Early Ginger Disease Detection Using Deep Learning Approach

Mesay Gemeda Yigezu[1](✉), Michael Melese Woldeyohannis[2], and Atnafu Lambebo Tonja[3]

[1] Wachemo University, Hossana, Ethiopia
mesaygemeda@wcu.edu.et
[2] Addis Ababa University, Addis Ababa, Ethiopia
michael.melese@aau.edu.et
[3] Wolaita Sodo University, Wolaita Sodo, Ethiopia
atnafu.lambebo@wsu.edu.et

Abstract. Ethiopia is one of the countries in Africa which have a huge potential for the development of different varieties of crops used for traditional medicine and daily use in society. Ginger is one among the others which are affected by disease caused by bacteria, fungi, and virus being bacterial wilt is the most determinant constraint to ginger production. Detection of the disease needs special attention from experts which is not possible for mass production. However, the state-of-the-art technology can deploy to overcome the problem by means of image processing in a mass cultivates ginger crop. To this end, a deep learning approach for early ginger disease detection from the leaf is proposed through different phases after collecting 7,014 ginger images with the help of domain experts from different farms. The collected data passed through different image preprocessing to design and develop a deep learning model that can detect and classify with a different scenario. The experimental result demonstrates that the proposed technique is effective for ginger disease detection especially bacterial wilt. The proposed model can successfully detect the given image with a test accuracy of 95.2%. The result shows that the deep learning approach offers a fast, affordable, and easily deployable strategy for ginger disease detection that makes the model a useful early disease detection tool and this analysis is also extended to develop a mobile app to help a lot of ginger farmers in developing countries.

Keywords: CNN · Deep learning · Image detection · Image classification · Ginger disease

1 Introduction

Agriculture is one of the leading sector in Ethiopian economy accounting for about 68% of employment and 34% of GDP [1]. In addition to this, more than 3/4 of the Ethiopian population highly relies on the agriculture as a means of securing the necessities of life. In line with this, for the country like Ethiopia, the demand for economic growth of the agriculture sector is increasing at the alarming rate

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over the past decades. As a result, the rate of production in the agriculture sector has doubled in the last two decades [2]. This resulted in the expansion of land, labour and extension worker beside the modern inputs for the agriculture sector [3]. Accordingly, the production of cereals in last decode becomes three times more than that of the year 1995/16 while the yield produced increased by 86% for an increment of the 70% area cultivated [4]. Despite the increment of area, yield and modern inputs, the level of productivity remained low due to the unavailability and use of fertilizer and improved seeds [5]. Agriculture is one of the area that leads the economy of the country, but still it is done by using traditional techniques which leads to different structural problems including the quality and quantity [6]. The productivity of crops are highly affected by the disease that influence the quality of product.

Ethiopian farmers produce different crop and cereal products for the export market. Among these product, Ginger crop is one of that earns a sizeable amount of foreign exchange for the country. Traditional disease detection primarily depends on the skills and the visual inspection of the agricultural extension worker [7]. However, for the country like Ethiopia, with low logistical and human infrastructure capacity, detecting and classifying disease at the earliest stages are difficult and expensive to scale up specially when it comes to mass production. Similarly, smallholders farmers rely on the previous knowledge they have which make less effective in overcoming the challenges of farming. Therefore, early detection of pests and disease in the field is one of the crucial step for the early interventions resulting reduced impacts of food supply chain.

Ginger production in Ethiopia is handicapped by shortage of high yielding, absence of innovate technologies and weak role of private sectors in spices production [8]. In addition, the production of ginger is being affected by various disease. The decision-making capability of human inspector also depends on different condition. This include; the stability of the weather, work load, physical condition of the extension worker, such as fatigue and eyesight, and the biases. As a result, it is difficult to predict the type of disease by using observation which may leads also to biased prediction towards the disease type. This in turn leads farmers and extension worker to lose of money because of the wrong medicine which is difficult to control at its early stage.

Hence, it is not feasible and manageable to detect the ginger disease by digging out the root. Rather, it better to use the leaf of the plant because when plants become diseased. A diseased ginger displays a range of visual symptoms either in colored spots or streaks on different part of the plants [1,9]. The visual symptom of the disease continuously change in color, shape and size depending the progress of the disease.

In country like Ethiopia, farmers do not have proper facilities how and when they have to contact experts due to the high cost and time consuming to get the consultant. In such conditions, it is difficult to provide fruitfully ginger products specially when diseases are detected at the earliest stage. Different sectors benefits from the advancement of the state-of-the-art Artificial Intelligence (AI) technology which favours the high productivity and efficiency [10]. AI based solutions are supporting to overcome the challenges of traditional methods of detecting diseases and respond smartly to improve the efficiency while reducing the environmental hostile impacts. Deep learning is one of the technique for detecting and classifying the various crop diseases through image processing [11]. Previous research work has validated that, the AI-based detection and classification of crop diseases were effective to maximize production of goods [12,13]. Thus, there is a need to use a computerized early detection of disease in a short period by looking at the plant symptoms in easier and cheaper way to strengthen the agricultural fields and the economy of the country by increasing the productivity and quality of ginger crops.

2 Related Work

One of the research attempt is to detect cassava disease and used deep convolutional neural network approach through a transfer learning to train and detect the disease type [13]. As a result, an overall accuracy of 93% were achieved but experts extracted images manually from the dataset supported on the visibility of the most severe symptoms of every category.

In addition to this, under a controlled environment, a disease detection attempted on a public data set consisting of 54,306 using CNN through automatic feature extraction [14]. The first experiment conducted without any pretrained and has an accuracy of 99.35% on the test set. Beside these, using a transfer learning based approach using a ResNet50 and InceptionV2 pretrained models resulted a better performance than that of the MobileNetV1 [7].

Beside the use of deep learning, a classical machine learning has been applied in a cotton leaf disease classification using K-means clustering for segmentation and Support Vector Machine (SVM) for classification [15]. This has been achieved through the image converting from RGB to HSI, contrast enhancement and extracting a better features to identify disease through the process. Furthermore, groundnut disease identification and classification based on a back propagation [16]. However, the work were only applicable for limited diseases without the use of shape feature for the enhancement of image application.

In the research attempt [17], the researcher shows that, the application of image processing and Artificial Neural Network (ANN) to addresses the problem of cotton plant disease detection. The efficiency of the cotton plant disease detection were feasible with numerous techniques as well as ANN is employed as a classifier for testing using MATLAB to detect the kind of diseases on cotton leaf. The potency of the planned work were around 84% accuracy. Similarly, another the development of disease detection for maize disease [18]. The researcher collected massive amount of data for one plant disease from different platforms beside the data augmentation to assist the system for real-time observation. However, all the image dataset were collected from the single source using drones equipped with CNN model. This limit the generalizability of the data, as symptoms of equivalent disease in alternative regions could present in different ways.

In this review it has been observed that so many methods were proposed and implemented to identify, detect plant diseases using digital image processing. Most of the researchers used their datasets from internet that is publicly available databases such as in Plant Village. Using publicly available dataset is recommended but the images in most of the previously conducted researches are captured under controlled environments like in the laboratory setups; there are a lot of laborious pre-processing stages such as handcrafted feature extraction, color histogram, texture features, and shape features; most importantly the methods used by previously conducted research works are not state of the art, i.e. most of the studies in the literature of crop disease identification follows traditional image processing techniques.

As mentioned by different researcher [13,15,18], the studies shows that computer vision is widely used particularly for tasks like disease detection and identification has shown fascinating result specially in the field of agriculture. Moreover deep learning algorithms like CNN and ANN are most commonly used. Generally, a plant that has symptom seen on leaf as well as bacterial wilt however, currently there is a desire to come up with a model that is more correct and efficient. In general, more precise and efficient model development is necessary for a plant with symptoms on the leaf, such as leaf wilt and bacterial wilt.

3 Methodology

Deep learning techniques have obtained very high performance in different areas including image recognition, image segmentation, speech recognition, natural language processing and emotion recognition given sufficient data for learning [19]. We evaluate the pertinence of CNN from deep learning approach that is leading state-of-the-art in computer vision task. Before classification and prediction, traditional techniques to training classifiers need explicit extraction of the features to be examined from the image. CNN learns the feature hierarchy from pixels to classifier and train layers, which are made up of several consecutive layers, each of which changes one volume of activation to another using distinct functions. We have often utilized CNN layers such as the convolution layer, which is accomplished by sliding the feature detector on the provided image from left to right across dimension and computing between the filter and also the input image with dot product at every location to obtain a feature map.

Finally, we stake all the feature maps together and it is the final output of the convolution layer. The size of the output (the feature map) is controlled by the depth, stride, and padding parameters. These parameters should be decided before the convolution operation is performed [20]. Following the convolution layer, we used a pooling layer to reduce the size of the parameters and extract the main characteristics of a specific spatial location. The computational complexity of the model and to control the problem of over fitting in the CNN, we added it between some successive convolution layers [21]. In last, we flattened the matrix into a vector and sent it into a fully connected layer of a neural network, which contains neurons that are directly connected to neurons in the two adjacent layers but not to any layers within them.

In addition, We have used activation function on the hidden layer that is ReLU to apply non linearity and by using Sigmoid in last layer of fully connected we performed classification based on training data. Accordingly, the CNN architecture in this work has a of 11 layers, 5 convolutions, 3 pooling layers and 3 dense layers. Figure 1 presents a CNN based feature extraction and classification. The CNN algorithmic program extracts key features that are then used to classify images. The feature in this case has a different color mode than the given image. Then, to add non-linearity to the network, each feature map value is passed through a trigger function. Following non-linearity, the feature map is reintroduced into the pooling layer to minimize feature map resolution and network computational complexity. The extraction of useful features from a given image, which includes several similar steps such as cascaded convolutional layers, adding non-linearities, and layer pooling.

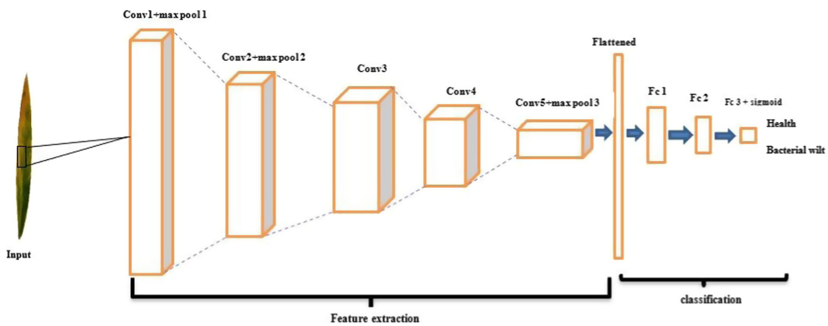

Fig. 1. CNN feature extraction and classification

The classification of the proposed model is performed in fully connected layers. As shown in the Fig. 1, we have a total of three fully connected layers, including the output layer. The main function of these layers is to classify the input image based on the features extracted by the convolutional layer and the detection layer. Before entering to the fully connected layer, the output layer is connected and flattened into a single vector value. The first fully connected layer accepts the output of the convolutional layer and the pooling layer. Each value of the vector represents the probability that a certain feature belongs to a class.

4 Data Preparation

Compared to the classical machine learning, deep learning requires large amount data to train the model [22]. For this, a data collected with the help of domain experts including; farmers, extension and agriculture researcher experts for the purpose of training the model. Accordingly, a total of 7,014 images the ginger dataset has been collected from Southern region of Ethiopia particularly from Boloso Bombe and Hadaro Tunto. From these, 7,014 dataset 2,734 images are labelled healthy while the remaining 4,280 images are labelled as infected. The image data has a 150 * 150 pixel size and Fig. 2 shows a leaf images collected for healthy and infected ginger.

(a) healthy ginger leaf

(b) infected ginger leaf

Fig. 2. Healthy ginger leaf and infected ginger leaf

After collecting the data set, the leaf image passes through a number of images pre-processing task including; noise reduction, data labeling, data augmentation and data splitting takes place which is used to be the major and important task when we want to work with image processing. Before training a data to develop model, we pesrformed noise reduction from background of each images which may not predict accurately and all images sized uniform then labeled with appropriate label (healthy and bacterial wilt).

After labeling, Data augmentation were applied on the original image data to obtain other images and overcome the problem of small data as well as to get a better training and classifier model. For the detection of ginger diseases, a feature parameter namely color feature, is used. This feature is considered to be because the visual color distinction is used in the traditional system to identify whether the crop is infected with the disease through human vision. Therefore, the proposed model provides an output (pre-defined class) based on the color features of the input image learned during training.

5 Experimental Setup and Setting

In order to select a suitable tool to implement the CNN algorithm for ginger image classification, the entire experiment was tuned. Samsung galaxy S10 (16 Megapixel camera and 1440 * 3040 pixel display size and resolution) has been used to capture an images from the field. For building a classification model convolutional neural network were used. Along with this, a Python programming language with TensorFlow and Keras libraries on Google Colab environment which offered 12.72 GB RAM and 68.40 GB with GPU which is the most important hardware in deep learning for computer vision research. The proposed model has totally 974,561 parameters. Thus, the reason we had recommended the above experimental setting in order to handle the detection of ginger disease in more efficient manner and within short period of time using high computing.

5.1 Hyper-Parameter Setting

Before the start of the training process, experiments have been conducted with different hyperparameter settings. There is no standard rule for selecting the best hyperparameters for a given problem [23]. Therefore, many experiments have been done to select hyperparameters and improve the performance of the model. The hyperparameters selected for the model are described below.

Dataset Ratio:-Evaluate the results obtained from experiments using different ratio of training and testing, and get better results from experiments that use 80% for training and 20% for tests.

Learning Rate:-The result of the experiment is that by using different learning rates, when we apply a higher learning rate, its accuracy is lower than that of a smaller learning rate. Therefore, in the proposed model, a learning rate of 0.001 is considered the best.

Activation Function:-We examined different activation function which are Tanh, Softmax and Sigmoid and finally Sigmoid activation function in the output layer is better than others because this is more suitable for binary classification problems.

Batch Size:-It is too hard to give all the data to the computer in a single epoch therefore we want to divide the input into several smaller batches which is preferred in model training to reduce the computational time of the machine.We've used maximum number batch-size and got a good performance thus we should always strive with maximum batch size our GPU can handle; therefore, it depends on the memory of GPU. In this experiment can run until batch size 128.

Epochs:-In the experiment, the model was trained using different epochs from 10 to 50. During the training process, we see that when we use too small or too large epochs, there will be a big gap between the training error and the validation error of the model. After many experiments, the model reached its optimum at epoch twenty five.

Optimization Algorithms:-The proposed model is trained by using the Adaptive Moment Estimation (Adam) optimizer which updates the weight of the model and tunes parameters.

Loss Function:-The experiment was done by using Binary Cross Entropy (BCE) loss, Mean Squared Error (MSE), and categorical cross entropy (CCE) loss. we have chosen BCE loss as a loss function. It performed well for models that output possibilities.

6 Experimental Result

During the experiment, different classification scenarios were carried out to test the classification performance. The results obtained from the proposed model experiment are shown in the following table, using the classification accuracy metrics in the form of percentages of training data, validation data, and test data, respectively. Accordingly, the experimental result shows a training accuracy of 96.19% with 13.59% loss and validation accuracy 96.16% with 13.44% loss while the testing accuracy 95.22% with 11.67% loss. In this work we analyzed that the key feature to detect ginger disease is color because which appears on the leaf and can differentiate a healthy ginger from infected. Among deep learning approach, CNN is best approach to apply in ginger disease detection and after several experiments, all of the parameters were evaluated to find a good classifier result from developed model and achieved 95.22% accuracy of classifying ginger in the correct category during test data evaluation.

7 Conclusion and Future Work

A limited research attempt has been done on automatic detection of Ginger crop diseases using the symptoms are seen on the leaves. Therefore, this paper aimed to develop a model to detect ginger disease at early stage which are very useful to farmers, extension workers, pathologists and also agriculture scientists not only that, it increases both quality and quantity of ginger crops in agriculture production.

During the experiment, we used images collected directly from the farm with the help of agricultural experts. Thus, the experiment has two main phases. In the training phase, the data is repeatedly presented to the classifier, while the weights are updated to get the required response. In the testing phase, apply the trained algorithm to data that the classifier has not tested before to evaluate the performance of the trained algorithm and we have developed a model with a deep learning technique using CNN by improving the performance under different parameters.

Additionally, the size of data, using different pre-trained model, capturing in different angle of the leaf may increase the performance of the predictive model and considering other types of disease may be better model to identify disease and by extending this research, we hope to have a valuable impact on sustainable development and strengthen the ginger value chain.

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