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IMPROVED DETERMINATION OF THE OPTIMUM MATURITY OF MAIZE BASED ON ALEXNET

Ayuba Peter[1,*], Luhutyit Peter Damuut[2], Sa'adatu Abdulkadir[3]

[1]Department of Mathematical Sciences, Kaduna State University, Kaduna, Nigeria
[2,3]Department of Computer Science, Kaduna State University, Kaduna, Nigeria

*Corresponding Author's Email Address: ayubng@kasu.edu.ng

ABSTRACT
The increase in the number of humans and animals, particularly livestock in Sub-Sahara Africa without a correspondent increase in land resources has led to shortages, and consequently metamorphose into unhealthy clashes between farmers and herders. The unpredictable changes in climatic conditions in recent times and human activities has also contributed to deforestation and desertification. The maize plant is being considered to mitigate for the shortage by the application of Computational Intelligence technique and image processing in the determination of the optimum maturity of the maize. There are different varieties of maize that are quite suitable for different climatic conditions in Sub-Saharan Africa. In this paper, the optimum maturity of SAMMAZ 17 variety of maize seedling is selected due to its high resilient to drought, striga condition and its good composition of nutrients. The maturity is determined by the application of Alexnet on 3000 samples of maize comb captured at different maturity stages cultivated in the same farm land. The network gave an accuracy of 72.44%. The result obtained showed a 4.44% improvement over an earlier result obtained by the use of Resnet-50. The finding is a window of opportunity for improvement in the determination of the optimum maturity of maize.

Keywords: Artificial Neural Networks, Computational Intelligence, Convolutional Neural Networks, Maize, Optimum Maturity, Alexnet, Resnet-50

1.0 INTRODUCTION

The uncertainties pose by changes in climatic conditions are enormous. In Sub-Sahara Africa, especially in Nigeria, several owners of livestock and agricultural crop farmers are faced with the problems generated by these changes and those caused by human activities that has resulted in deforestation and desertification. This has led to massive movements of herders in search for available grazing sites. The results are conflicts, loss of lives, and properties (Peter, Abdulkadir, & Abdulhamid, 2017). The decline in meat production and dairy foods are other consequences experienced (Gambari, 2018). The growth in human and livestock population on a global scale requires a corresponding provision of adequate resources (food) to meetup the challenging needs of both humans and livestock. The maize plant is widely cultivated amongst several agricultural crops in Sub-Sahara Africa for its nutrient contents, and it is a staple food in the region (Olaniyan, 2015). It has variety of usage than any crop in Sub-Sahara Africa: it can be roasted, cooked with its comb, used for pudding, milled into flour, pop, porridge, etc. The high energy and water contents of the maize plant is a very good source of grazing for livestock and it is cultivated under different climatic conditions and all-round the year due to its vast genetically modified varieties with vitamin A (Muzhingi et al., 2011; Pingali, 2012). In Sub-Sahara Africa, the maize plant is usually harvested at biological maturity and its yield per unit hectare is much as compared to other crops (Plessis, 2003). This leaves the plant with little or no nutritional value for livestock consumption. However, it can be harvested between the hard dough stage and physiological maturity. The traditional method of determining its maturity at such state is not without challenges, due to weariness of the human eye and differences in vision as reported in (Damiri & Slamet, 2012), hence the application of image processing (IP) for acquiring the images and Neural Networks (NNs) for classifying the images that have overcome the challenges of humans (Peter, Damuut & Abdulkadir, 2020).

Convolutional Neural Networks (CNNs) are improvements upon the classical Artificial Neural Networks (ANNs) that are electrical analogue of the biological neuron with the capacity of imitating the characteristics of the biological neuron such as pattern recognition, motor control and perception. In this section, literature review of related works on the identification and classification of agricultural produce using techniques that possess the capability of computational intelligence are presented. Yulcin and Razavi (2016) applied CNN in classifying 16 species of beans, pomegranates, cherries and apricot from 1,200 images obtained in a Turkey agricultural location, with 97.47% accuracy. Suma, Shetty,Tated, Rohan & Pujar (2019) also reported the use of CNN in the identification and classification of leaf images from an ordinary environment with 99.32% classification accuracy. Loss of about 10%-20% profit incurred annually by cotton farmers in India as a result of infections from plant diseases is reported in (Prashar & Kant, 2019). They used CNN model with the overlapping Pooling method and Multiple Layer Perceptron (MLP) technique to identify and classify healthy leaves, and obtained 96% identification accuracy in an effort to solving the problem of profit loss in the cotton production. Boulent, Foucher, Theau, & St-Charles (2019) reported that CNN can generate better performance in handling complex conditions of image processing and classification of crop infections. Three sets of data images were utilised in the work: the first set of images are under constrained conditions of identical background and illumination, the second set of images are under unconstrained situation, except that focus is placed on unique plant organ, and the third set of images are also under unconditioned situation, but without special attention to any plant organ. In other to improve upon the extraction capability of CCN, Jiang, Chen, Liu, He, & Liang (2019) proposed an innovative identification technique using a deep-CNN obtained from Single-Short multi-box Detector(SSD) and GoogleNet Inception module. Rainbow combination technique in R-SSD is included to improve the feature integration performance by many angle feature amalgamations. INAR-SSD, the enhanced model gave a mean identification precision of 78.80% when applied in the identification of Mosaic, Grey spot, Rust, Alternaria leaf spot and Brown spot of Apple leaf infections. A matrix-based CNN (M-bCNN) proposed by Lin et al. (2019) for addressing issues of slope disappearing and over-fitting of data was made by parallel organization of convolutional layers in array format and the inclusion of exponential unit, DropConnect, Local reply normalization, etc. 8 categories of 16652 images of experimental samples were augmented to 83260 images; 96.5% validation accuracy and 90.1% testing accuracy were obtained outperforming Alexnet and VGG-16 pre-trained networks in the work. Li, Chen, Wang, & Xie (2019) proposed a CNN that combined Zeiler and Fergus networks with area proposed network having non-maximum dominance in removing overlapping identifications and reported an average identification precision of 88.5% of a known dangerous pest called wheat mite that retards the growth of wheat. Agricultural crop productions are directly proportional to the health of the crops. A comparative analysis of ResNet-50 version2, Inception version3 and Mobile-Net version2 on Adagrad, Adadetta, and Adam optimizers to identify and classify black rot, measles and blight, three infections on grape is reported in (Suresh, Gnanaprakash, & Santhiya, 2019). Inception version3 outperformed the rest pre-trained networks with a classification accuracy of 99.9%, then Mobile-Net with 99.3%. Corn seedling species or any crop having great resistance to cold effects are of advantage for cultivation as stated in (Yang, Yang, Hao, Xie, & Li, 2019). Extraction of ghostly features under visible-close- infrared space from corn seeds is done by CNN for approximating cold damage. Cold damage levels of BxM as 25.6%, W22 as 41.8%, PH207 as 20%, B73 as 25.6% and Mo17 as 14% of corn seed species. The results obtained from chemical approach has a high coefficient of correlation of 0.8219. CNN has a high capability for improving identification and classification accuracies in plant infections (Saleem, Potgieter, & Arif, 2019). In achieving mechanization in harvest management, Gonzalez, Arellano, &Tapia (2019) used a network that hinge on Mask R-CNN to identify blueberry images. Pre-trained networks such as Mobile-Net version1, ResNet50 and ResNet101 are tested on the images. The results show that Resnet50 outperformed the other CNNs with 0.759 average precision on a bench mark of 0.5 connection on unification error. The quick identification of sheath blight infection, rice blast and bacterial blight of rice diseases from 3010 images of rice by the application of faster R-CNN fusion and K-Means Clustering algorithm is reported in (Zhou, Zhou, Chen, & He, 2019). Results obtained show the following detection accuracies: 98.26% for sheath blight infection, 97.55% for bacterial blight and 96.71% for rice blast. An innovation from Mobile-Net CNN in recognizing 10 known types of Tomato leaf infections was proposed in (Elhassouny & Smarandache, 2019). Results show that lower learning rates gave better recognition accuracies of the infection. In an effort to improve upon crop breeding, Li et al. (2019) proposed an approach for counting Soya beans. The approach combined density estimation and Convolutional Neural Network techniques. The results show potential in future breeding task. Distinguishing of indistinct crop differences is implemented on many temporal data using integrated approach of CNNs and Gated Recurrent Unit Networks. Excellent performance was obtained on classes having similar phonological rules as stated in (Li, Chen, & Zhang, 2019). In the prediction of the accuracy of maize production, CNN model was used and a mean prediction accuracy of 99.58% was obtained as reported in (Abdullahi, Sheriff, & Mahieddine, 2017). Performance of CNN was improved by altering the number of Pooling layers and the Convolutional layers in AlexNet, Caffe-Net, and VGG pre-trained networks for classifying remote sensing scenes as reported in (Li, Xia, Du, Lin, & Samat, 2017). Their results show that there is a proportional relationship between the number of layers and accuracy of prediction as reported in (Sinha, Verma, & Haidar, 2017; Haryanto, Wasito, & Suhartanto, 2017). Accuracy and scalability of the ripeness of Tomatoes by Tomato maturity robot for classification and prediction was determined by the use of CNN in (Zhang et al., 2018). The result show 91.9% accuracy and less than 0.01 prediction time. Harouni, Karargyris, Negahdar, Beymer, & Syeda-Mahmood (2018) stated that a general network model that is built upon the architecture of Unet, with the capability of segmenting distinctive organs of diverse modalities was used in the segmentation and classification of many organs in the medical discipline. The result show 99% classification accuracy and an average dice score of 89% for segmentation. In the hyperspectral detection and classification of ripe species of oilseeds: Ning You 22 and Ning Za 19, Xia et al. (2018) reported that ANN produced a better result than Support Vector Machine (SVM). Time series have remarkable capacity to describe timely features of crops, however, do not possess very good classification accuracy as reported in (Hu et al., 2016). Facial recognition and non-facial recognition classification task by CNN are reported in (Do, Kim, Yang, Lee, & Na, 2018).

The application of Computational Intelligence technique has been deployed in (Peter et al., 2017; Peter & Abdulkadir, 2018), for determining the optimum maturity of maize from its leaves, however, Peter et al. (2020) argued that the use of maize leaf for classification cannot give a reliable result, as the green coloration is due to the presence of nitrogen, phosphorus, potassium and chlorophyll used for photosynthesis that gives the intensity of the green coloration. The need to identify the maize variety is also essential, as there are different modified varieties cultivated under different climatic conditions (Garba & Namo, 2013). NNs, when applied in the classification of the of maize comb, can give a beneficial development for both crop farmers and herders (Konar, 2005). NNs basically handle numerical data having components with the potential of distinguishing configurations (patterns) (Bezdek, 1994). The result showed that Resnet-50 outperformed the classical ANN. However, the performance of the pre-trained Resnet-50 which is a directed acyclic graph (DAG) network using feature layer extraction of fully connected layer 1000 (fc1000) was below an acceptable threshold of 70%. The use of fc1000 without refining of layers by increasing the number of layers must have been responsible for the percentage drop below threshold of 70% (Peter et al., 2010). There is need to improve upon the result in other to get a more reliable result when made operational. In this paper, Alexnet, a pioneer and deep Convolutional Neural Network (CNN) with more filters per layer that won the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVR C) and

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reduced the top5 error rate from 26.5% to 15.9% is used by extracting the features of the images using the pool2 layer which has the potential of overlapping pooling that can reduce error and overfitting as not all layers a good at extracting features (Zhang, Allen, Unger, & Cruz, 2018). To further reduce overfitting problem, the images are augmented by generating image translations and horizontal reflection that increased the training set by a factor of 1000 is propose for an improvement. This has demonstrated that CNN has a better potential in the classification of agricultural crops as well as other images. This work is an extension of and improvement upon the research reported in (Peter et al., 2020); and to the best of our understanding it has not been address in this manner before. The remaining paper is organised as follows: in section 2, the layout of the methodology for farming, acquiring the maize comb images and subsequent classification are presented. Section 3 presents the results and discussions. In section 4, the paper is concluded with future research direction and recommendations.

2. MATERIALS AND METHODS

Materials and methods used in the research are presented in this section. Maize variety, climatic conditions, farming site selection, land preparation, maize comb images acquired and the capturing device represent the materials. The approach for processing images and classifying the images represent the methods. The framework for the method of training and testing is presented in figure 1.

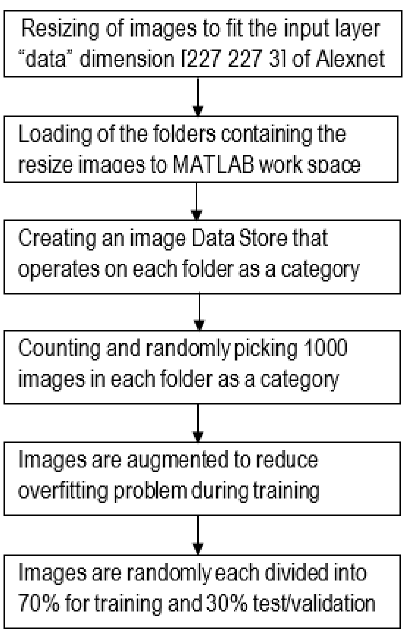

Figure 1: Framework of the System

2.1. Maize Variety

SAMAZ 17, a highly improved potent variety of maize suitable for varying climatic conditions was cultivated for the research. The variety can resist high drought condition, striga situations and has substantial quantity of nutrients (Garba & Namo, 2013; Garba, Ahmed, Katung, Lawal, & Abubakar, 2017).

2.2. Climatic Condition

SAMAZ 17 maize variety was cultivated under a tropical climatic condition. The mean daily temperature of 83^{0}F from the months of June to October. The probability of rainfall within the period is 0.46 inches as reported in (Gelaro et al., 2017).

2.3. Farming Site Selection and Preparation

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

2.3.1. Pre-emergence

Weed seeds that were dispersed by wind after the expiration of glyphosate application in two weeks are destroyed by applying a treatment of paraquat and combi plus in a solution of 1litre of water to 2.5 litres of paraquat and 5 sachets of combi plus per hectare.

2.3.2. Post-emergence

Two litres of a selective herbicide for maize (guard force) and a powdered sachet of same were applied per hectare after the germination of the maize variety planted. In two weeks 3bags of NPK (Nitrogen, Phosphate and potassium) are applied per hectare. In five weeks' period from plantation another 3bags of NPK are applied. At the eighth week, Urea fertilizers are applied in the farm land in the quantity of 2 bags per hectare.

2.4. Image Collection

A Full High Definition Charge Couple Device (CCD) digital camera FINEPIX Z35 placed at 90^0 and 3 inches from the maize comb was used to capture over a thousand maize comb images at the tenth week of plantation and mark as low representing the soft dough stage. This was repeated at the eleventh and twelfth weeks' period and marked as medium, and high; representing the hard dough stage and the optimum maturity stage respectively. See figures 2 for the sample of images of maize comb at different maturity period.

Figure 2: Stages of Maize Comb Image Maturity (Peter et al., 2020, p.5)

2.5. Hardware and Software experimental setup

The experiment was conducted using a script written and run on MATLAB R2018a software, with Windows7 Ultimate 64-bit OS, service pack1. Intel® Core(TM) i7, 2620M CPU @2.70GHz processor. RAM size is 8.00GB and 500GB HDD.

2.6. Image Preparation for Alexnet pre-trained network

The Alexnet pre-trained is a deep learning CNN with a series network having 25 layers (See figure 3). Since the Alexnet

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network takes input size of [227 227 3], meaning 227 rows by 227 columns(227X227) dimension 3 channel images that represents red, green, and blue (RGB), the images acquired are first resize to 227X227 by a MATLAB script before loading the images for processing, training and classification.

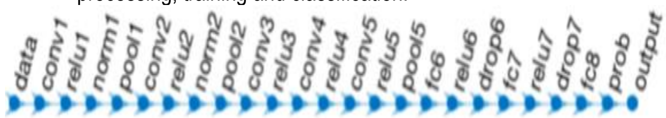

Figure 3: Simple Alexnet Architecture (Zhang et al., 2018, p. 3)

2.7. Images Processing

The images resize are labeled in three different folders with the names low, medium, and high representing the soft dough stage, hard dough stage, and the maturity stage respectively. The images are loaded on the MATLAB work space and an image data store (imds) was created using *imageDatastore ()* method in MATLAB that helps manage data by operating on the image folder. The number of images in each category (low, medium, and high) were counted and the images updated to have equal number of 1000 random images each.

3. RESULTS

3.1. Image Training

The 1000 images in each category were divided randomly in the data store into 700 images (70%) each for training and the remaining for testing/validation and then augmented to reduce overfitting problem. The images are trained generally by 15 layers including the input and classification layer. The convolutional layers padded the images with additional pixels of 3rows, 8columns to accommodate the filter kernel after the input layer has taken 227X 227 pixel images. This is followed by batch normalization of the images to guarantee generalization and reduce errors at the normalization layer. The Rectified Linear Units (ReLU) layer is next, it is used in place of hyperbolic tan function, with the advantage in the training error rate by reducing the number of epochs. Then the pooling layers, where the layers summarized output from neighboring pooling units. This cycle was repeated, but with an increase in the number of columns from 8 to 16 to 32 columns, while the rows padding remain constant (3rows pixel) for the convolutional layers and all other layers remain unaltered.

The fully connected layers are used to extract features. The Softmax layer finally reduces the overfitting problem before the classification layer takes it response. The Network was fine-tuned by removing the other layers as they are not suitable in extracting features of the images (Peter et al., 2020). Figure 4, is the training progress of the Alexnet pre-trained CNN. The learning rate is 0.0001, stochastic gradient descent momentum, maximum number of epochs are 20, ReLU activation function and pooling size of 6X6X256.

3.2. Image Classification

In the classification of the images, Pool2 layers having a feature map of 256, size of 6X6X256, kernel size of 3X3, stride of 2 units and ReLU activation function is used to extract features for the classification. Figure 5 is the confusion matrix for the 72.44% classification accuracy to one decimal place obtained for the classification.

Figure 4: Alexnet Training Progress

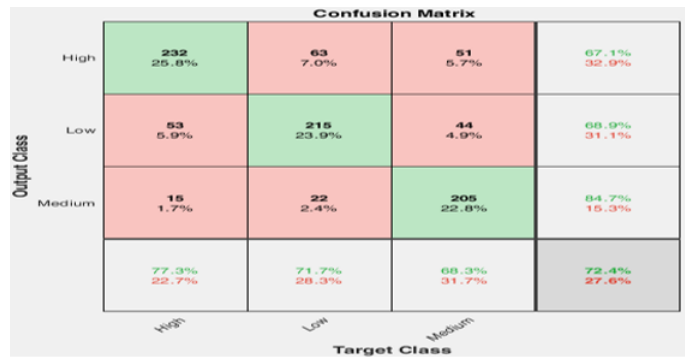

Figure 5: Confusion Matrix for the Classification accuracy

4. DISCUSSION

In figure 4, the percentage accuracy training progress of the pre-trained Alexnet CNN starts at about 38.5% accuracy and proceeds to about 91.5% accuracy, and the loss starts from 2 and drops to as low as 0.4, which show that the network is able to adapt to the maize comb images in the different categories. In figure 5, the confusion matrix of the target class verses the output class show that the high category, representing the mature maize are corrected classified by 67.1% and wrongly classified as 32.9%. In the medium category, the hard dough stage the network classifies 68.9% correctly and misclassified 31.1%. While in the low category, which is the soft dough stage, the network classifies 84.7% correctly and misclassified 15.3%. The average classification accuracy is 72.44%.

5. Conclusion and future research direction

In this paper, an attempt has been made to improve upon an earlier work reported by Peter et al. in [8] that tries to address the problem of grazing field faced by herders and the resulting effect on agricultural crop farmers in Sub-Sahara Africa by the use of Neural Networks to classify maize crop. Resnet-50 was compared with the classical ANN, and it is reported that the CNN outperformed the ANN by achieving 68% prediction accuracy as against 64.5% obtained by ANN. In this work, Alexnet pre-trained CNN is used for classifying the same maize comb images, however, by resizing the images to 227X227 dimension to fit the input layer 'data' of the Alexnet, the resized images were augmented to reduce overfitting of the data. In the training phase, the network is fine-tuned by including additional pixel of 3 rows and 8 columns in the Convolutional layer to accommodate the filter kernel after the input layer has received 227X227 pixel images. The padding was repeated for 16 rows, 32 rows in two more Convolutional layers. Batch normalization of the images are performed to ensure generalization and reduction at the normalization layers. The Rectified Linear Units are used in place of the tanh function, with the advantage of reducing the number epochs for the training error rate. The Softmax layer was used to reduce the overfitting problem before the classification layer. The pool2 layer is use for feature extraction and summarization of output of the neighboring layers in other to reduce error and overfitting in the classification task. An average classification accuracy of 72.44% was obtained. Results obtained are clearly the function of maize comb images at varying maturity stages of the maize. In the future, other pre-trained Networks shall be considered for classification as the present results still gives a window of opportunity for improvement.

5.1 Data Availability
The data from the maize comb images are available from the corresponding author upon request.

5.2 Conflict of Interest
The authors declare that there is no conflict of interest regarding the publication of this paper.

5.3 Funding Statement
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