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Plant Stress Detection Accuracy Using Deep Convolution Neural Networks

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ABSTRACT

Plant Stress detection is a vital farming activity for enhanced productivity of crops and food security. Convolution Neural Networks (CNN) focuses on the complex relationships on input and output layers of neural networks for prediction. This task further helps in detecting the behavior of crops in response to biotic and abiotic stressors in reducing food losses. The enhancement of crop productivity for food security depends on accurate stress detection. This paper proposes and investigates the application of deep neural network to the tomato pests and disease stress detection. The images captured over a period of six months are treated as historical dataset to train and detect the plant stresses. The network structure is implemented using Google's machine learning Tensor-flow platform. A number of activation functions were tested to achieve a better accuracy. The Rectifier linear unit (ReLU) function was tested. The preliminary results show increased accuracy over other activation functions.

Keywords: Deep Learning, Neural Network, Tensorflow, Rectifier Linear Unit

I. INTRODUCTION

Agriculture forms the basis of food security and economic growth in most countries. However, in spite of the climatic conditions, most farmers often have to deal with different pests and diseases attacking their crops. In order to overcome this challenge, accurate and timely detection of the pests and diseases would likely lead to appropriate application of remedial measures. On the contrary, inaccurate and untimely detection of pests [1] and disease [2] in plants is a common problem in the agriculture industry among farmers. This not only increases the cost of crop production, but also leads to massive losses leading to hunger and food insecurity [3], [4]. This crop failure is as a result of plant stress caused by the pests and/or diseases.

Plant stress can either be biotic or abiotic. Biotic stresses are as a result of living factors such as fungi, parasites and bacteria, and lead to deficiencies in nutrients [5]–[7]. Conversely, abiotic stresses are as a result of non-living factors mostly environmental related [8], [9]. Coincidentally, all these stresses mainly manifest themselves in the physical appearance of the plant. Consequently, distinguishing between the different types of plant stress and their stressors is common challenge. Additionally, a number of these stressors may exhibit similar symptoms on a plant. To resolve this, a deeper understanding of image signatures [10] of the various plant stresses is crucial.

Appropriate understanding of these signatures will not only aid in comprehending how the several input variables affect the resulting output, but also provide an insight on how the variables are correlated. Nonetheless, data related to plant stress detection is non-linear in nature, hence plant stress prediction becomes a challenge. Even though, regression [11] techniques can be used to solve the plant stress problem; regression aids in estimation of relationships between dependent and detector (independent) variables. However, it results to over fitting and is too simple to capture a variety of datasets. Similarly, Logistic regression [12] also results to overfitting. Random forest [13] calculates the mean of decision trees faster and can be used to train models.

Neural networks [14] are well known for detection and prediction of stresses in plants. The multiple layers enable it to accurately handle highly complex tasks. However neural networks require high processing power and time which may not be available to farmers which also lack the desired knowledge. A modification of the conventional neural network is a deep neural network which is made up of more than three layers [15]. A deep neural network is able to abstract features of both the input and output patterns and offers more accurate results. However, just like its predecessor, it requires even more processing capability beyond the reach of many farmers. Nevertheless, the increasing processing power of smart phones at a lower cost is a promising trend which if properly harnessed, can alleviate this challenge.

This is strongly reinforced by the fact that several researches depict the use of smart-phone [16], [17],[18] cameras in the assessment of plant stress. This paper focuses on detection of multiple plant diseases in different conditions. Deep Convolution Neural Networks (CNN) was applied for analysis based on tomato images captured over a period of six months. Our empirical results show that accuracy in early detection of plant stress using smartphone cameras improved as images were subjected to pre-processing and training using deep convolution neural networks.

The rest of this paper is organized as follows, Section II presents the methods and materials that were used in the study; images were captured preprocessed and classified then accuracy measured using mean absolute percentage error. Section III, illustrates the deep convolution neural network model developed, and analysis of the accuracy of the model done based on the SoftMax activation function, and confusion Matrix. Section IV outlines the System Model; Section V the Results and Discussion, outlining accuracies assessed based on the training steps and the training set. Discussed in Section VI is the Conclusion and recommendation for future work.

II. METHODS AND MATERIAL

This section discusses the different methods and materials that were used in the study. It also explains the data utilized in the study and how it was collected.

A. METHODS

To assess the accuracy of the plant stress detection digital imaging model, several metrics were tested which include mean absolute percentage error (MAPE), root mean square error (RMSE) and mean square error (MSE).

The mean absolute percentage error (MAPE) was used to measure how accurate the digital imaging prediction system was able to measure accurately the accuracy of the model in percentage format and calculate the average absolute percentage error for a given period of time minus actual value divided by actual value. Where A_t is the actual value, F_t the prediction value. The model confusion matrix (figure 5) contains higher values along the diagonal from top left to bottom right pointing the model accuracy. The precision score and the recall score were arrived at by passing in the actual and the predicted classes.

$$M = \frac{1}{n}\sum_{t=1}^{n}\frac{A_t - F_t}{A_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

The Root Mean Square error (RMSE) utilizes the regression line to predict the average y value associated with a given x value, where y' is the forecast load or prediction load, y is the actual load and n is the test set size.

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}(\bar{y}_i - y_i)^{\ \ 2}}{n}} \ \ldots\ldots\ldots\ldots (2)$$

The Mean Square Error (MSE) measures the average squares of the errors as compared between the actual value and the estimated value.

$$MSE = \frac{1}{n}\sum_{i-1}^{n}\overline{(Y_i - \bar{Y}_i)^{\ \ 2}} \ldots\ldots\ldots\ldots\ldots (3)$$

B. MATERIALS

The choice of a convolution neural network structure relies on; identification and selection of both the output and input variables to be used, building of the convolution neural network model, pre-processing, training, testing, and validation of the data, training the deep CNN model with the training data set and validation of the deep CNN model.

The identification and selection of the required input images to the CNN is a vital component in the design. Disease signatures informed the input for normalization [19] to accommodate the application of activation functions where diseases detected represents the actual data value with relation to the neural network model.

The SoftMax for hidden layers in the model were applied to provide probable output options. The activation function for the neurons is SoftMax based on the sigmoid function in classification of tasks.

The datasets are categorized into training set, validation set and testing set. The test and validation sets are used for evaluation of errors through comparison of the actual data with the results acquired. Training of the convolution neural network results to the determination of the weights used in the network inorder to minimize the error; for network validation at the end of the training process.

In [7] Deep Convolution Neural Network-based algorithm was applied based on fungal infections ensuing to yield losses as a result of infestation that were detected late after losses had been caused. Deep CNN among other image analysis-based methodologies has proven to be efficient in autodetection of diseases in plant images. In this work we extend previous work by [7] in real-time detection of plant diseases by extending on CNN algorithm. This paper analyses early identification accuracy of tomato diseases by use of TensorFlow deep learning platform.

III. IMPLEMENTATION OF THE DEEP CONVOLUTION NEURAL NETWORK MODEL

The TensorFlow deep learning [20] platform was utilized in the development of the Deep Convolution Neural Network (DCNN) Model for the development of the digital imaging model for plant stress detection. TensorFlow [21] is applied in numerical computation of mathematical graphical data. The edges of the graphs are composed of multidimensional data arrays known as tensors that communicate between nodes.

The architecture of the TensorFlow is later deployed to either Central or Graphical Processing Units on a smartphone device, server or desktop with a single

Application Process Interface (API). Originally TensorFlow was developed by Google research team for machine learning and deep neural network research [12]. In this study we develop model for a deep convolution neural network on a TensorFlow platform and test it using SoftMax activation function in the output layer to provide a range of probabilities to the various output options.

A. Structure of the DCNN

Neurons and Layers are key in the modeling of neural network structures. For CNN the number of input and output neurons is predetermined based on the dimension of the training set and the prediction sets. The structure of the CNN model used in this study is given in Figure 1.

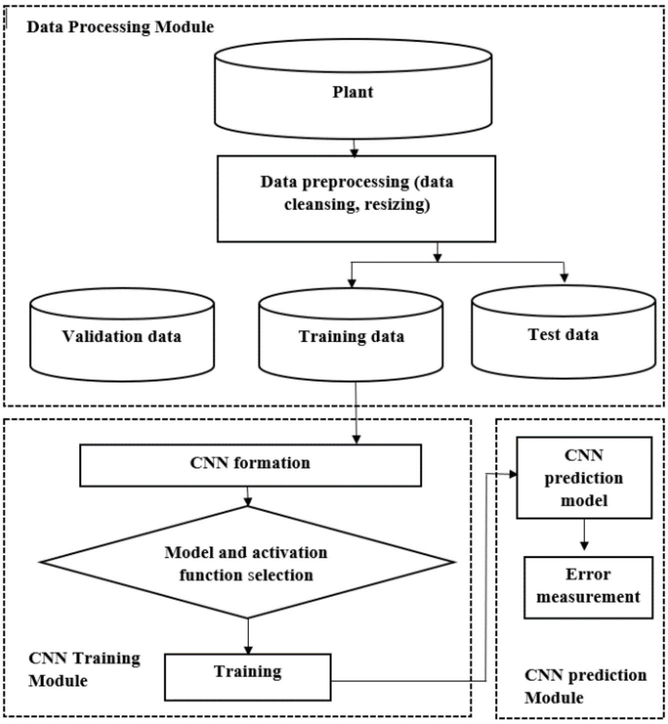

Figure 1 : CNN based plant stress detection

Progressive image resizing [22] is a technique applied on the dataset during the training to build an image classifier using Keras. Specifically, this study uses progressive resizing on the dataset to build a CNN that learns to distinguish between twenty seven different kinds of tomato diseases and pests in where in this study is called Tunza Leaf Tomato Model Dataset. Progressive image resizing affects the accuracy, training, and transfer of learning within the convolution neural network.

B. Activation Function

An activation function is a deciding parameter used for evaluation and capturing the trends or feature patterns from within the data. If the output value originating for the activation function is zero, the feature is absent and if the value is one the feature is present in the data. In computational networks, the activation function of a node defines the output from that node given an input or a set of inputs. A standard computer chip circuit function of "on" and "off" corresponding to '1' and '0' depending on the input. This relates to how linear perceptron in neural networks operate. In artificial neural networks this function is also referred to as the transfer function. An activation function was used for the neural network to determine which neurons should be activated.

$$y = Activation\ (\sum(Weight\ \times Bias) + Bias)\ \ldots\ (4)$$

In training of this neural network model, activation function plays a very important function in regulation of the weights. In this study, we have used a non-linear sigmoid for hidden layers in the model.

1) SoftMax

Since our model comprises of 3 possible outputs, the SoftMax method (equation 5) is used to determine the probable disease that the passed image may be suffering from. The CNN Model based algorithm was used in this study in detection of multiple tomato diseases. The performance of the model was analyzed in detection of three tomato plant diseases: Fungal Diseases including, Early Blight (Alternaria leaf spot), Fusarium wilt, and Bacterial Disease including bacterial speck, spot and canker. The formula used in classification tasks like this one.

$$\sigma(z)_j = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}} for \quad j = 1, \ldots, K \ldots \ldots \ldots \ldots \ldots \ (5)$$

This activation function reduces the output of each class in this case to between 0 and 1 and divide by the sum of outputs therefore giving their probability.

IV. SYSTEM MODEL

A training data set necessary for development and implementation of the convolution neural network is vital. It is necessitated by the availing of historical image data during the design phase so as to determine how many neurons, layers, and activation function to be used. In this study the system model required parameters including the various plant stresses that consists of pests and diseases as input. Plant diseases that were detected from the mobile phone cameras using a combination of various activation functions in the model were classified as seen in Figure 2.

Figure 2 : Prediction of Multiple images of diseases

SoftMax Activation Function combined with the Sigmoid Combination, and four hidden layers were selected to do the prediction of the plant disease. The number of neurons is randomly varied to obtain better accuracy.

TensorFlow is used to train and test the designed digital imaging model. TensorFlow provides TensorFlow program (TensorBoard) for easy understanding debugging and optimization. TensorBorad graph in TensorBoard is shown in Figure 3.

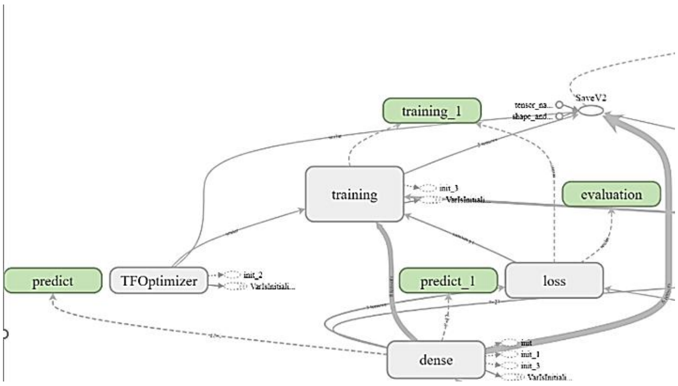

Figure 3 : TensorBoard for Case 1.

V. RESULTS AND DISCUSSIONS

An ADAM optimizer inside TensorFlow framework was used to train our model. ADAM Optimizer uses a gradient-descent algorithm. The method has a faster convergence rate.

The model summary shows that the input layer is a four-dimensional tensor with batch, height, width, and channels. The height is 224 pixels and the width are 224 pixels, the channels are 3 representing the RGB and the image batch shape was tested. The figure 4 shows the digital imaging model summary.

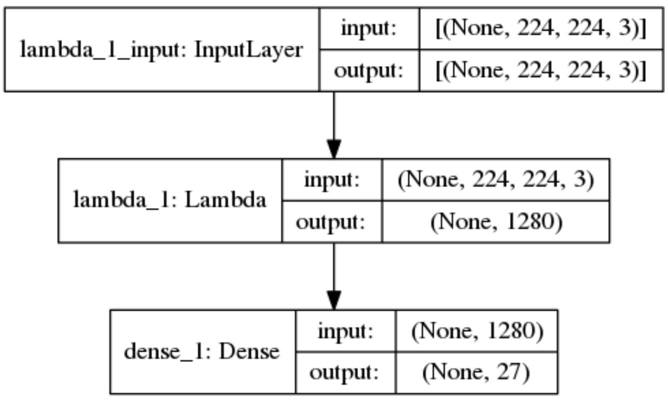

Figure 4 : Digital Imaging Model Summary

A. Graphs and Confusion Matrix of Accuracy

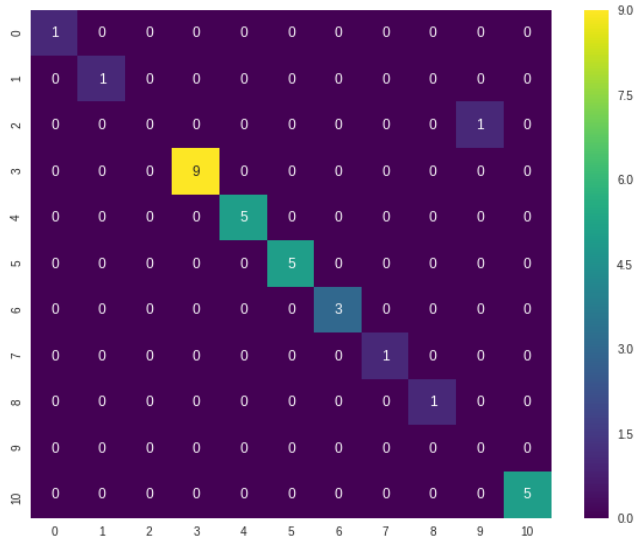

Figure 5 : Confusion Matrix showing the accuracy level of the Digital imaging model

An 8 by 8 matplotlib graph was created to measure the result of the model with regards to accuracy and loss related to the training steps. The y axis was limited from 0 to 1 to represent percentage. As the training increased the accuracy increased while the loss decreased. This has been illustrated in Figure 6.

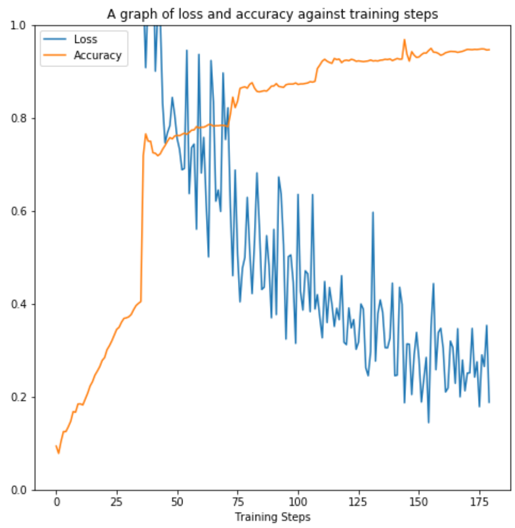

Figure 6 : A graph of loss and accuracy against training steps

The accuracy of the model continues to increase with the increase in the training set. This is illustrated in the graph in Figure 7.

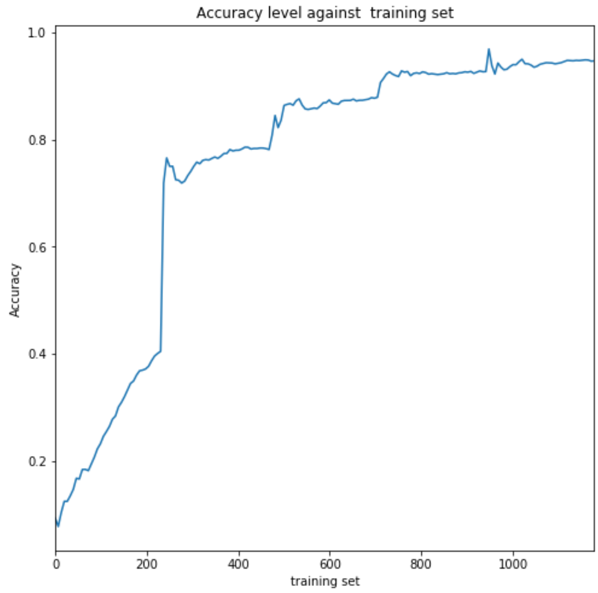

Figure 7 : Graph of accuracy level against training set

VI.CONCLUSION

Food security is achievable through application of deep convolution neural networks to detect diseases in plants at an early stage. Tomato image datasets captured over a six month period was used to predict detection accuracy of plant stress. A selected category of activation functions was trained, tested, and validated with neural networks. The results indicate that the SoftMax and ADAM optimizer performs better resulting to higher accuracy levels. Accuracy against training sets and training steps increase as losses reduce to levels of over 90% accuracy. The scalability of the model in future can be done so as to achieve accuracy as applied for pest stress in tomato and maize crops.

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