ABSTRACT

One of the major challenges faced by agricultural industry is the need for accurate and early detection of diseases that affect crops. Diseases affect the quality of crops and are capable of wiping out hectares of crop yield resulting in major loss to farmers. Current diagnostic techniques are time consuming and require the presence of highly skilled professionals to analyze the affected plants, understand the symptoms, identify the disease and thereby suggest suitable remedies. The limitations of such techniques have enforced the need to look for alternative techniques which can detect and classify diseases. Smart farming using suitable infrastructure can help in tackling and providing solutions to such problems. Data mining techniques, in the recent years have shown great promise in identifying and classifying patterns in similar areas of research. this project aims to evaluate the performance of algorithms like Convolutional Neural Network (CNN) and its architectures like SqueezeNet and GoogleNet coupled with data augmentation and transfer learning against traditional machine learning algorithms like Support Vector Machine (SVM), random forest and measure their effectiveness in identifying and classifying maize plant diseases in terms of accuracy and training time. Training of the models were performed on an open source database containing close to 12332 images, encompassing four distinct classes, including healthy plant images. Out of the models developed, SqueezeNet architecture of CNN with transfer learning performed the best by achieving an overall accuracy of 95.12 percent, thereby satisfying the need of building an effective and robust classification model. Also, the performance of the models developed were found to improve with increase in amount of training data. The results obtained using transfer learning techniques on CNN architectures are highly promising and can be extended further to form a comprehensive plant disease identification system that is capable of operating in real world environment. It can thus empower the agricultural community to diagnose diseases and initiate timely treatment without the intervention of trained experts.

Keywords: Plant Disease Detection, Machine Learning, Support Vector Machine, SqueezeNet, Convolution Neural Network, Data Model, Googlenet, Transfer Learning

INTRODUCTION

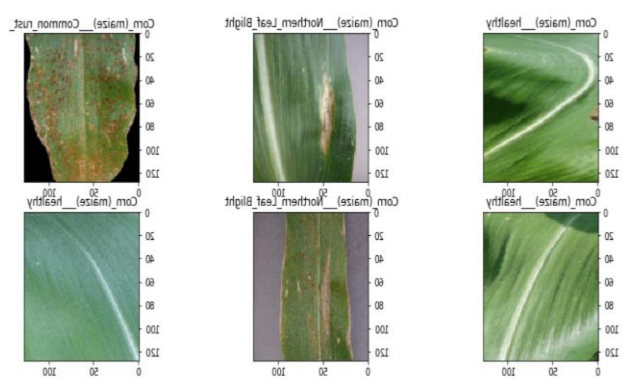
Agriculture is a lifeline for a vast majority of the population in the world with close to 70 percent of people directly dependent on it as means for living and in Nigeria also [1]. The crops grown by farmers in different regions across the world are mainly based on weather, yield potential, type of soil, etc. Of the crops grown, maize, alternatively known as corn is largely cultivated worldwide and is the third leading crop of the world after rice and wheat, and third in Nigeria after Cassava and Yam mainly because of its nutritional value and yield potential. Close to 1100 million metric tons were produced last year with countries like India, China and USA being the top cultivators and 10.1 million tons were produced in Nigeria (14th largest cultivators in the world). Although, the numbers look quite impressive, it doesn't paint the full picture as high volumes of the produce are also lost due to various factors. A good yield not only helps the cultivators, but also significantly boosts the economic growth of the country. However, achieving desired levels of yield is challenging as it is influenced by various aspects like climate, pests, diseases amongst many others. Maize, like majority of the crops grown is very sensitive to such factors with close to 35 percent of its production lost to diseases and pests on average every year [2]. Northern leaf blight, Common rust and gray leaf spots are some of the diseases that can create major havoc to these plants. Therefore, mentioned statistics strongly indicate the need for an effective detection of diseases in these plants as negligence and delay can lead to significant losses.

Traditionally, visual observation by experts were done to diagnose the plant diseases. However, they carried a high risk of subjective perception and were time consuming in nature. In due course of time, spectroscopic and imaging techniques were used with researches like [3] making use of hyperspectral data of strawberry leaves for identification of diseases. They obtained accuracies close to 70 percent. However, these methods required precision instruments and bulky sensors for analysis which in turn placed the need for expert intervention. Digitization and evolution of machine learning techniques that can detect underlying patterns have been become popular alternatives to diagnose plant diseases in recent years. Conventional classification algorithms like Support Vector machine (SVM), K means clustering, etc. coupled with complex preprocessing and feature extraction techniques have been used and have produced satisfactory results. The rapid advancements and research in this domain have led to development of new brand of models and techniques called deep learning. The introduction of these deep learning techniques into agriculture, and in particular into the field of disease diagnosis, has only started a couple of years back and to a rather limited extent.

MATERIALS AND METHODS

DATA SELECTION

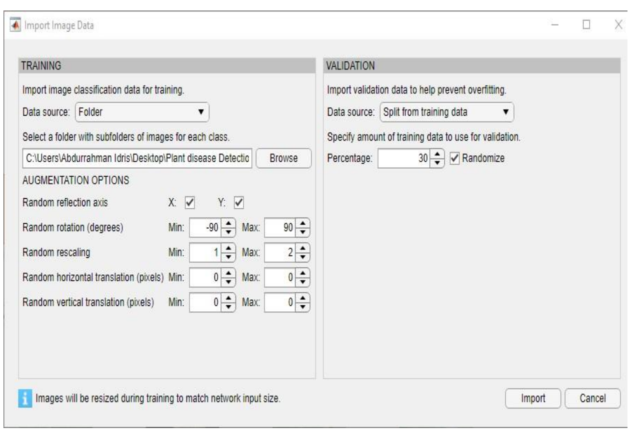
One of the major challenges of projects in agricultural domain is the lack of data that are publicly usable and is discussed by authors [4] in their study. Most of the projects done are on proprietary data that are collected by authors. This is a time consuming and expensive proposition in itself. It is only recently that a public project initiative called Plant Village made such data available for public. It contains leaf images of various plants that are healthy or are affected by diseases, categorized and labelled into various folders. This data is available on GitHub and has been used for analysis by various authors. Current system only uses data related to maize plant from the above dataset. Although the data is available in various formats like colored, grey scale and segmented; only colored data has been used for the study as they seem to have produced better results in many previous systems [5]. The data used has images that belongs to four different categories namely gray leaf spot, common rust, northern leaf blight and healthy maize and their sample images are as shown in Figure below

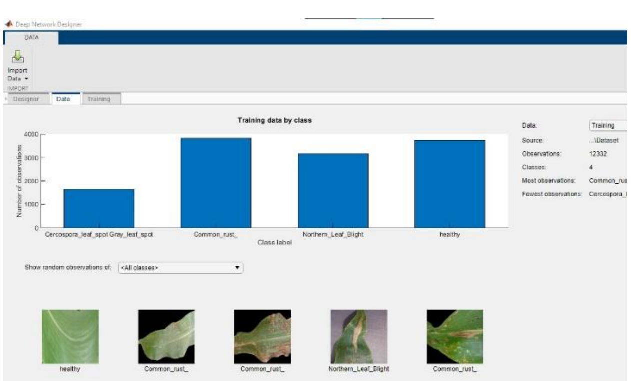


Maize Disease Images

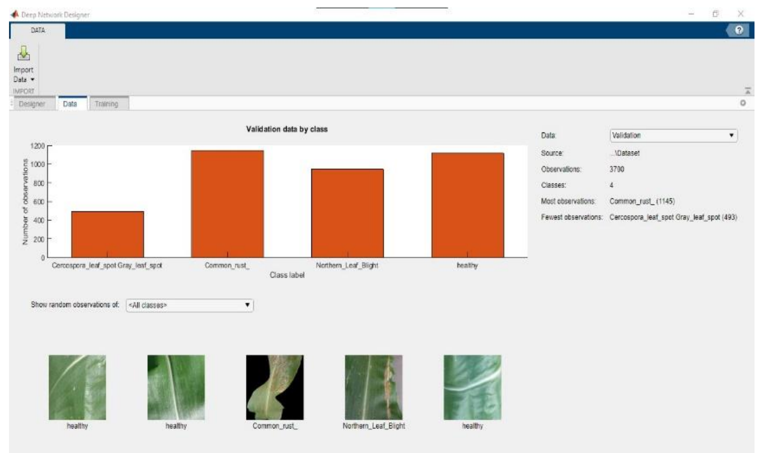
DATA PRE-PROCESSING

The dataset on the whole had data related to 14 different plant species. As the current system focusses only on maize plant, other folders were removed from the data repository resulting in a sample size of 12322 images spread across four folders as shown in Figure above. These images were then loaded through these folders. This was followed by resizing them to satisfy the dimensionality constraints of various algorithms and to provide uniformity so that the classification algorithms perform well. They were also labelled based on the class they belonged taking from there various folder names. Further, a bar chart plotted automatically to check for distribution of images in various folders. which would enable us to build efficient models. Models were then built on this data and validated for test train splits of 70:30.



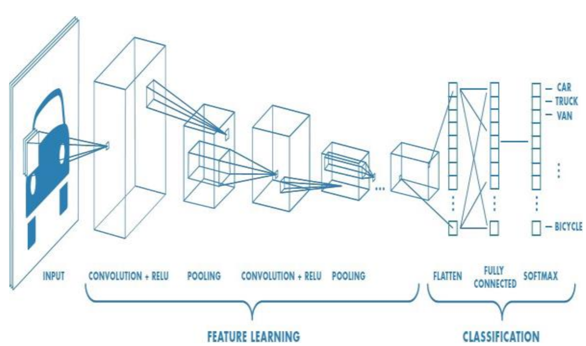


Bar Chart displaying the proportion of each class for training dataset



Bar Chart display for Validation and accuracy test

Convolutional neural networks (CNNs) consist of multiple layers of receptive fields. These are small neuron collections that process parts of the input image [6]. The outputs of these collections are then tiled so that their input fields overlap, to obtain a high-resolution representation of the original image; This is repeated for every such layer. Tiling allows CNN to bear the translation of the input image. Neural networks may include local or global pooling layers, which combine the output of neuron clusters. They consist of various combinations of confessional and fully connected layers, with pointwise nonlinearity applied at or after the end of each layer.



Various Layers in CNN

Functionalities of some of the layers used in the design are briefly described below:

Convolution layer: A layer used to extract features from an image by making use of filters that learn from small squares of input data. It receives the input maize leaf images in the form of pixel values that is convolved with the filter to extract low level characteristics of image like curves and edges and generates a feature map.

Pooling Layer: It is used to reduce the dimensionality of image which reduces the computational power needed for successive layers. Max pooling is used in the project and it selects the maximum value in a region based on filter size.

Fully Connected Layer (Dense): These are part of the final layers of CNN are capable of recognizing features that are highly correlated with output class. The output is a one-dimensional vector obtained by attending the results of previous pooling layers.

Dropout layer: Used to reduce overfitting of the model by randomly discarding certain set of neurons in that layer.

SoftMax layer: final layer in the network that helps in classifying the input images of maize into various classes based on the characteristics learnt by the network

TRANSFER LEARNING

It is a niche in the deep learning domain that is gaining prominence off late. It basically works by transferring knowledge acquired from data in one domain into other domains. The main advantages include the lack of need for huge datasets to train the model and less computational power as model weights are already pretrained [7]. They also generalize well on new data as they are built to prevent overfitting. The models used in this project SqueezeNet And GoogleNet are pretrained on ImageNet database containing 1.6 million images belonging to over 1000 classes. These models are known to provide best results and excellent performance when used for image classification as they have learnt several features from the huge database it had been trained on. Only the final few layers of the model have been retrained using maize dataset to make the model predict better. A brief description of the architectures chosen for transfer learning is given below:

SqueezeNet: is a convolutional neural network that is 18 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. This function returns a SqueezeNet v1.1 network, which has similar accuracy to SqueezeNet v1.0 but requires fewer floating-point operations per prediction. The network has an image input size of 227-by-227.

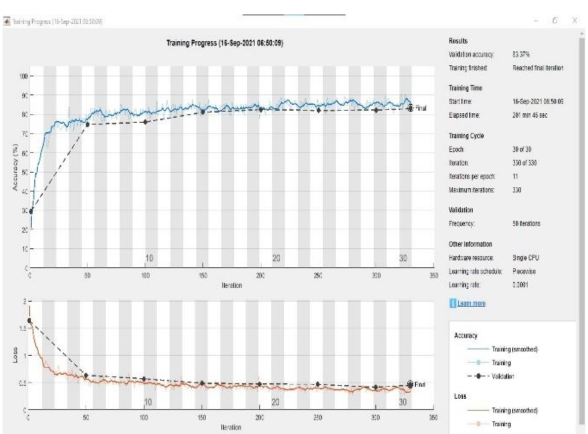
GoogleNet: is a convolutional neural network that is 22 layers deep. You can load a pretrained version of the network trained on either the ImageNet or Places365 data sets. The network trained on ImageNet classifies images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. The network trained on Places365 is similar to the network trained on ImageNet, but classifies images into 365 different place categories, such as field, park, runway, and lobby. These networks have learned different feature representations for a wide range of images. The pretrained networks both have an image input size of 224-by-224.

TABULAR COMPARISON OF TECHNIQUES USED IN THE PAST RECENT YEARS

Year	Contributors / Authors	Technique Used	Accuracy
2019	Raj Priyanka, Dr. Neha Mangla,	Canny edge detection algorithm and CBIR	92.3%
2019	Jiangsheng Gui, Mor Mbaye	CNN Network	90.5%
2018	Saradhambal.G, Dhivya.R, Latha.S, R.Rajesh	ok-suggest clustering algorithm	91.5%
2018	Jihen Amara, Bassem Bouaziz, Alsayed Algerawy	Deep learning	83%
2018	Rafel C.Gonzalez and Richards E.Woods	Classification of image processing techniques	89%
2017	M. Akila, P. Deepan (Assistant Professor)	Histogram approach	71.2%
2017	P. Krithika and S. Veni	Multiclass Support Vector Machine	70%
2016	Dr. Neha Mangla, Priyanka B Raj, Soumya G Hegde, Pooja R	Canny edge detection algorithm and CBIR	92.3%
2016	Sharayu S. Tambe, Gulve Pranita	PNN and extract color and texture feature	86%
2015	Vishnu S, A. Ranjith Ram	BPNN, SVM to detect plant leaf disease	73%
2015	V.Surendrababu, Dr.C.P.Sumathi, E.Umapathy	Chaos and fractal dimension	81.2%
2014	Vijai Singh, Varsha, A K Misra	Capture, resize and enhancing contrast	71.6%

RESULTS AND DISCUSSION

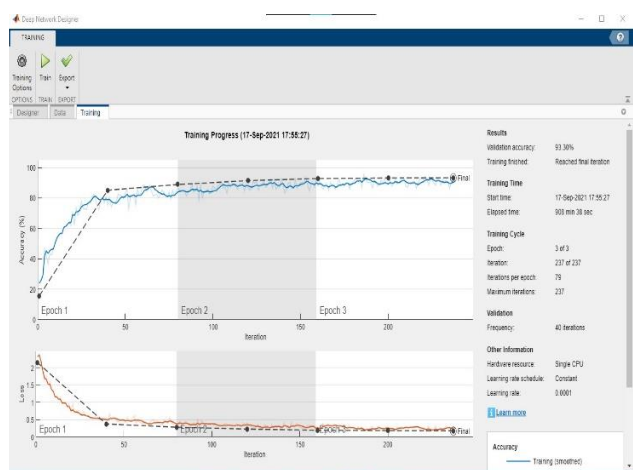
MODEL 1:**CNN**



Validation accuracy of 83.3%

MODEL 2: **USING GOOGLENET**

A validation accuracy = 93.30%



MODEL 3: **SQUEEZENET**

validation accuracy = 95.12% s

with a detailed analysis of all the results that are obtained with regards to achieving objectives of the project. The transfer learning models that have been developed were built to demonstrate the feasibility and robustness of such techniques in the field of disease classification.

TABLE OF RESULT

MODELS	ACCURACY (%)
CNN	83.3
GoogleNet	93.30
SqueezeNet	95.12

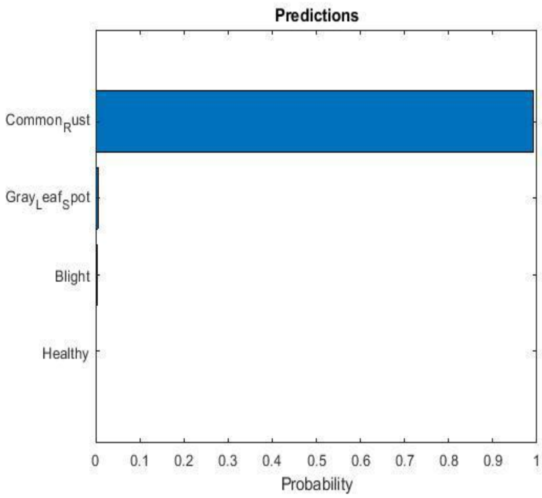
MODEL COMPARISON

From the values shown in Table we can conclude that SqueezeNet transfer learning architecture works best for classifying the maize disease as it has better accuracy with GoogleNet following closely at second place, then training network from scratch. This result confirm that transfer learning techniques based on CNN are better suited for identification and classification of maize plant than traditional models. With pretrained image net weights and only modifying the final few layers, the models developed can perform better in real world scenario. The training data also contained augmented images which improved the model efficiency and the values of accuracy and other metric values substantiate it.

EXECUTION TIME

Apart from evaluating the models based on accuracy and other related metrics, training time was also compared to understand how each of these models stack up against each other. As the final layers of the transfer learning-based algorithms were retrained, model training time of these were relatively more with SqueezeNet taking 2334 seconds per epoch compared to 18172 seconds per epoch of GoogleNet. This indicates that SqueezeNet is better, both in terms of training time and accuracy when compared with GoogleNet.

RUNNING THE SYSTEM USING SQUEEZENET



DISCUSSION

The primary objective of the project was to build models that are efficient in identifying and classifying maize plant diseases. A thorough literature review was done to understand the current limitations. These mainly revealed the need for models that could generalize well on unseen data. Transfer learning solutions are tailor made for such issues with models like SqueezeNet and GoogleNet developed to address this problem. Necessary pre-processing which involved resizing of images was done before building the models. Augmentation of images and validation for every epoch run was done to ensure that they are robust. Results indicated that transfer learning models were better when it comes to predicting almost every class of disease on which it was trained.

Although the project was successful in achieving its objectives, it is not short of limitations and faced some roadblocks in due course of its development. One major roadblock was the lack of data captured from different places and backgrounds which could have been used to further test the model and improve on it. Also, the models developed were trained on three types of disease classes. This might result in models underperforming when it makes predictions on unseen classes of maize disease. Images with multiple leaves or those affected by multiple diseases can also be a challenging affair and their classifications are also not tested. Apart from this, training the last few layers of transfer learning were highly time consuming and can be improved by making use of higher configuration machines or by running the models using GPU. The amount of training time taking by these algorithms was one of the reasons for training them on images of reduced dimensions. Better accuracy could probably have been achieved if higher dimension images were used for training the models

CONCLUSION

The results obtained, as discussed in previous chapter highlight and support the use of CNN based transfer learning technique in order to accurately identify and classify maize leaf diseases, thus satisfying the objectives stated for the project. As image augmentation and transfer learning are used, it is a given that these models are capable of generalizing well and can predict better on unseen data. SqueezeNet performed best among the models developed. However, they took a lot of training time which is concerning.

REFERENCES

1. https://agriculturegoods.com/why-is-agriculture-important/
2. E.-C. OERKE (2006) 'Crop losses to pests. Journal of Agricultural Science', volume 144, pp. 31 – 43.
3. Lu, J., Ehsani, R., Shi, Y., Abdulridha, J., de Castro, A. I. and Xu, Y. (2017). 'Field detection of anthracnose crown rot in strawberry using spectroscopy technology',

Computers and Electronics in Agriculture, 135, pp. 289-299.

4. Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A. and Stefanovic, D. (2019). 'Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection', Symmetry 2019, 11, pp. 939.
5. Mohanty, S. P., Hughes, D. P. and Salathfe, M. (2016). 'Using deep learning for image-based plant disease detection', Frontiers in Plant Science, 7, pp. 1419.
6. Aravind, K. R., Raja, P., Mukesh, K. V., Aniirudh, R., Ashiwin, R. and Szczepanski, C. (2018). 'Disease classification in maize crop using bag of features and multi-class support vector machine', Proceedings of the 2nd International Conference on Inventive Systems and Control, ICISC 2018, pp. 1191{1196, IEEE Xplore Digital Library.doi:10.1109/ICISC.2018.8398993.
7. Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D. and Traore, D. (2019). 'Deep neural networks with transfer learning in millet crop images', Computers in Industry ,108, pp. 115-120.
8. Xinhong Zhang, Fan Zhang (2008) Congress on Image and Signal Processing, IEEE computer society, 773-776.
9. Zhang, S. and Wang, Z. (2016). 'Cucumber disease recognition based on Global-Local Singular value decomposition', Neurocomputing, 205, pp. 341-348, ScienceDirect. doi: 10.1016/j.neucom.2016.04.034.