



DETERMINING THE OPTIMUM MATURITY OF MAIZE USING GOOGLNET

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ABSTRACT

Climatic changes, animal and human activities that lead to desertification and deforestation have affected the increase in agricultural produce especially in sub-Sahara Africa. Several efforts have been put in place to reduce these effects. However, that has not fully resolved the problem food shortages due to the growing population in sub-Sahara Africa. The application of image processing and convolutional neural network in the determination of the optimum maturity of SAMMAZ 17 variety of maize plant is being considered to mitigate for the shortage of food production. The optimum maturity is determined by using GoogleNet pre trained network on 3000 samples of maize comb captured using a camera at different maturity stages in a farmland. GoogleNet pre-trained network gave an accuracy of 82.44%. The result obtained showed a 10.44% improvement over an earlier result using Alexnet pre-trained network. The results suggest that when made operational there is a window of opportunity for increase in the production of food in sub-Sahara Africa.

Keywords: Convolutional Neural Networks, Maize, Optimum Maturity, Googlenet

INTRODUCTION

There is several challenges cause by changes in climatic conditions in sub-Sahara Africa. In Nigeria, being the most populous African country is faced with these challenges and those cause by human activities. Notable amongst these problems are deforestation and desertification. These have led to shortages in food supply as a result of inadequate land for grazing and agricultural activities, conflicts, loss of lives and properties (Peter, Abdulkadir, & Abdulhamid, 2017; Gambari, 2018). The increase in both human and livestock has necessitated the generation of different varieties of crops to combat desert encroachment in both lowlands and uplands in sub-Sahara Africa. This is to ensure the supply of adequate food for sustenance. The maize plant is one amongst the many agricultural crops that can be cultivated under different climatic conditions and meets the nutritional requirement of both humans and livestock in sub-Sahara Africa (Olaniyan, 2015; Peter, Damuut & Abdulkadir, 2020). The common method of harvesting maize in sub-Sahara Africa is at its biological maturity. At this stage, the nutrient level has seriously decline, and livestock do not usually benefit much when grazing on the maize plant stalk; sometimes the stalk are burnt. The maize maturity periods in term of days varies from one variety to the other. However, their maturities in terms of visual features like changes in coloration, texture, etc. are common amongst several varieties of maize. The use of vision to determine maize maturity is not very reliable as human eyes have differences in vision, weariness of sight, fatigue, etc., these can impair the right judgment. The use of image processing and Neural Network (NN) in determining the optimum maturity of maize for harvesting has mitigated for the classical approach of using human eyes (Peter, Damuut & Abdulkadir, 2020).

Convolutional Neural Networks (CNNs), or ConvNet are unique

multilayer NNs that detect visual configurations from picture elements (pixel) image from little preprocessing of the images acquired. In this section, literature review of related works on the identification and classification of agricultural produce using CNNs techniques are presented. CNN was applied in Yulcin & Razavi (2016) for detecting sixteen varieties of beans, cherries, pomegranates, and apricot, the classification result is 97.47% accuracy. Suma, Shetty, Tated, Rohan & Pujar (2019) used CNN to identify and classify the images of leaves from a common location, and obtained a classification accuracy of 99.32%. Prashar & Kant (2019) in an effort to reduce loss in profit by cotton farmers in India reported the use of CNN model having overlapping pooling technique and many layer perceptron methods in the identification and classification of good leaves. 96% identification accuracy was obtained. Boulent, Foucher, Theau, & St-Charles (2019) used 3 set of images under different conditions and applied CNN in the classification of crop diseases. They claimed that CNN gives better performances when dealing with complex situations. Jiang, Chen, Liu, He, & Liang (2019) improved upon the extraction potential of CNN by introducing a Nobel identification method from Single-Short Mult-box Detector (SSD) with GoogleNet Inception unit. 78.80% identification accuracy was obtained when the innovation was applied on five infectious leaf diseases. Lin et al. (2019) proposed a matrix-based CNN (M-bCNN) and used it in classifying eight categories images that were augmented, and obtained 96.5% validation accuracy and 90.1% testing accuracy. They claimed their results are better than those generated by pre-trained Alexnet and VGG-16. Zeiler and Fergus networks were modified in the work of Li, Chen, Wang, & Xie (2019), the resulting CNN reported a classification accuracy of 88.5% when applied in the identification of wheat mite. Suresh, Gnanaprakash, & Santhiya (2019) reported that Inception

version3 gave better results than ResNet50 version2 and Mobile-Net version2 when applied in the identification and classification of three types of infections on grape fruit. Ghostly features of Com seeds were extracted using CNN and cold damages was estimated in (Yang, Yang, Hao, Xie, & Li, 2019). CNN has a great potential for improving identification and classification accuracies in plant diseases (Saleem, Potgieter, & Arif, 2019). Gonzalez, Arellano, & Tapia (2019) compared ResNet50, ResNet101, and Mobile-Net version1 in the identification of blueberry images; ResNet50 gave a better result with 75.90% mean precision. Faster R-CNN combination and K-Means Clustering method was compared in the identification of certain rice diseases, and the results showed a very impressive performance (Zhou, Zhou, Chen, & He, 2019). In the work reported in Elhassouny & Smarandache (2019) shows that lower learning rates in identification and classification of Tomatoes leaf diseases generates better results. Li et al. (2019) combined CNN methods and density approximation in counting soya beans which is promising in breeding task. Combined approaches of Gated Recurrent Unit Networks and CNNs in differentiating similar crops have yielded excellent results (Li, Chen, & Zhang, 2019). Average classification accuracy of 99.58% was obtained in predicting maize production using CNN model (Abdullahi, Sheriff, & Mahieddine, 2017). Li, Xia, Du, Lin, & Samat (2017) altered the number of pooling layers and convolutional layers in three pre-trained networks to improve their performance. The results obtained suggest a correlation between the accuracy of classification and the number of layers as seen in (Sinha, Verma, & Haidar, 2017; Haryanto, Wasito, & Suhartanto, 2017). Zhang et al. (2018) obtained 91.90% accuracy within a time less than 0.01 predictions by using CNN in determining the accuracy and scalability of Tomatoes. A general network model based on U-net architecture was used to classify and segment several organs in the medical field. The results are 99% for classification and for segmentation 89% (Harouni, Karargyris, Negahdar, Beymer, & Syeda-Mahmood, 2018). Xia et al. (2018) used ANN and Support Vector Machine (SVM) in the identification and classification of matured varieties of oilseeds. ANN outperformed SVM in their results. Hu et al. (2016) stated that though Time series can explain seasonal characteristics of agricultural crops, they are not good in classification tasks. Do,

Kim, Yang, Lee, & Na (2018) reported facial identification and non-facial identification and classification task by CNN.

The use of ANN methods are reported in (Peter et al., 2017; Peter & Abdulkadir, 2018) for determining the optimum ripeness of maize from its leaves. However, Peter et al. (2020) stated that maize leaves are not very reliable for classification purposes. And the maize variety is of importance as their maturity period varies as well as climatic conditions for cultivation as reported in (Garba & Namo, 2013). Maize comb can give beneficial outcome to herders and crop farmers (Konar, 2005). NNs possess the capability of distinguishing patterns (Bezdek, 1994). In the work reported in Peter et al. (2020), Resnet50 outperformed the orthodox ANN. However, the performance of Resnet50 in the classification of the maize comb is not quite impressive. The non-refinement of layers must have affected the performance of Resnet50. The need to refine the layers or perhaps use a different pre-trained CNN to enhance the result in order to obtain a better classification when made operational is inevitable. In this paper, GoogleNet, a pioneer and deep Convolutional Neural Network (CNN) that utilizes the Inception module leveraging on feature identification at diverse measures through convolution with diverse filters with the result of dimensionality reduction by means of 1x1 convolution block which reduces the arithmetic operations in the layers. This characteristic has made Googlenet resolve the problems of over fitting, fading gradient or explosion that arises when there are many convolutional layers and units in a network, though with increase performance. (Zhang, Allen, Unger, & Cruz, 2018). The current work is an extension and enhancement upon the work in (Peter et al., 2020) which has not been address in this way before. The paper is organized as follows: Section 2 gives the approach used in cultivating the maize variety, image acquisition and classification. The results and discussions are presented in Section 3. Section 4 concludes the paper with future research direction and recommendations.

MATERIALS AND METHODS

SAMMAZ 17 maize variety, acquired maize comb images and the capturing device represent the materials. The method of processing images and classifying them represents the methods. The system framework is presented in Figure 1.

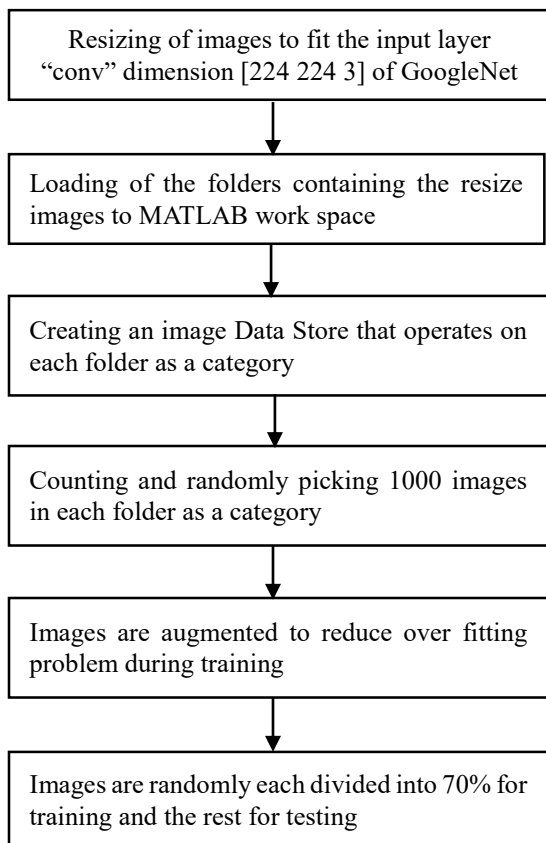


Figure 1: Framework of the System

The Maize Variety

The maize variety was SAMMAZ 17; a potent variety of maize suitable for different climatic conditions was cultivated for the research. It has a high resistance for drought, striga conditions with high nutrients (Garba & Namo, 2013; Garba, Ahmed, Katung, Lawal, & Abubakar, 2017).

Climatic Condition

SAMMAZ 17 maize variety was cultivated in highland. The area has an average daily temperature of 83^oF from the months of June to October with a probable rainfall of 0.46 inches as reported in (Gelaro et al., 2017).

Selection of Farming Site and Preparation

A three hectare farm site having good drainage was used for the cultivating of SAMMAZ 17 maize variety. In an effort to guarantee that glyphosate did not affect the maize seeds while destroying the weeds, the farm site was left for two weeks after glyphosate application before plowing, harrowing and ridging.

Pre-emergence

Two and half liters of Paraquat and five sachets of combi plus are prepared in one litre of water per hectare and used to destroy weed seeds disperse after application of glyphosate.

Post-emergence

After the germination of the maize, two liters herbicide (guard force) and powder sachets were applied per hectare. Three bags of NPK were applied after 2 weeks. Additional three bags of

NPK were applied after 5 weeks of plantation. Two bags of Urea fertilizer were applied per hectare during the eighth week.

Image Collection

A thousand maize comb images at the 10th week of cultivation were captured using a Full High Definition Charge Couple Device (CCD) digital camera FINEPIX Z35 placed at 90^o and 3 inches from the maize comb. The capturing of images was repeated at the 11th and 12th week. The differences in the period of image acquisition represents the maturity periods which are soft dough stage, hard dough stage and optimum maturity stage respectively.

Experimental setup

MATLAB R2018a software running on Windows7 Ultimate Operating System 64-bit service pack1 was used for the experiment. The processor is Intel® Core(TM) i7 with 2620M CPU @2.70GHz. 8.00GB RAM size and 500GB HDD.

Preparation of Images for GoogleNet pre-trained network

The images were resized to fit the input layer "Conv" having an input size of [224 224 3], which stand for 224 rows by 224 columns with three channels of the RGB image format.

Processing of Images

The resized images were labeled asLowRGB224, MediumRGB224 and HighRGB224 in three different folders representing the soft dough stage, hard dough stage, and the maturity stage respectively. The images are loaded on the

MATLAB work space and by applying *imageDatastore* () method an image data store (imds) was formed which assist in managing data by working on the image folder. The numbers of images in each category were randomly updated to one thousand each and used for input.

RESULTS AND DISCUSSIONS

Image Training

The input images from each category are randomly divided into 70% for training and the rest for testing. The initial conv layer reduced the input images through the use of large filters, however, the three-dimensional information were retained. In the second conv layer the image sizes are further reduced by four times and eight times prior to the first inception module, however, generating very high number of feature maps. Also at the second conv layer the computational burden are drastically reduced through the 1x1 conv block. The max pool layers located in between the inception modules primarily reduce the height and width of the input data when fed forward in the

network. This equally reduces the computational burden. The average pooling layer calculates the mean of all the feature maps generated in the second conv layer and subsequently decrease the image height and width to 1x1. In order to ensure that over fitting is reduced during training, the dropout layer is used to regularize the number of neurons interconnected within the network. To further regularize and reduce over fitting an auxiliary classifier is embedded within the third and sixth Inception modules during training. This is to guarantee that classification is performed based on the input. The components in the auxiliary classifier are average pool layer, conv layer, 2 fully connected layers, dropout layer and softmax layer with the softmax activation function. Finally, to ensure the desired event occurs for each class, the softmax activation function was used at the softmax layer being the final layer. The learning rate is 0.0001, stochastic gradient descent with momentum, 20 epochs are used. Figure 2 and figure 3 are the results of the classification.

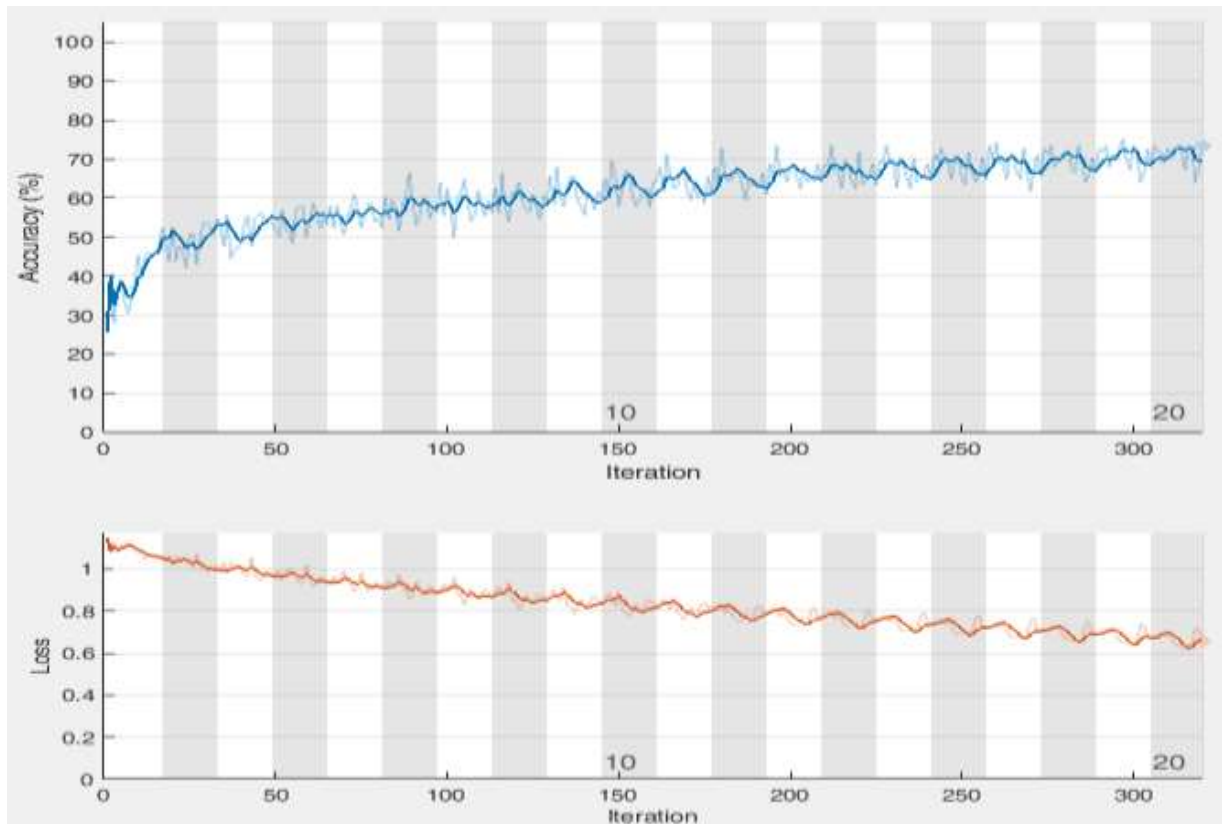


Figure 2: Classification Performance of GoogleNet

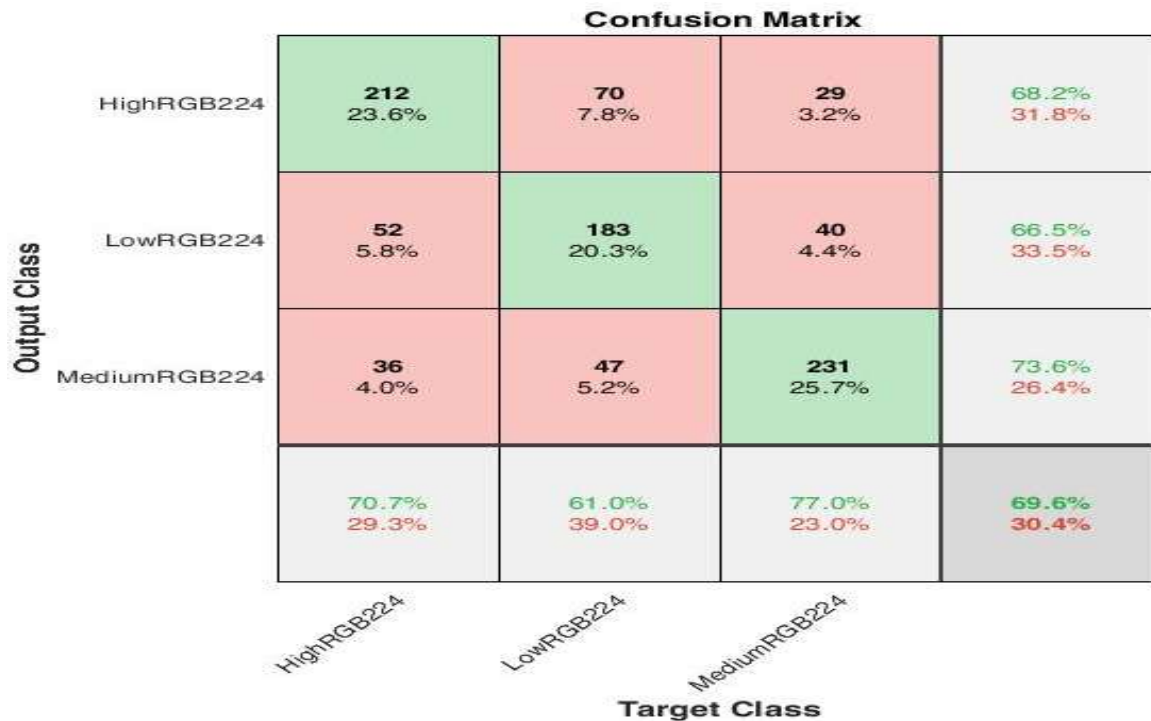


Figure 3: Confusion Matrix

In Figure 2, the accuracy of the GoogleNet classifier is about 70% and the loss is around 0.6 which is fairly above the result reported in (Peter et al., 2020). In Figure 3, being the confusion matrix depicts the target class versus the output class. The HighRGB224 category, being the optimum matured maize is correctly classified by 68.2% and wrongly classified as 31.8%. In the MediumRGB224 category, being the hard dough stage is correctly classified as 73.6% and 26.4% misclassified. Finally, the LowRGB224 categories, being the soft dough stage, 66.5% are correctly classified and 33.5% are misclassified. The overall accuracy of classification is 69.6%.

CONCLUSION

In this paper, an extension and improvement upon an earlier work reported in Peter et al. (2020) is presented. The work attempts to encourage the integration of farmers and herders by proposing an optimum period of harvesting maize crop that would allow for herders to graze on the fresh maize stalk. This would encourage more food production, mutual and peaceful coexistence between herders and farmers. The ANN variant used is the deep NN of the GoogleNet pre-trained network. An auxiliary classifier concept was applied to the third and sixth Inception module to ensure regularization and reduce over fitting problem prior to the classification. An average classification accuracy of 69.6% was obtained. The result shows that the network can identify the hard dough stage more followed by the optimum mature stage.

Future Research Direction

The findings suggest a window for future work in the area of classifying maize on the basis of optimum maturity in other to

improve food production and betterment of farmers and herders livelihood.

Data Availability

Upon request the data of the maize comb images are available.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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