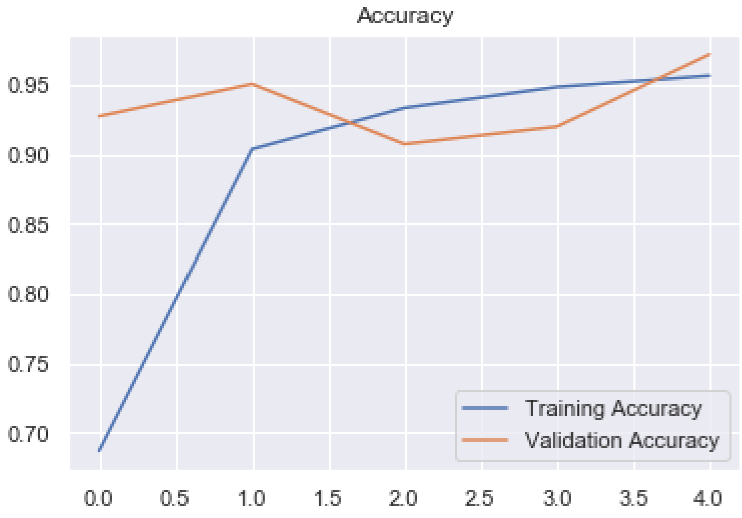

Figure 8: Accuracy

Conclusion

In this project, has proposed a deep learning approach for identification of four common grape leaf diseases. Based on 5,769 collected grape leaf images and rest 13,198 images were created by image augmentation. By analysing the features of grape leaf diseases, and to predict this CNN model for the identification of grape leaf diseases. The deep convolutional was applied to the model to alleviate overfitting and reduce the number of parameters. In visualizing various sizes of grape leaf disease spots, Inception structures were applied to the model for enhancing the ability of the multi-scale feature extraction.

This CNN model is used to identify approaches for grape leaf diseases was implemented in the Tensor Flow and Keras frameworks on the GPU platform. With the data set, this proposed CNN model was trained to classify four type of grape leaves disease. According to the experiment result, the proposed algorithm realizes a recognition accuracy of 98%, which gives better performance. Than other popular learning techniques. The proposed of CNN model is to realizes higher convergence speed during the training process and higher accuracy.

Reference

1. Ji, Miaomiao, Lei Zhang, and Qiufeng Wu. "Automatic grape leaf diseases identification via United Model based on multiple convolutional neural networks."*Information Processing in Agriculture* 7.3 (2020): 418-426.
2. Xie, Xiaoyue, et al. "A Deep-Learning-Based Real-Time Detector for Grape Leaf Diseases Using Improved Convolutional Neural Networks." *Frontiers in Plant Science* 11 (2020).

3. Liu, Bin, et al. "Grape Leaf Disease Identification Using Improved Deep Convolutional Neural Networks." *Frontiers in Plant Science* 11 (2020): 1082.
4. Ali, H., Lali, M. I., Nawaz, M. Z., Sharif, M., and Saleem, B. A. (2017). SymptomBased Automated Detection of Citrus Diseases Using Color Histogram and Textural Descriptors. Comput. Electron. Agric. 138, 92–104. doi: 10.1016/j.compag.2017.04.008
5. Heisel, S., Kovačević, T., Briesen, H., Schembecker, G., and Wohlgemuth, K.(2017). Variable Selection and Training Set Design for Particle Classification using a Linear and a Non-Linear Classifier. Chem. Eng. Sci. 173, 131–144.doi: 10.1016/j.ces.2017.07.030
6. Kaur, P., Pannu, H. S., and Malhi, A. K. (2019). Plant Disease Recognition Using Fractional-order Zernike Moments and SVM Classifier. Neural Comput. Appl., 1–20. doi: 10.1007/s00521-018-3939-6
7. Xie, Xiaoyue, et al. "A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks." *Frontiers in Plant Science* 11 (2020).
8. Liu, Bin, et al. "Kiwifruit Leaf Disease Identification Using Improved Deep Convolutional Neural Networks." *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)*. IEEE, 2020.