Deep Learning Based Image Processing For Cotton Leaf Disease And Pests Diagnosis: A Case Of Ethiopia

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Summary
Cotton is one of economically significant agricultural product in Ethiopia since Agriculture is backbone of this nation economy. It is believed that Ethiopia is one of suitable nation for several cultivated crops including cotton which is also known as "White Gold" and "The King of Fibers", that is the world's leading natural textile fiber crop and a significant contributor to the oilseed for consumption. Cotton is known to be affected by different biotic and abiotic constraints occurring on the leaf areas which reduces productivity from 80 to 90% and hard to detect with bare eyes. This study focused to develop a model to boosts performance of identification of cotton leaf disease and pests using Deep Learning technique, CNN. To do so, the researcher used common cotton leaf disease and two pests which are bacterial blight, spider mite, and leaf miner. K-fold cross-validation strategy was used to dataset splitting and boosts generalization of the CNN model. For this research 2400 instances (600 images in each class) are used to train the model. This developed model implemented using python version 3.7.3 and the model is trained on the deep learning package called Keras, TensorFlow backed and Jupyter is used as the development environment. This model achieves an accuracy of 96.4% for identifying the four classes of leaf disease and pest in cotton plants. These all show the feasibility of its usage in real-time applications and the potential need for IT-based solutions to support traditional or manual disease and pests identification.
Keywords:
Image Processing, Deep Learning, Cotton Leaf Disease and Pests, CNN, K-fold cross-validation, Keras.

1. INTRODUCTION

In Ethiopia, Agriculture is the basis of the national economy from which 85% of livelihood and 90% of total foreign trade comes from the agricultural sector [1]. It is believed that Ethiopia is suitable for many farmable crops including cotton. Cotton (Gossypiumspp.) is also called "White Gold" and "The King of Fibers". It is the world's leading natural textile fiber crop and a significant contributor to the oilseed for human consumption. For growers, processors, exporters, and producing countries cotton is the earnest point of supply [2]. According to the Data of African report, only 428,120 hectares are harvested with the total production value of about $596,000,000 in SNNPRS.

For the past growth and transformation plan, GTP-II, Ethiopia’s government planned to achieve 1.13 million metric tons of seed cotton production in the country to satisfy the demands of rising textile and garment manufacturing industries [3]. In Ethiopia, performance evaluation of GTP-I showed that there is a constraint to fulfill the world’s standards in cotton quality and quantity of production. This is because different biotic and abiotic constraints affected the total economy of the farmers as well as the country [1]. Approximately 18% of crop yield was lost due to different diseases and pests which attacked every year resulting the loss of millions of dollars worldwide. Among different diseases and pests occurred, about 80-90% where on the leaves of cotton [4].

Cotton diseases and pests are difficult to identify through bared eyes. So the symptom on plant leaves incorporate rapidly increasing the complexity and decreasing its accuracy. Due to this complexity, even experienced agricultural experts and plant pathologists often failed to successfully identify specific diseases which consequently lead to mistaken conclusions and concern solutions [5]. Designing an automated system will help to identify diseases by plant’s appearance and visual symptoms could be of great help to amateur with agricultural process. This will prove as a useful technique for farmers to alert themselves at the correct time before the disease spreads over a large area.

Image processing and machine learning are the two most popular and widely used techniques adopted for plant leaf disease and pests diagnosis. Deep learning using Neural Networks is the part of machine learning with huge variety of applications. The development of this technology can help farmers to identify diseases and pests in plants. Image processing can be used in agriculture for identifying diseased leaf, stem and fruit, size and shape of the affected area.

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Deep learning incorporates image processing and data analysis, with accurate results and large potential. As it has been a successful application, now it has entered the domain of agriculture. Today, several deep learning-based computer vision applications such as CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), DBN (Deep Belief Network), DBM (Deep Boltiz-mann Machine) are performing tasks with high accuracy. But the most prominent application for this research work is CNN. CNN has multiple layers; including convolutional layer, nonlinearity layer, pooling layer and fully connected layer [6].

For deep learning, CNN technique is applied to create a model for automatically identifying the diseases in cotton leaf. Nowadays, CNN techniques are considered as the leading method for object detection and to perform automated feature extraction from the raw inputs in an analytical way. Classification is based on selecting the features with the highest probability values [7].

2. Statement of the Problem

In Ethiopia, the economic loss of cotton produced on 2018 is estimated to be 5 %-15 %. However, without control measures, it can cause 30%-50% of loss. The performance evaluation of GTP-I stated that these diseases and pests are the main constraints in the production of cotton quality and quantity. This epidemic may lead to a downfall in economy and in farmers' lives.
Identifying these diseases and pests on cotton leaves through naked eye is complex and may lead to decrease accuracy and precision. In fact, experienced agricultural experts and plant pathologists often fail to identify these diseases and pests which lead to mistaken conclusions. These mistaken conclusions results in using highly toxic pesticide which badly affects cotton health and pollutes the environment. Problems identified in various previous researches lack performance in accuracy, small number of instances or images in dataset, traditional dataset splitting technique and old machine learning technique. As a contribution, developing such an automated system to assist farmers and experts to diagnosis cotton disease and pests by leaf visual symptoms can be helpful. The result proves that automated system as a useful technique for farmers to reducing complexity, time and cost of diagnosis and will alert them at the right time before spreading the disease and pests over a large area.

Hence this study aspires to answer the following three research questions.

1. Which is the suitable technique for diagnosing cotton disease and pests?
2. How to develop an automatic cotton disease and pests diagnosis system?
3. How to evaluate the performance of the model?

Objectives of the Study

General Objective of this research study is to design a model to identify cotton disease and pests using deep learning-based image processing techniques to boost accuracy. Specific Objectives are aimed to attain general research objectives; several objectives are considered to be achieved as follows:

- To study and analyze the cotton diseases and pests for formulating the research problem.
- To review works of literature to find a researchable knowledge gap.
- To design a logical model of cotton leaf disease and pest diagnosis.
- To train the deep learning-based model.
- To inspect the performance of the model.
- To develop a prototypical demonstration of the model.

Related Works

Based on the investigation and analysis of different researcher's they have identified the critical analysis from previous research studies which includes salient approaches, novel ideas, knowledge gaps, performance analysis and tools which are relevant to provide significant importance to understand the existing problems for this research study. Several related research works are describes and listed in table 1.

This research study is an effort for a better understanding of diseases and pests in cotton plants leaf. Some of the issues are identified after the survey such as machine learning techniques and covered in a novel approach are missing in training data, Limited live datasets, Machine learning developments, Traditional dataset splitting [9][8][12][13].

Table 1: Summary of Focused and Related Research Works & Critical Remarks

Authors, Year	Plant	Diseases and pests	Results	Remark
S.Arivazhagan and S.Vineth Ligi[8], (2018)	Mango	- 3 classes Anthracnose -1200 images dataset	CNN, Deep learning 96.67% accurate	-A limited number of datasets
Yang Lua, Shujuan Yi, Nianyin Zeng, Yurong Liu, Yong Zhang[9], (2017)	Rice	-10 classes Rice blast, Rice false smut -500 image dataset	Deep CNN 95.48% accurate	-Limited number of datasets -Exposed to over fitting
Serawork Wallelign, Mihai Polceanu, Cedric Buche,[10] (2018)	Soybean	-4 classes Healthy Leaf -12673 image dataset	CNN, Deep learning 99.32% accurate	-Data sample used in this work is unbalanced
Jihen Amara, Bassem Bouaziz and Alsayed Algergawy[11](2017)	Banana	-2 classes Black sigatoka and Black speckle -3700 images dataset	CNN, Deep learning 98.6% accurate.	-No balanced dataset in each class -

3. Research Methodology

All tasks undergone in this research work passes through a series of steps or procedures that are applied to classify a new cotton image, in which each new item is classified into one of a predefined label based on observed attributes or features. To answer the research question, the study used here is design science build or evaluates approach.

The motivation to select Design Science for this research is that it can create innovations that define ideas, practices, technical capabilities, and products using qualitative or quantitative data. The DSRM output model is a conceptual representation and abstraction of a set of propositions or statements expressing relationships among constructs. According to Hevner [14] as shown in figure 1 design science research methodology has six basic activities namely; Problem identification and motivation, the objective of the result, design, and development, demonstration, evaluation, and Communication.

There are four entry points in design science these entry points depend on the nature and type of research. Among these entry points, 'problem-centered initiation' is the best for this design science research. The problem centered initiation entry point is applicable because the problem is observed by the researchers and businesses within the cotton disease identification domain [15]. The figure 1 depicts the DSRM proposed by the research study [16] and the activities adapted to this research. The absence of an automated fast and accurate cotton plant disease diagnosis system made the diagnosis expensive, time-consuming and prone to error. The need for a more effective automated diagnosis of the disease for cotton plant generates a lot of advantages.

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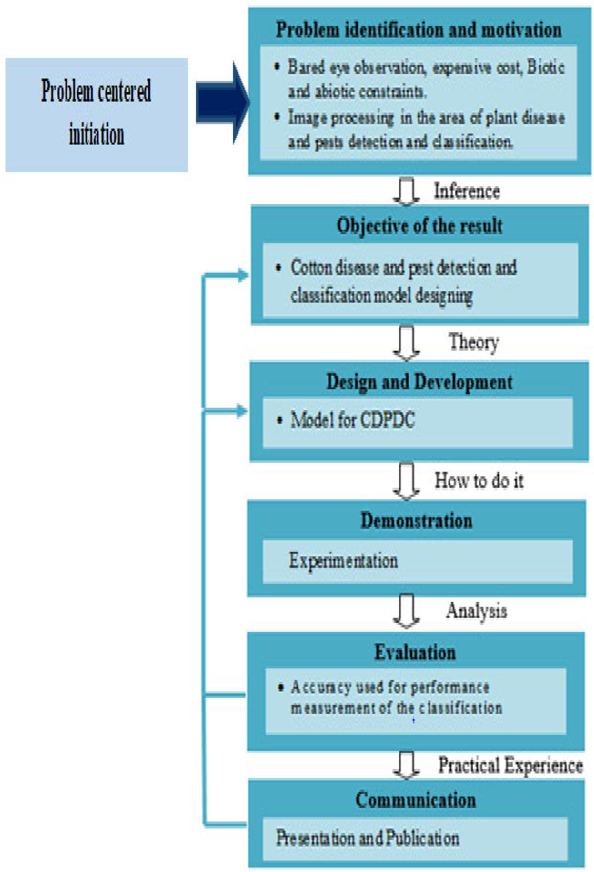

Fig 1: DSRM Processes Model

Research Study Design

This methodology, developed by Hevner and his colleagues, provides a clear guideline for conducting and evaluating good design science research and has been used in numerous design science studies. In this study, the artifact that was designed is the process of designing the

Detection and Classification of Cotton Leaf Disease and Pests. The underlying idea is that an effective process that incorporates the key elements should be considered by the researcher designing a model which led to the creation of an artifact that satisfies users' needs. The details of the methodological approach in this research are given below.

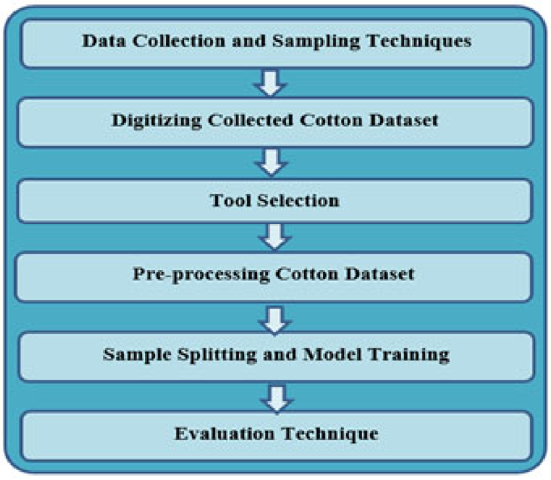

Fig 2: Model Development Approaches

Data Collection and Sampling Technique

The sample leaf images which the researcher used in this research are both primary as well as secondary types of dataset. Primary data is a type of data collected as fresh and for the first time. In this study, the primary data is collected from July to August 2019 in Arba Minch, from Shele Woyto cotton farms where cotton plant is widely planted and there is high infection in SNNPR. Besides, the secondary data collected in each class and their symptom samples are obtained from Melaka Worere agricultural research center and Internet sources. Melaka Worere is administrated under the Ministry of Agriculture and Rural Development found in the Afar region in Ethiopia. It is important to conduct research on the cotton crop to give support to cotton farms found in the Awash valley and SNNPR.

For this study, the researcher used purposive or judgmental sampling techniques selecting three infected and a healthy leaf from the population. During data collection, 2400 images of data were captured which were taken after 5-10m from the border of the farm. Those collected images data are distributed into four equal classes such as bacterial blight, healthy, leaf-miner, and spider mite used to train balanced dataset as shown figure 3.

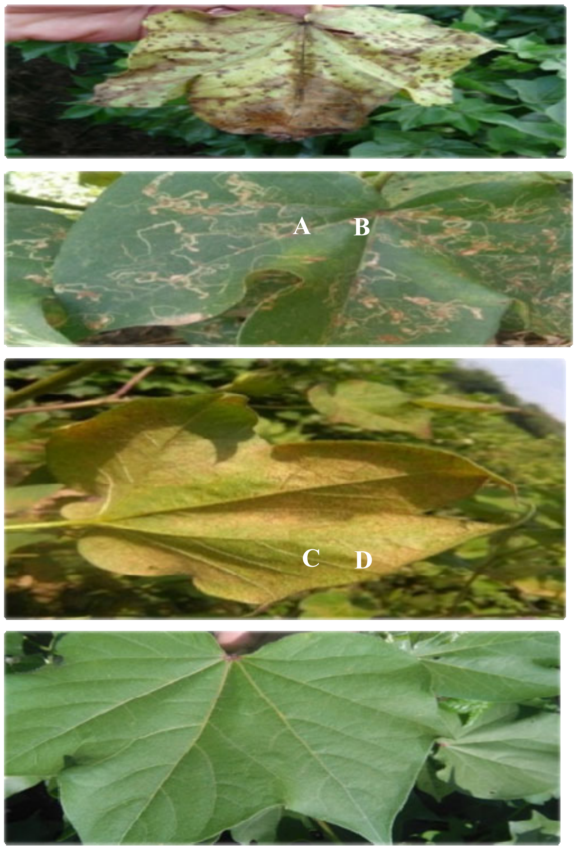

Fig 3: Dataset classes, (A) Bacterial blight, (B) Leaf miner (C) Spider mite (D) Healthy

a) Cotton Images Sample Digitization

The data acquisition system in this research is clear, unbiased and simplified digital images of leaf in the cotton plant sample database for further analysis and processing. The main aim is to provide the digitizing system with uniform lightning or balanced illumination. These images captured using smartphone camera and digital camera are then transferred to a computer and are by weight to view, it is then hoarded into hard disk in PNG format as digital color images.

b) Image Data Pre-processing

Inserting preprocessed images into a network is a first and foremost task in all image processing projects. Common image pre-processing tasks in deep learning projects are vectorization, normalization, images resizing and image augmentation. First, the images are resized to match the size of the input layer of CNN. Secondly, the images are normalized known as data normalization, it helps the model to mingle more quickly as well as helps to generalize the unseen data. In general, it isn't safe to feed into a neural network data that takes relatively large values. Data augmentation generates more training dataset from existing training samples, by augmenting these samples through several random transformations we get more accurate images.

c) Feature Extraction

Deep learning solves different shortcomings of machine learning, extracting feature manually [10] by using the best and robust technique is called CNN. The first layer of a neural network examines the image details; the next layer combines the previous knowledge to make more complex information. In the CNN, the feature is eradicated using filter. To check the availability of similar images a network applies a filter to the picture. If similar images are available, the network uses the filter image .This process of feature extraction is done automatically.

d) Dataset Partitioning and Model Selection Methodology

Used datasets partitioning technique is a K-fold cross-validation process which splits the available datasets into K partitions (typically K = 4 or 5), instantly into K identical models, and trains each one on K – 1 partition while evaluating the remaining partition. The validation score used for the model is the average result obtained from the K validation score. For this research, the study researcher assigns K value as 10 because it is recommended for deep learning [7][9]. Therefore, K=10 means 10-fold cross-validation, so dividing the total dataset into 10, we get D=2400/10=240 data for each fold. By using this method, we ought to get 80% (2160 leaf image) to perform training and the remaining 20% (240 leaf image) for testing and validation for this proposed system.

e) Tool Selection

In order to collect cotton leaf images for this research, two image capturing devices are used such as smartphone and digital camera. The proposed model is implemented using python version 3.7.3, which is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. Also, this model is trained on the deep learning package called Keras (Keras Version: 2.2.4-tf) TensorFlow backed. TensorFlow (Tensor Flow Version: 1.14.0) is recommend as the default for most of the deep-learning needs because it is most widely adopted, scalable, and production-ready. To evaluate the performance many experimental setups are conducted with the help of a graphical user interface using Tkinter. From hardware training and test are done on CPU on Intel(R) Core (TM) i3-4160 Clock Speed 3.60GHz desktop is selected development environment for this study to implement the prototype of the system.

f) Evaluation Techniques

To determine the overall achievement of the system the researchers used various techniques in different period during the development of the cotton leaf diseases and pests detection and by the end of the evaluation the model is designed. Initially researchers try to evaluate the performance of the model, which is produced for cotton plant disease diagnosis. The settlement is based on the number of correctly classified and incorrectly misclassified cotton plant disease in terms of accuracy and error rate. Four evaluation metrics of confusion matrix reports such as F1-score, Precision, Recall, and Accuracy on the test dataset are used to summarize the performance of a classification model. Secondly, for subjective evaluation the researcher used a questionnaire to measure the performance of a prototype by domain experts. An objective evaluation is made using the experimental analysis to test an artifact. Finally, the result of the evaluation depicts the practical applicability of the model.

4. Designing of Cotton Plant Disease and Pest Identification Model

The first task in this model is image acquisition from the field using a digital camera and smartphone. Then image pre-processing techniques are applied to prepare acquired images for further analysis. After this, preprocessed images are inserted into the CNN algorithm to feature extraction, which is a deep neural network specialized for image classification. Then, the features that are best suited to represent the image are extracted using an image analysis technique. Based on the extracted features the training and testing data are extracted. Finally, a trained knowledge base classifies the test images according to their classes of diseases and pests. Figure 3, depicts all the steps in the proposed model of cotton leaf diseases and pest classification.

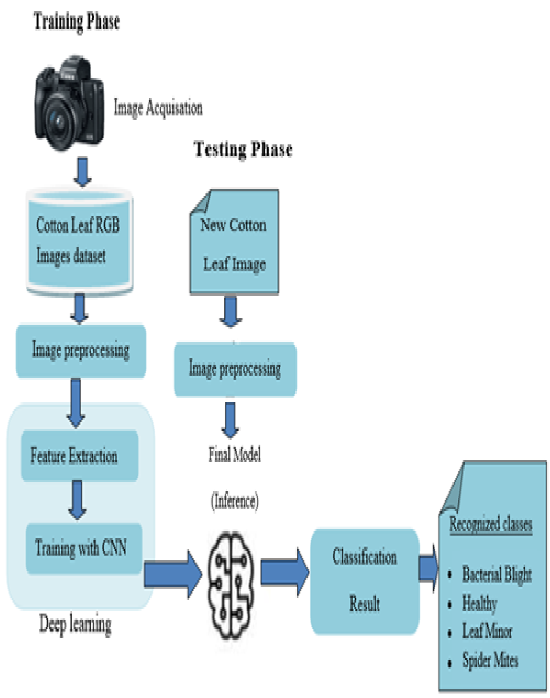

Fig 4: Cotton Leaf Diseases and Pests Recognition Model Process

The Architecture of CNN for the Model

CNN architecture consists of two broad sections; they are feature learning and classification section. The hidden layers of feature learning consist of the convolution layer, pooling layer, Rectified Linear Unit and dropout layer. In the case of image classification, the input is an image of a cotton leaf and the output will be the class name of such an image also called label of cotton leaf diseases or pests. In general, for this architecture, each cotton leaf image input goes into a neuron and is multiplied by weight. The result becomes the input of next layer. This process continues and the final layer known as output layer provides the actual value for the prediction task and of each classification task. The neural network updates the weight of all the neurons using mathematical algorithm. The neural network is fully qualified if the output value is approximate to the actuality. For illustration, a well- trained neural network can recognize the object on a picture with higher accuracy than the traditional neural net. All layers involved in the CNN algorithm for cotton leaf diseases and pests model training are discussed below [9]:

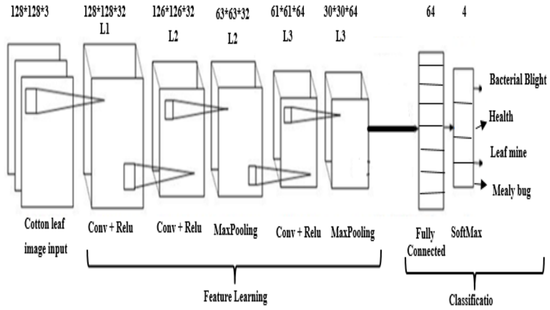

Fig 5: Developed CNN Architecture for Training [9]

Model design for cotton leaf diseases and pest identification is achieved after constant improvement to get desired output since CNN architectures differ with the type of problem. This proposed model consists of three convolution layers each followed by a max-pooling layer as it highlights the most present feature in the patch but not the features of average pooling.

This works better in practice than on average pooling for vision tasks like image classification. The final layer is fully connected to MLP. ReLU activation function is applied to the output of every convolution layer and fully connected layer. The first convolution layer filters the input image with 32 kernels of size 3x3. After the ReLU activation function is applied without max-pooling, the output is then given as an input for the second convolution layer with 32 kernels of size 3x3. Then 50% of dropout is employed to deactivate the least learned features. The output of the second layer given as an input for the last convolution layer with 64 kernels of size 3x3 followed by a fully connected layer of 512 neurons. The output of this layer is given to softmax function which produces a probability distribution of the four output classes of bacterial blight, healthy, leaf-miner, and spider mite. The outline of the model is shown in figure 20. The model is trained using adaptive moment estimation (Adam) with a batch size of 32 for 100 epochs.

5. Experimental Results

During experimentation different experiments take pace to get efficient model by customizing varies parameters that provide different results. Researchers try to present each experiment result with each parameter such as dataset color, number of epochs, augmentation, optimizer, and dropout. According to Serawork Walleign[10], after augmentation RGB colored image provided about 15% improvement on accuracy than that of not augmented. Also the very important components of CNN architecture are customizing number of epoch, regularization and dropout. So researchers used RGB colored image dataset for experiment as it helps to overcome the over fitting as well as to boost the accuracy of the model.

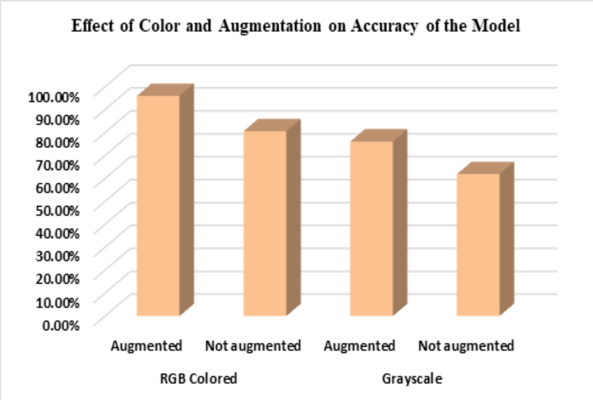

Fig 6: Color and Augmentation Parameters Experiment Result

For this new model researcher trained three different numbers of epochs they are 50, 100 and 150. However, in first number of epoch, trained model shows very low performance or reduce accuracy by 10% in other words this trained model behaves under fitting. The training with last epoch number takes long time, consumes high power and requires hardware capacity. However, the model shows best performance on 100 number of epoch.

According to Nitish Srivastava[18], adding dropout in the CNN gives additional performance(2.70%) to the model. Therefore, during experiment the researcher used 0.25 and 0.5dropout percent in each layers and achieved best performance in 0.5 dropout percent. Finally, very important experiment done on regularization method using optimization algorithms could minimize the loss through iterations by updating means according to a gradient. The two most recent and used optimization algorithms; RMSProp and Adam are used for this research study. However, Adam optimization algorithm is considered as best and it reduces loss by 2.5%.

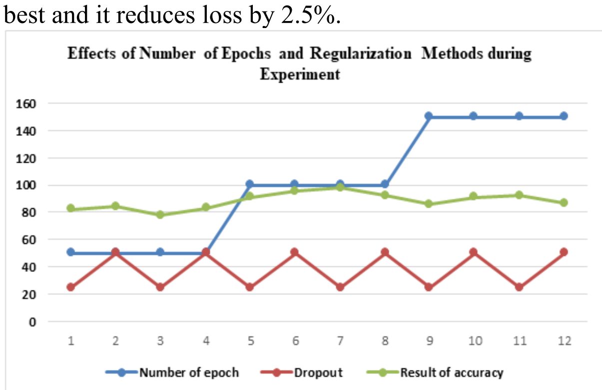

Fig 7: Effects of Number of Epochs and Regularization Methods during Experiment

Researchers observed during the training, the highest training accuracy of the 100th epoch as 0.990. The graphs flow shows all the training and validation success rates that the network achieved during the process is given in figure 7 and about the loss graph in figure8.

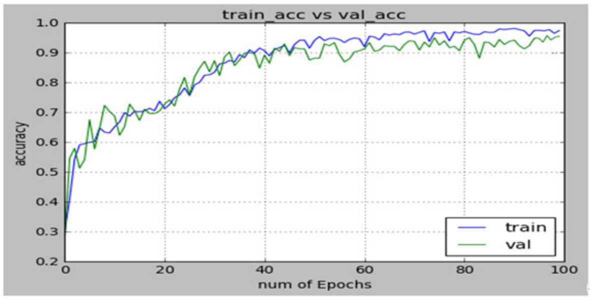

Fig 8: Training Accuracy and Validation Accuracy of the Model

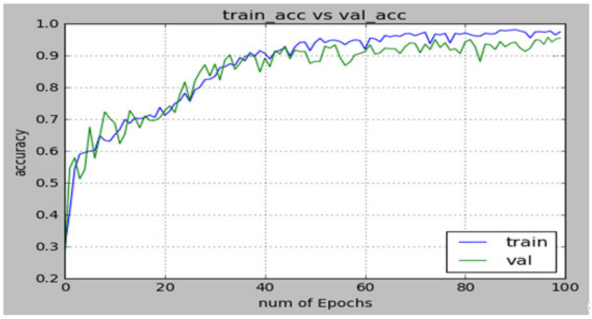

Fig9: Training Loss and Validation Loss of the Model

6. Result and Discussion

Then researchers compared and contrasted the results among different parameters such as dataset color, number of epochs, augmentation, optimization techniques, and regularization for infected cotton plant leaves which can also evaluate the overall performance of CNN. Based on the analysis done on the performance results the parameters predicts the cotton disease and pests using 10-fold cross validation, RGB colored image dataset with augmentation provides 15% best performance for the model. Number of epoch with 100 iteration and Adam optimization method are very significant to boost the model performance by 10% and 5.2% respectively. At the end this developed CNN model achieves 98% of bacterial blight, 94% of healthy, 97.6% of leaf minor and 100% of spider mite which are correctly classified. Additionally, researcher used different pre-processing techniques for noise removal, the main factor for the misclassification of the result like misclassification exist in between bacterial blight, healthy and leaf minor. The overall performance of model as shown in confusion matrix is 96.4% accurate for diagnosis of leaf disease and pests of cotton plants.

7. Prototype Development

For the prototype, researchers focus on the convention of the digital forensic investigation process, i.e., ISO and IEC to evaluate the prototype in terms of efficiency, effectiveness, fault tolerance, helpfulness, learnability, and to control the assess quality of the prototype. System prototypical test is done as desktop application which is conducted with the help of Tkinter, graphical user interface in Python programming language.

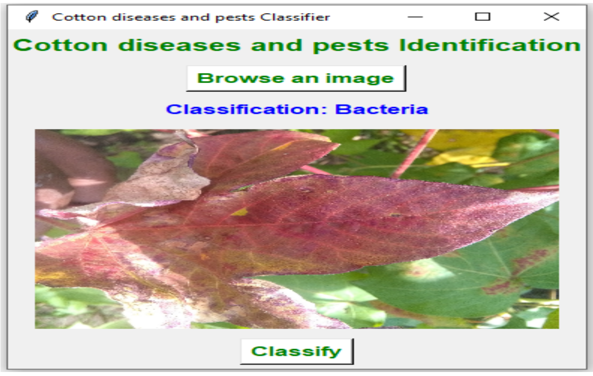

Fig 10: Cotton Diseases and Pests Identification Prototype

8. Conclusion

This deep learning based model implemented using python and Keras package and Jupyter is used as a tool for the development of environment. Different experiments are done in this research study to get efficient model by customizing varies parameters such as dataset color, number of epochs, augmentation, regularization methods.RGB colored image dataset with augmentation provides 15% best performance for the model. Numbers of epoch and regularization methods are very significant to boost the model performance by 10% and 5.2% respectively. The model achieves an accuracy of 96.4% for identifying each class of leaf disease and pests in cotton plants. Developing such an automated system to assist farmers and experts to identify cotton disease and pests by leaf visual symptoms can be very helpful. Achieved results prove as a useful technique for farmers to reduce complexity, time and cost of diagnosis and will alert them at the right time before spreading the disease and pests over a large area.

9. Recommendation

The main challenge while developing an object detection model on deep learning is to collect a large number of train high-quality images with different shapes, sizes, with different backgrounds, light intensity and orientation in different classes. Therefore, future researchers should try to include solution for such challenges into their works and not only identify but also suggesting remedies for diseases and pests. The current technology is capturing resolution and remotely- accessing satellite images, but it is not available, as many governments don't allow researchers to take more detail images due to security reasons. Meaning, researcher won't be able to access better quality unless having security clearance. However, fortunately our country, Ethiopia launched the satellite in 2019to solve such kinds of problems on agriculture sectors. So, this is best initiative for future researchers to access remote-accessing high resolution satellite images in order to train high performance deep learning technique based model.

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