Automated Plant Leaf Identification and Classification using Deep Learning Methods

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Abstract:

Artificial Intelligence provides huge support for image processing. With the use of artificial intelligence methods the image detection and recognition is done. The deep learning methods are useful to handle images and produce results with its methods. Deep learning is one of the machine learning methods which is more useful in image processing. In this paper, the convolutional neural network method is used for plant leaf identification. This research work will be useful for farmers to identify the 14 different plants. The VGG-16 architecture model is used for implementing this plant leaf identification and classification process. The developed model produced more than 85% of accuracy in classification.

Keywords: *Plant leaf identification, Deep learning, Convolutional Neural Network, VGG-16, Image Pre-Processing, Feature Extraction.*

1. Introduction

Agriculture is the essential sector which satisfies the food requirements. The technology improvements are used for the development of agriculture domain which can enhance the productivity of agricultural process. By using the innovative methods, the farmers can avoid losses in agriculture process. To improve the increased productivity, the advanced techniques are required. Deep Learning methods are effective which can handle the images and produce good pattern matching. These deep learning methods are classified into two main types. Those are supervised techniques and unsupervised techniques. The supervised methods are used pre-training methods. These pre-training methods are used for provide training to the convolutional neural network to classify the images. The unsupervised methods are used for classifying the images without pre-training. The convolutional methods are processed based on pre-training methods. This Convolutional Neural Network supports different types of architectures like AlexNet, VGG-16, Inception v3, GoogLeNet and etc.

Convolutional Neural Network contains four main layering processes. Those are

- Convolutional Layer
- Pooling Layer
- Fully connected layer and
- Activation Function

The initial layer in convolutional Neural Network is Convolutional layer. These layers are used to provide filtering techniques in images. This filtering process can take essential features form the input images. The feature map is created for input images and this will be useful for effective prediction. The pooling layer is the next followed layer which can use this feature map and dimensionality reduction process. The max pooling is the famous methods that will be used to take the maximum value of feature map for classification process. Fully connected layer is used

for providing connection to all the input nodes with all output nodes. This provides the classification function for classifying the images. Various activation functions are used in convolutional neural network. For this research work Softmax activation is used.

2. Literature Review

Yu Sun et al (2017) proposed the plant identification system with the use of deep learning methods. For this research work, they used real-time images which are captures by mobile phones. The collected dataset contains more than 10,000 images and 100 different plants. These images were collected from University campus of Beijing forestry. They used deep learning model with 26-layers. They used convolutional neural network methods for plant classification. Their execution results provided 91.78% accuracy.

Konstantinos G.Liakos et al (2018) reviewed use of machine learning methods in agricultural domain. They analyzed the crop management, livestock management, soil management and water management for the crops. The filtering and classification methods are discussed in the process of image processing. Different machine learning methods are used for classification of agriculture crops. This work reviewed the various classification methods and their accuracy in various processes.

Nanyang Zhu et al (2018) presented the use of deep learning methods are used for smart agricultural processes. They highlighted the different deep learning method which are used in image processing and pattern matching. This research work presented the deep learning concepts, limitations and tools used for agricultural process. They reviewed convolutional neural network, recurrent neural network and Generative Adversarial Network methods which are used for agricultural domain.

Konstantinos P. Ferentinos (2018) proposed the deep learning models for plant disease identification. The dataset contains training data ad testing data for making effective detection. The pre-training is given to the deep learning models with the use of training dataset. The testing dataset provide the efficiency of used model in plant disease identification. The proposed system provides 99.53% of accuracy in disease prediction.

Vinit Bodhwani et al (2019) proposed the Deep residual Networks for identification of plants. for providing the fact performance in plant identification, the convolutional neural network model is used. The proposed mode contains 50-layer in deep which produced 93.09% of accuracy in identification of plants. For this research work, they collected real-time images using digital cameras.

3. Proposed Work

For this Automated Plant leaf identification and classification process, the dataset is collected from Kaggle Repository. This dataset contains 14 different plant leafs are selected. Those are Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper, Potato, Raspberry, Soybean, Squash, Strawberry and Tomato. After collecting the dataset, the image pre-processing methods are executed to find the repeated images and noisy images. These images must be removed because these images can decreased the prediction accuracy of the developed system. The convolutional neural network supports the process of feature extraction. This will be used for

finding the important features form the images. The unwanted details are removed from the images in the continuous layering process of CGG-16 model.

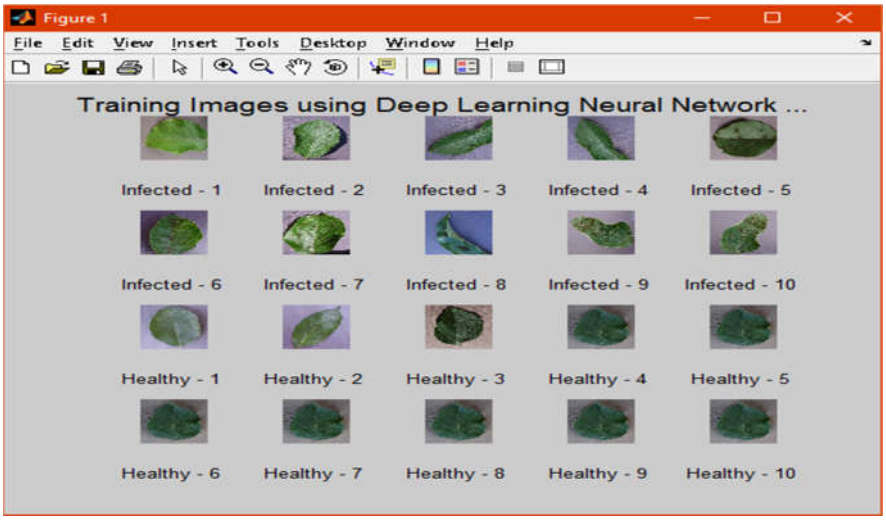

Figure-1: Collected image samples for Training

4. Architecture Model

The VGG-16 model is used for identifying and classifying the plant leaf using pre-training methods. This architecture model contains 16 layers for this research work. The training model contains 80% of images sample to avoid overfitting and produce effective results in detection and classification of plant leafs.

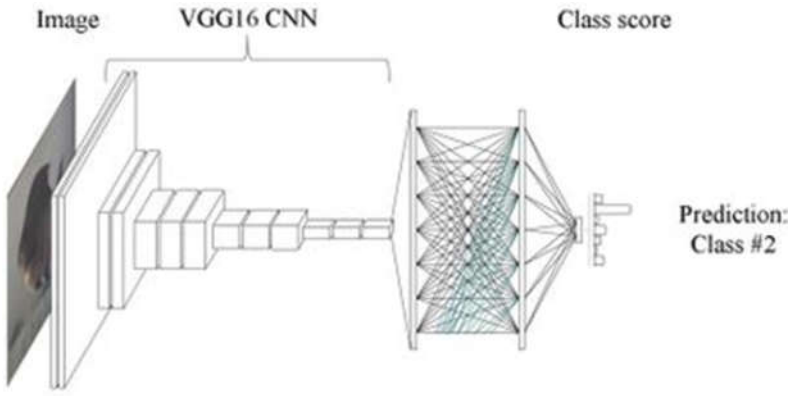

Figure-2: VGG-16 architecture model

The collected images are divided for training and testing processes. For providing training to VGG-16 model all the plant leafs are randomly selected and gave training to classify the correct leafs. After that, the testing process is done. This research work used Softmax activation function which provided effective results in major classification problems. This has the following formula:

$$\frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

This Softmax activation function is used for building a multi-class classifier. This can give possibilities in each class for the defined multi-class problem.

5. Execution Results:

MATLAB tool is used for the execution of VGG-16 architecture model for the identification and classification of 14 different plants. The execution results are resented in this chars. This is used to know the values which are used for performance measurements.

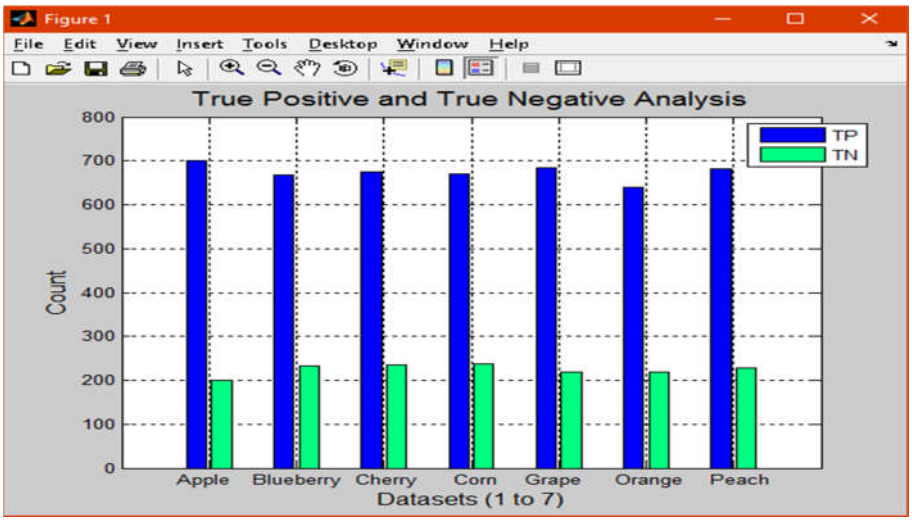

Figure-3: Testing Results: True Positive and True Negative (1-7 plants)

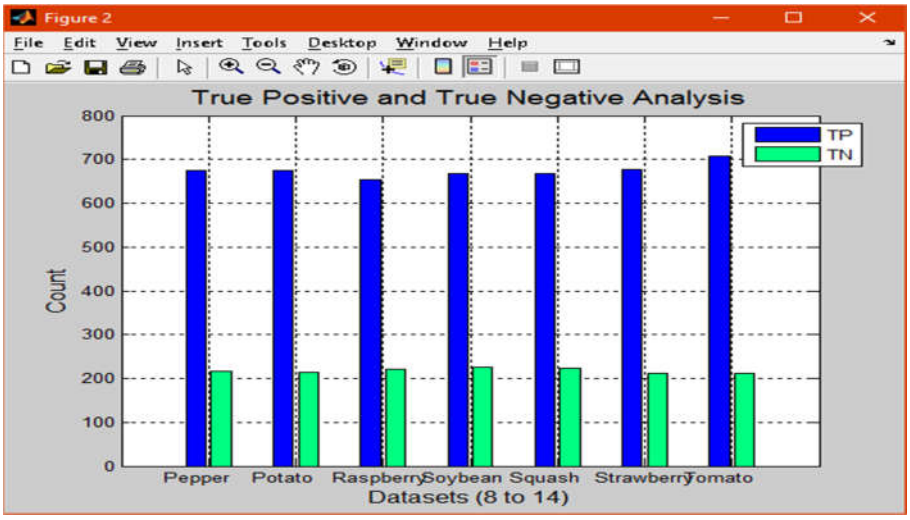

Figure-4: Testing Results: True Positive & True Negative (8-14 plants)

The execution results are used for analyzing the effectiveness of used model in the plant leaf identification and classification process.

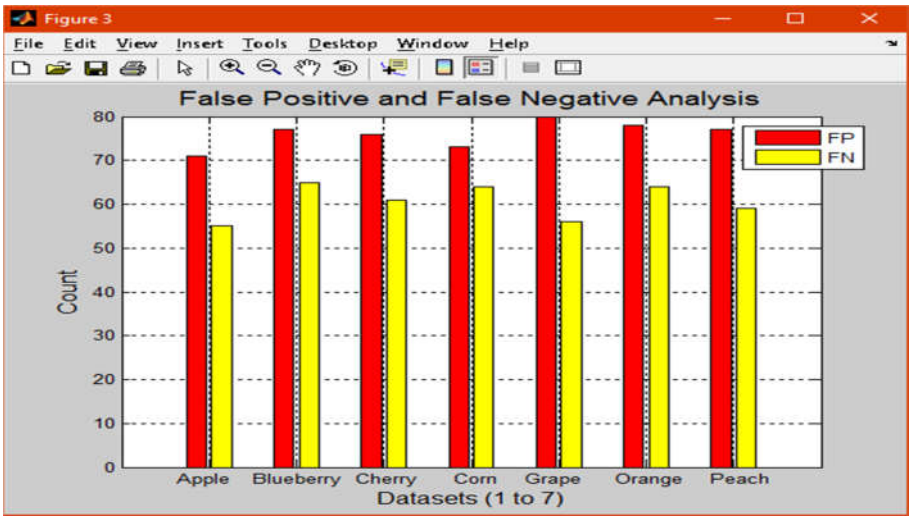

Figure-4: Testing Results: False Positive & False Negative (1-7 plants)

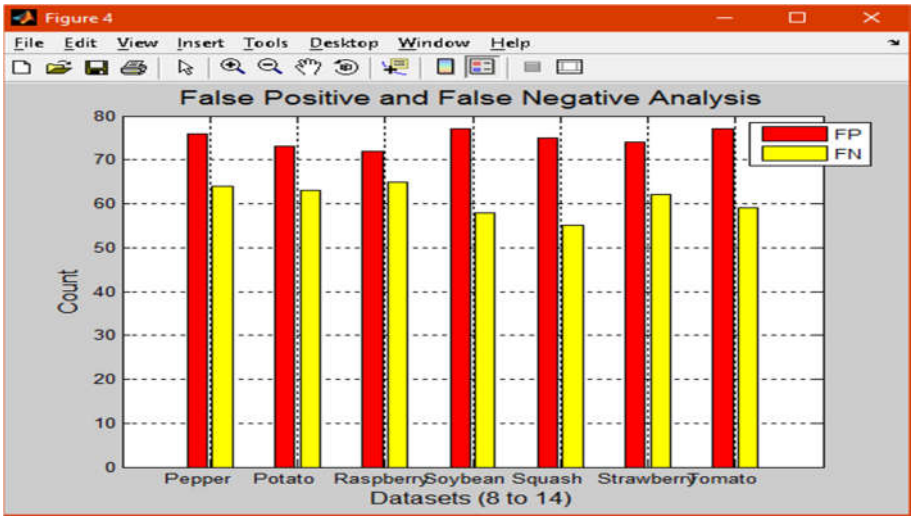

Figure-5: Testing Results: False Positive & False Negative (8-14 plants)

These execution results are used for calculating the performance efficiency of the VGG-16 model. For this process, the confusion matrix formula is used.

5.1 Confusion Matrix

Confusion matrix is used to find the classification accuracy using true positive, true negative, false positive and false negative values. These values are given by the execution results of VGG-16 architecture model.

Confusion Matrix and ROC Curve

		Predicted Class	
		No	Yes
Observed Class	No	TN	FP
	Yes	FN	TP

TN	True Negative
FP	False Positive
FN	False Negative
TP	True Positive

Model Performance

Accuracy	= (TN+TP)/(TN+FP+FN+TP)
Precision	= TP/(FP+TP)
Sensitivity	= TP/(TP+FN)
Specificity	= TN/(TN+FP)

This formula is used for calculating the accuracy of used model. I this work, this formula is used for calculating both training accuracy and testing accuracy of plant leaf identification and classification. The accuracy chart is given below.

S.No	Name of the Plant Leafs	TP	TN	FP	FN	Testing Accuracy	Training Accuracy
1	Apple	701	201	71	55	87.74	91.81
2	Blueberry	667	233	77	65	86.37	90.92
3	Cherry	674	234	76	61	86.89	90.63
4	Corn	671	238	73	64	86.91	91.56
5	Grape	685	219	80	56	86.95	91.53
6	Orange	639	219	78	64	85.76	89.60
7	Peach	682	227	77	59	86.96	90.64
8	Pepper	674	216	76	64	86.41	90.30
9	Potato	676	214	73	63	86.72	91.76
10	Raspberry	654	220	72	65	86.44	90.31
11	Soybean	669	225	77	58	86.92	90.87
12	Squash	669	223	75	55	87.28	89.82
13	Strawberry	677	211	74	62	86.69	91.99
14	Tomato	707	211	77	59	87.09	91.32

Table-1: Accuracy table for 14 different plants

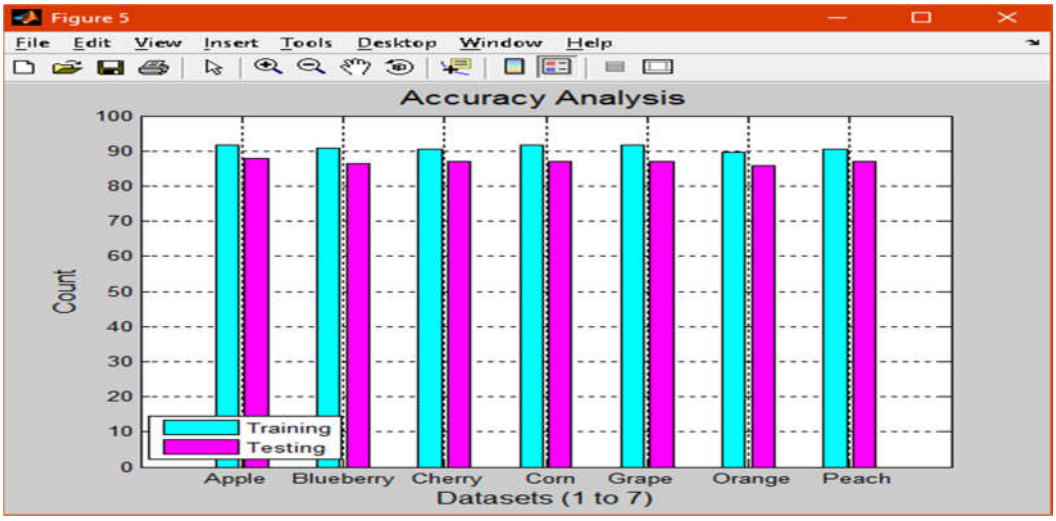

Figure-6 Training and Testing accuracy for the class 1-7

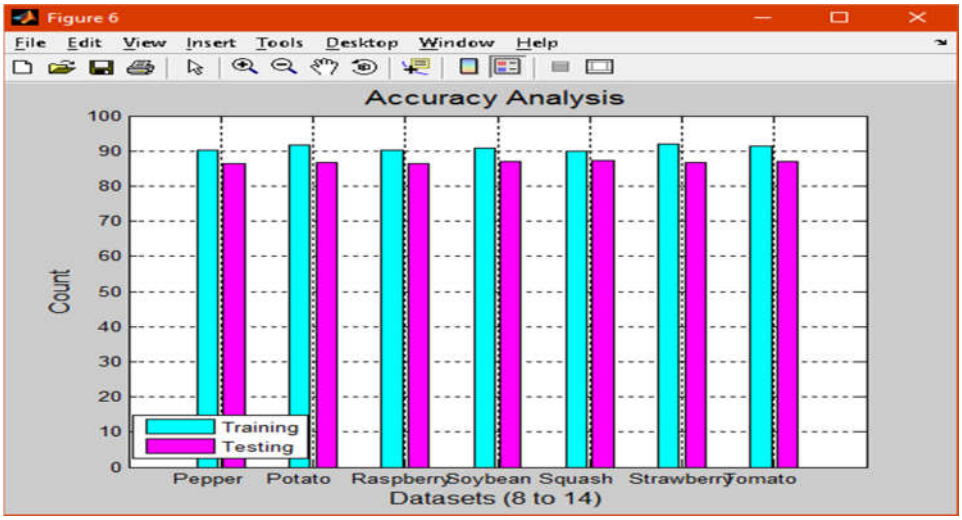

Figure-7: Training and Testing accuracy for class 8-14

The execution results highlighted that the training accuracy is higher than testing accuracy in plant leaf classification. The used VGG-16 model is effective in classification of multi-class problem.

6. Conclusion

The developed automated plant leaf identification system used deep learning models which was more efficient to handle images. For this paper, the use of convolutional neural network is discusses. To classify 14 different classes, the VGG-16 architecture model is used. The Softmax activation function is use for processing the multi-class problem. The dataset contains more than 5000 images with 14 different class labels. The pre-training methods are used to give training to the VGG-16 architecture. This system provided more than 90% of training accuracy and 85% average accuracy for testing process.

7. References:

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