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# Classification of Nitrogen Deficiency for Maize Plants Using deep learning algorithms on Low-End Android Smartphones

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**Abstract**

*Maize comprises about one-fifth of the calories eaten in Sub-Saharan Africa. However, farmers in Sub-Saharan Africa have been unable to produce enough food for consumption. This is mostly due to a shortage of nutrients and the adoption of antiquated agronomic methods. Nitrogen deficiency or deficiency is a significant factor contributing to this poor yield of maize crop. Many smallholder farmers lack the necessary information to recognize this nitrogen deficit early on, when it is still reversible, before it damages their fields and maize yields. The purpose of this project is to determine a way for developing a mobile app for low-end Android phones that use a machine learning model to detect nitrogen insufficiency. The model is constructed by utilizing the Tensorflow and Keras libraries to train a pre-trained Single Shot Detector (SSD) Mobilenet model. Additionally, the approach takes advantage of Keras's built-in Image Augmentation algorithms to produce additional photos for our datasets. The model generated is 81 percent accurate. The Android application enables a smallholder farmer to maintain and analyze the soil health of several farms, as well as to determine the necessary fertilizer application to help rectify the nitrogen shortfall. Future directions in this field of study have also been highlighted for the benefit of interested scholars.*

**Keywords:** Keras, Tensorflow, Computer Vision, Image Augmentation, Machine Learning, Image Classification, Algorithms, Agriculture, Nitrogen Deficiency, Smallholder farming.

## 1.0 INTRODUCTION

Maize is one of the most important staple crops in Nigeria and West Africa as large. It accounts for one-fifth of the calories and protein consumed by households and is a major source of food and income for smallholder farmers [1].

Smallholder farmers in Nigeria still use agricultural practices handed down to them from their forefathers and are ignorant of modern practices. [2]. This has ensured that maize yield in Nigeria and sub-Saharan Africa has remained low at approximately 1.5tons/hectare which is about 20% of the yield in developed countries [3]. This poor yield is caused by several issues, which include poor soil fertility, lack of access to key inputs such as quality seed and fertilizers, low levels of mechanization as well as poor post-harvest management. Many researchers have tried to document new modern practices and build predictive machine learning models to help with most of the problems smallholder farmers experience such as soil classification, germination analysis among others.

However, the required research and utilization of artificial intelligence technology is complex, and in most cases out of reach to smallholder farmers. To use the existing models, a smallholder farmer must have access to a powerful computer running GPUs and steady power. This is totally out of reach for them.

This research democratizes machine learning in agriculture by providing smallscale farmers with access to a variety of machine learning models developed by other researchers. Additionally, it aids in increasing maize plant yields in Nigeria by helping smallholder farmers to choose between proven and trusted contemporary agronomic approaches. This it will do by assisting in determining the soil health and nitrogen insufficiency of fields planted with maize, particularly in the early stages before permanent harm occurs. This will assist farmers in Nigeria and Sub-Saharan Africa overcome one of the primary impediments to high yields [3].

## 2.0 THEORETICAL BACKGROUND

### *2.1 Nutrients needed for Maize Growth and the Importance of Nitrogen*

Just like any other crop, maize needs a sizeable amount of nutrients to grow ideally. There are about 17 of

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these chemical elements needed for the growth of maize, with 3 naturally existing and can be obtained from air and water [4]. These nutrients and needed concentration are showed in Table 1 below.

**Table 1:** Nutrients needed for maize growth [4]

| Element | Source | Role in the Plant | Concentration |
|---|---|---|---|
| **Carbon (C)** | Air | Constituent of carbohydrates; necessary for photosynthesis. | 45% |
| **Oxygen (O)** | Air/Water | Constituent of carbohydrates: necessary for respiration. | 45% |
| **Hydrogen (H)** | Water | Maintains osmotic balance; important in many biochemical reactions, constituent of carbohydrates. | 6% |
| **Nitrogen (N)** | Air/Soil | Constituent of amino acids, proteins, chlorophyll, and nucleic acids. | 1-5% |
| **Potassium (K)** | Soil | Involved with photosynthesis, carbohydrates translocation, protein synthesis. | .5-1% |
| **Phosphorous (P)** | Soil | Constituent of proteins, coenzymes, nucleic acids, and metabolic substrates; important in energy transfer. | .1-.5% |
| **Magnesium (Mg)** | Soil | Enzyme activator; component of chlorophyll. | .1-.4% |
| **Sulfur (S)** | Soil | Component of certain amino acids and plant proteins. | .1-.4% |
| **Chlorine (Cl)** | Soil | Involved with oxygen production and photosynthesis. | .01-.1% |
| **Iron (Fe)** | Soil | Involved with chlorophyll synthesis and in enzymes electron transfer. | 50-250ppm |
| **Manganese (Mn)** | Soil | Controls several oxidation-reduction systems and photosynthesis. | 20-200ppm |
| **Boron (B)** | Soil | Important in sugar translocation and carbohydrates metabolism. | 6-60ppm |
| **Zinc (Zn)** | Soil | Involved with enzymes that regulate various enzymes. | 25-150ppm |
| **Copper (Cu)** | Soil | Catalyst for respiration; component of various enzymes. | 5-20ppm |
| **Molybdenum (Mo)** | Soil | Involved with nitrogen fixation and transforming nitrate to ammonium. | .5-.2ppm |
| **Nickel (Ni)** | Soil | Necessary for proper functioning of urease and seed germination. | .1-1ppm |

The first three nutrients are mostly ignored by farmers as they are almost always in sufficient supply and provided by air and water. They are however needed in very high quantities. The maize plant does a good job of telling farmers when these nutrients are lacking according to Professor Tony Vyn, however, many farmers miss out these signs until it is very late [5]. In maize, the signs show up on the leaves when they are older giving little chance to the farmers to completely correct the danger [6].

Nitrogen is essential for metabolism in maize, as well as other plants. It is however very critical as a component of chlorophyll, which is needed for photosynthesis. In the absence of enough nitrogen, it is impossible for the maize plant to reach its full genetic yield potential [7].

## 2.2 *Identifying Nutrient-Deficient Maize Plants*

Figure 1 and Figure 2 below show maize plants with nitrogen and phosphorus deficiency respectively.

**Figure 1:** Nitrogen Deficient Maize Plant [8]

Nitrogen deficiency causes stunted growth in maize plants with yellow discoloration showing at the bottom of the leaves and necrosis on the leaf tip. For phosphorus deficiency, the leaves get a reddish-purple discoloration [9]


**Figure 2:** Phosphorus-deficient maize plant [9]

A waterlogged soil can be very bad for the maize plant as it can cause denitrification, which releases the nitrogen from the soil and produces toxic substances such as hydrogen sulfide and ammonia [10].

### *2.3 Soil Quality, Classification and Crop Recommendation*

Ashwini et al [11] explored using machine learning to identify types of soil using color images. The authors used the Support Vector Machine Algorithm (SVM) to generate the classification model. SVM is a simple but efficient algorithm that is touted as an alternative to neural networks. SVM works by acting as a non-probabilistic binary linear classifier. The authors believe the proposed model can be used in auto-classification of soil samples at soil testing facilities.

The authors [12] worked on 2-pronged problem using two modules: grading the quality of soil provided while recommending the most suitable crop(s) that can maximise the quality of yield identified to get the best yield for the farmer. The architecture of the system is shown in Figure 3 below.

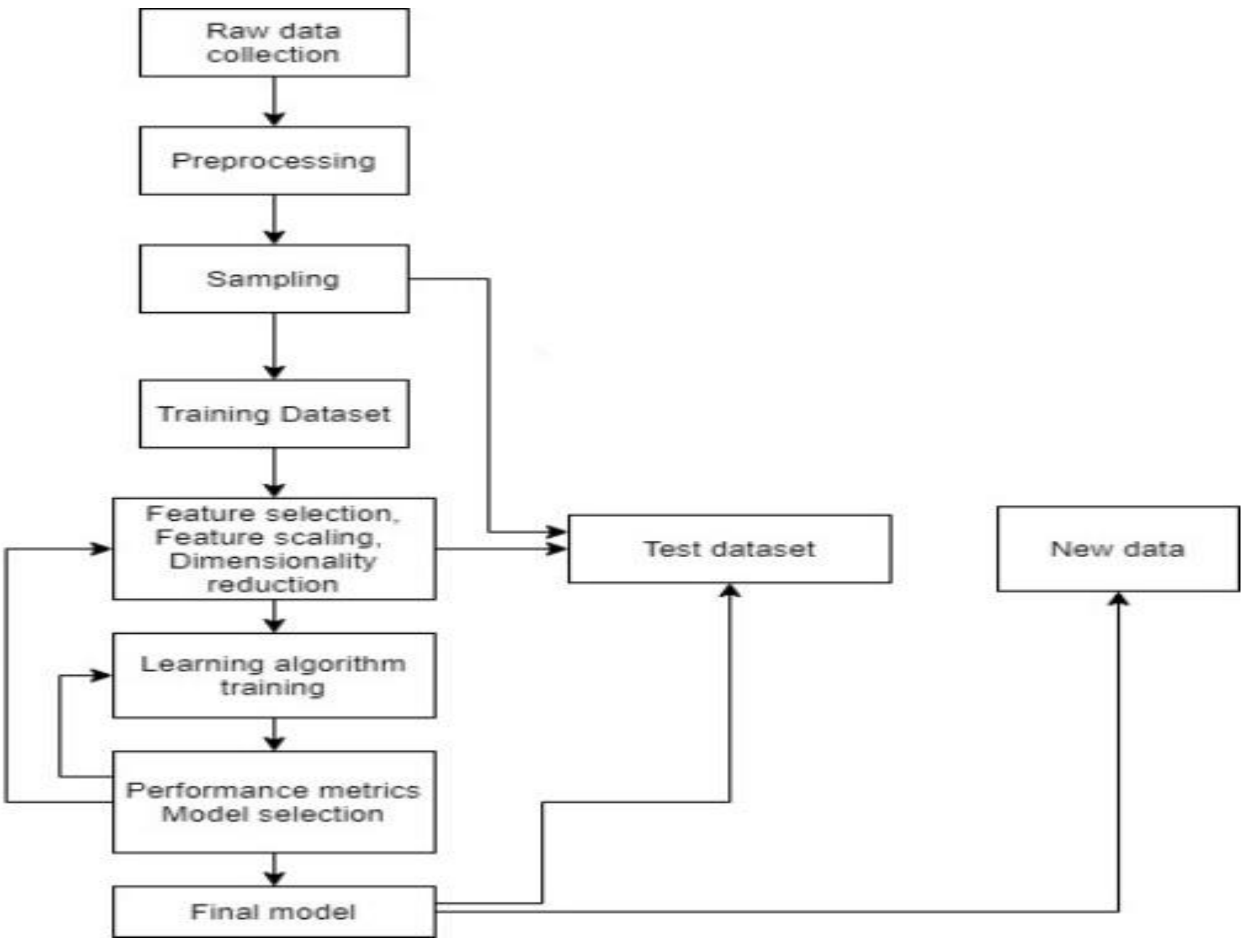

**Figure 3:** Architecture of the System (Keerthan, et al., 2019) [12]

Module 1 (for soil grading) takes in variables such as soil pH, Zn, Mn, K, S, soil type and other variables in as feature variables. It returns a target variable which is the grade of soil nutrient criterion. The model uses the Linear Regression algorithm.

Module 2 (for crop recommendation) uses the Random Forest algorithm to output recommended crop that will allow the farmer to get the maximum yield from his or her farmland. The different algorithms explored are shown in Table 2 below.

Before final models above were chosen, other algorithms were also tried as seen above in the accuracy table.

Table 3 below shows a comparison of all reviewed papers on soil quality, classification and crop recommendation.

**Table 2:** Accuracy of explored algorithms (Keerthan, et al., 2019) [12]

| **Algorithm** | **Corresponding Accuracy score** |
|---|---|
| Random Forest Classifier | 72.74% |
| Support Vector Machine (Linear Kernel) | 63.33% |
| Gaussian NB | 50.78% |

**Table 3:** Comparison of Reviewed Papers on Soil Quality, Classification and Crop Recommendation

| **Article** | **Dataset** | **Functionality** | **Model/Algorithms Used** | **Results/Conclusion** |
|---|---|---|---|---|
| [11] | Color images of soil | Autoclassification of types of soil samples | Support Vector Machine | |
| [12] | Historical soil analysis results and agronomical data | Soil grading and crop recommendation | Linear Regression (for soil grading), Random Forest Algorithm (for crop recommendation) | 72.74% on crop recommendation |
| [13] | Soil and weather data from 2012-2016 | Prediction of soil moisture | Deep Neural Network Regression (DNNR) | |
| [14] | Soil analysis | Soil grading and recommendation of level of chemical fertilizers | Extreme Learning Machine | ~90% accuracy for prediction of soil pH |

### 2.4 *Disease Detection*

Shima, et al. [15], proposed a Random Forest model to detect diseases in papaya. They first extracted a histogram of oriented gradients (HoG) with 3 feature descriptors from the labelled data: Hu moments, haralick texture and color histogram. The HoG was then trained using the Random Forest algorithm and a model was created. The architecture of the model is as shown in Figure 4 below.

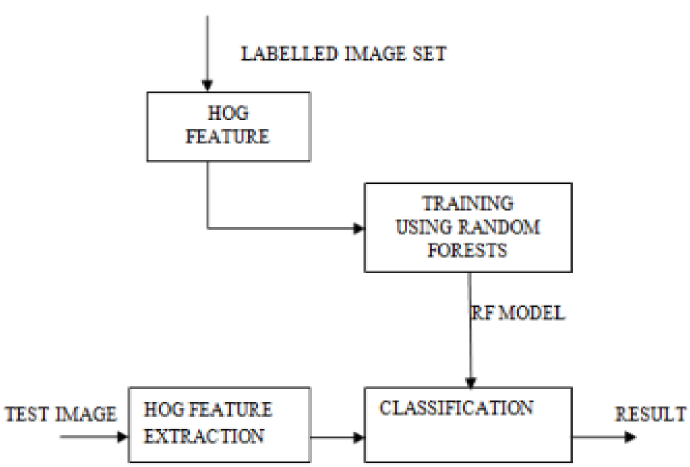


**Figure 4:** Architecture of the model. [15]


**Figure 5:** RGB to HSV Conversion when generating a Color Histogram. [15]

Figure 5 above shows how a color histogram is generated using RGB to HSV conversion. The accuracy of the model in the prediction of papaya disease was put at 70.14%, doing better than the closest model, k-nearest neighbour, at 66.76%. The authors expect the model to perform better when more images are added to the training dataset and other features are extracted for the training.

**Figure 6:** Samples of Tomato leaves with Early blight in varying conditions [16]

Konstantinos [16], attempted to classify diseases across 25 plants ranging from apples, to oranges among others using their leaves. He implemented 5 different CNN architectures: AlexNet, GoogLeNet, Overfeat, AlexNetOWTBn and VGG. Figure 6 below shows images from the dataset of Tomato with Early blight in varying conditions.

The dataset contains both laboratory and field-collected data. One major takeaway from the results of the study was the importance of training models with images taken directly from a field rather from a laboratory.

The comparison between explored algorithms is showed in Table 4 above. In conclusion, the VGG had a better performance than the others having a success rate of 99.48%.

Selvaraj, et al. [17] worked on disease detection on banana, using data gathered across various banana diseases hotspots in Africa and India using DCNN. The data comprised 18 different classes.

**Table 4:** Final models' performance with different training/testing scenarios in respect to laboratory-conditions and field-conditions images. [16]

| | Training: Laboratory – Testing: Field | | | | Training: Field – Testing: Laboratory | | | |
|---|---|---|---|---|---|---|---|---|
| Model | Success rate | Average error | Epoch | Time (s/epoch) | Success rate | Average error | Epoch | Time (s/epoch) |
| AlexNet | 32.23% | 3.5484 | 53 | 4375 | 62.57% | 1.9369 | 104 | - |
| VGG | 33.27% | 7.8541 | 54 | 4901 | 65.69% | 2.6786 | 134 | - |

The models were done by using transfer learning on the Resnet50, InceptionV2 and MobileNetv1. The author also experimented on SSD MobileNet, so as to determine the capabilities for detection using a mobile phone. The algorithm of the models is shown in Figure 7.

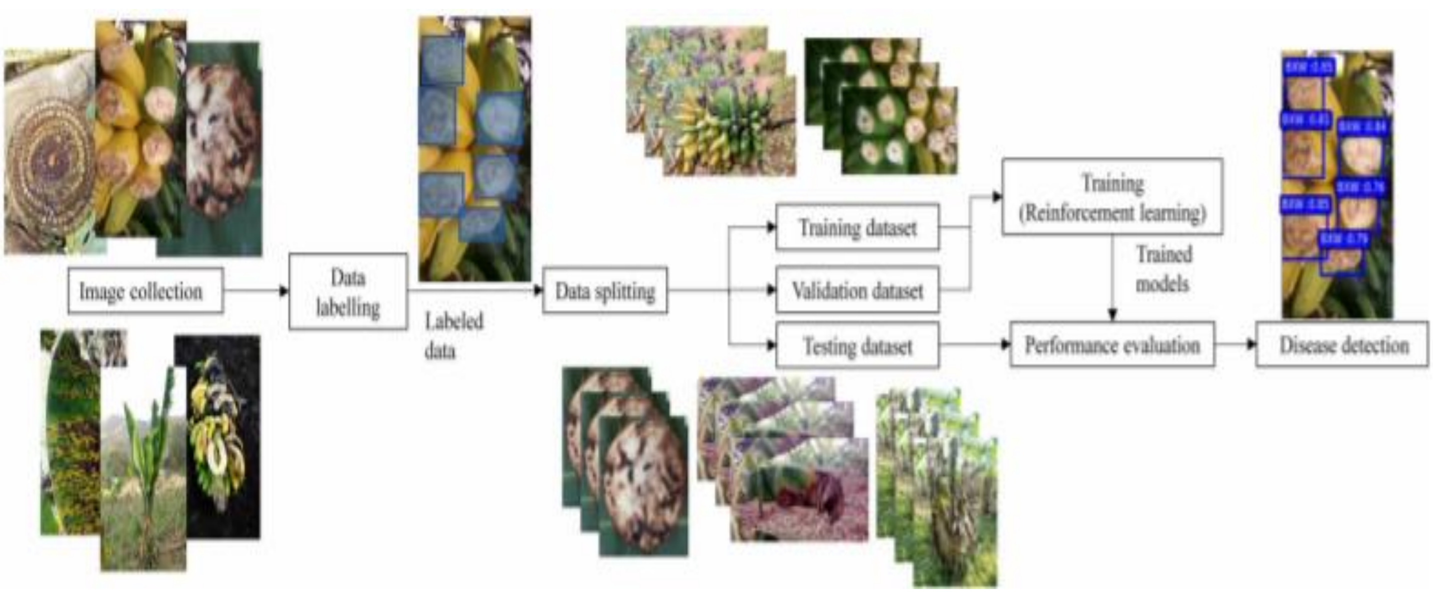


**Figure 7:** Architecture of the models. [17]


**Figure 8:** (a) Original image (b) Labelled image (c) Detection of disease [17]

### *2.5 Yield Prediction*

Yield, in agriculture, is a measurement of the crops harvested as a ratio of the unit of land it was cultivated on. It serves as a very important indicator of how activities on a farm went. Yield prediction is a particularly important part of precision agriculture and has received a good level of machine learning efforts in recent years. Some of those efforts are reviewed below.

Most of the models developed after the retraining of the InceptionV2, Resnet50 and SSD MobileNetV1 achieved an accuracy of about 90%, thereby showing that DCNN is suitable for plant disease detection. The original image in the dataset, a labelled image and an image showing diseases detected is shown in Figure 8 below.

Table 5 below shows a comparison of all reviewed papers on plant disease detection.

**Table 5:** Comparison of Reviewed Papers on Plant Disease Detection

| Article | Crop | Dataset | Functionality | Algorithm | Results/Conclusion |
|---|---|---|---|---|---|
| [15] | Papaya | Extracted (HoG) with focus on 3 features: Hu moments, haralick texture and color histogram | Detection of diseases in papaya | Random Forest | Accuracy: 70.14%, better than k-nearest neighbour at 66.76% |
| [16] | 25 Plants including apple and oranges | 87,848 open database of photographed images with 52 classes (health and diseased) | Classification of diseases across 25 plants using image classification | VGG | 1. Implemented AlexNet, GoogLeNet, Overfeat, AlexNetOWTBn and VGG, with VGG performing the best with 99.76% accuracy<br>2. Showed the importance of training models on images collected from actual fields, rather than laboratories |
| [17] | Banana | Images from banana disease hotspots in Africa, with 18 classes | Disease detection in banana using banana leave image classification | DCNN | Implemented InceptionV2, Resnet50 and SSD MobileNetV1 all achieving about 90%, showing the efficacy off DCNN based-alogrithms |
| [18] | General-purpose | | Disease detection | CNN | 86.26% accuracy |
| [19] | Cassava | Images of cassava leaves, including spectral data | Cassava brown streak disease and Cassava mosaic virus disease detection | Learning Vector Quantization | 1. Outperformed KNN, Linear SVM and Extemely Randomized Trees.<br>2. Shows LVQ outperforms even when limited data is passed into the algorithm<br>3. Accuracy of 97.3%. |
| [20] | Wheat, Cotton | Satellite imagery | Disease detection and | Canny Edge algorithm | |

| Article | Crop | Dataset | Functionality | Algorithm | Results/Conclusion |
|---|---|---|---|---|---|
| | | | pesticide recommendation | | |
| [21] | Apple | 3,642 Apple tree leaves | Diagnosis and Cataloguing of diseases in apple trees | Canny Edge algorithm, Ensemble of EfficientNet-B7, EfficientNet-B6, ResNet152V2 and DenseNet201. | Shows efficacy of ensembling with ensembled model having accuracy of 98.1%, compared to next standalone model, Inception ResNet152V2 at 97.5% |

Russello et al. [22] discuss in their paper the use of a novel 3D CNN framework to predict crop yield. They leveraged spatial, spectral and temporal dimensions of remote sensing images. Their work was built on the HistCNN proposed by [23]. The architecture of the 3DCNN is shown in Figure 9 below.

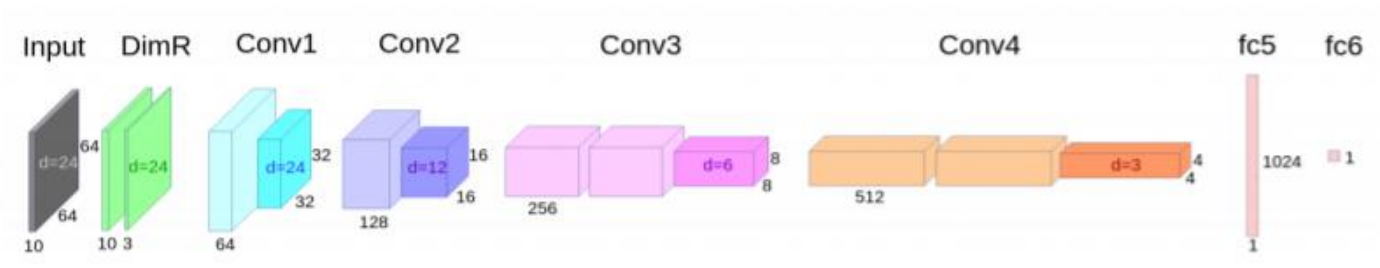


**Figure 9:** Architecture of the 3DCNN [22]

The figure above shows the different layers of the 3DCNN including the Convolutional and pooling layers. The model uses data spanning a long-range (2003-2014) for training and 2015 data for testing. When compared against other models such as HistCNN, Ridge, DN and DNN, 3DCNN was at least 28% better than the next best model, HistCNN.

Table 6 below shows a comparison of all reviewed papers on plant disease detection.

**Table 6:** Comparison of Reviewed Papers on Yield Prediction

| Article | Crop | Dataset | Functionality | Algorithm | Results/Conclusion |
|---|---|---|---|---|---|
| [22] | General | Satellite images (remote sensing) | Yield prediction leveraging spatiotemporal features | 3D CNN | 28% better than HistCNN |
| [24] | Maize | Crop Genotype, Environmental, Yield data (2001 – 2015) | Maize yield prediction, weather prediction | DNN | Yield: Validation correlaion coefficient of 81.91% (closest algorithm was Regression Tree at 73.%) |
| [25] | Rice | Rice production and weather data (1997 – 2013) from Kharif and Rabi regions of India | Prediction of rice plant yield using historic weather and production data | Random Forest | |

| Article | Crop | Dataset | Functionality | Algorithm | Results/Conclusion |
|---|---|---|---|---|---|
| [26] | Maize | Biophysical, socio-economic and crop management data | Studying the effect of biophysical, environment and management factors on yield | ANN | Miscalculation rate: 25% |

## 3.0 PROPOSED SYSTEM FRAMEWORK

### *3.1 Problem Formulations*

Out of the over 400 studies reviewed by Benos, et al. [27] on machine learning in agriculture, all required that produced machine learning models be ran on powerful computers. This excludes the bulk of farmers in developing countries who are mostly smallholder farmers who own a small piece of land and farm it for subsistence use or at a very low scale.

Despite the strong research on machine learning in agriculture, many farmers in underdeveloped nations have not benefited from it. In order to categorize soil and detect lacking nutrients, such as nitrogen, several machine learning models have been constructed. But most of these models need intricate and costly technology to work. If we start with maize nitrogen deficiency, we can assist smallholder farmers in Nigeria and Sub-Saharan Africa detect this issue early on, reversing it at minimal cost, improving harvest output and bringing them on level with their counterparts in richer nations. Because maize provides 20% of the calories eaten in Africa, this may considerably enhance food output.

#### *3.1.1 Specification of the Current System*

The current system employed by farmers is a completely manual process that relies on a farmer knowing what to check for on a farm and remembering to check when due. Figure 10 shows the use case of the existing manual system.

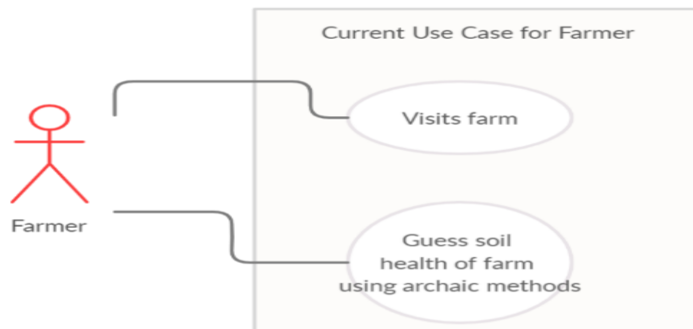


**Figure 10:** Use Case Diagram of Existing Manual System

#### *3.1.2 Process Design*

The process flow for the mobile app is shown in Figure 11 below.

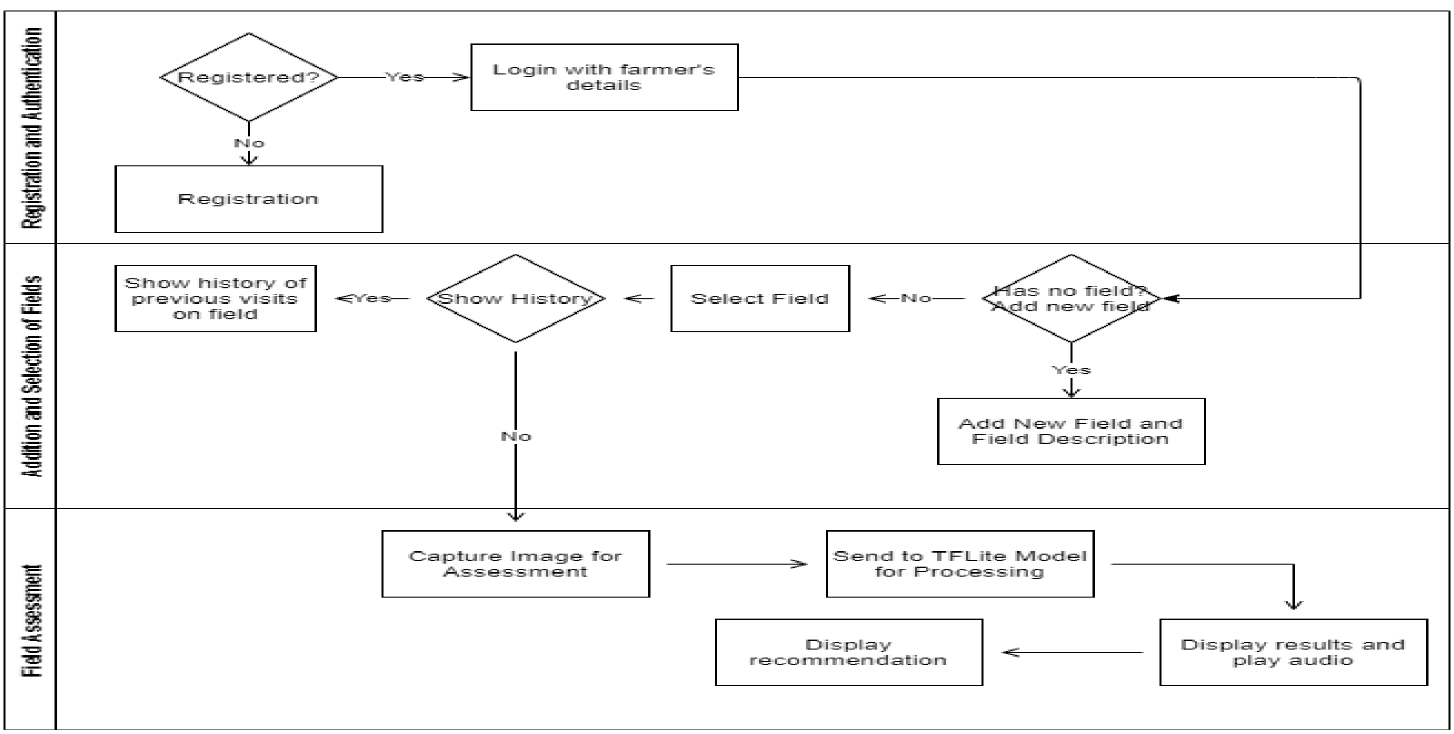


**Figure 11:** Process Design for New System (Mobile App)

### 3.1.3 Database Design

There are four entities to be used in the mobile app where

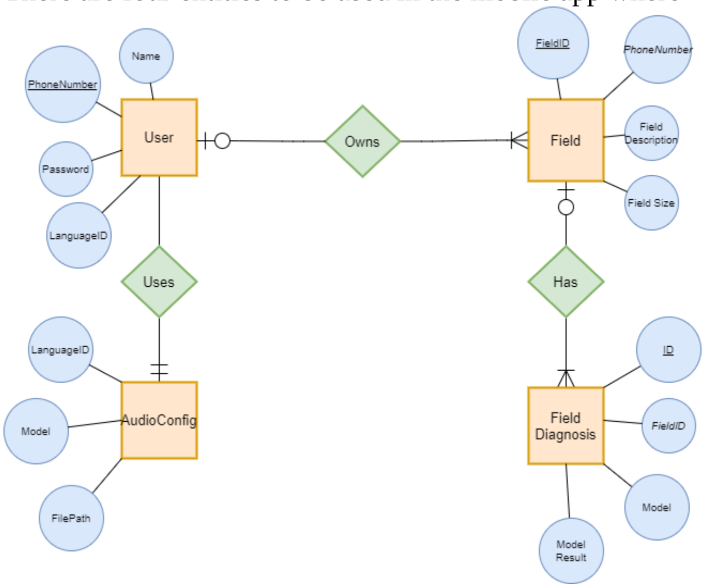


**Figure 12:** Entity Relationship Model for New System

data will be stored. They are:

1. User: to store the registered user details
2. Field: to store the fields owned by the registered users
3. FieldDiagnosis: to store diagnosis results
4. AudioConfig: to store data for the audio translations used

The relationship between these entities is shown in Figure 12 below:

### 3.1.4 Model Training Process

To generate the model, the following process will be followed. A pretrained model (SSD Mobilenet) trained using the Single Shot Detector algorithm will be used.

The Single Shot Detector (SSD) algorithm is one of the fastest object detection algorithms available. Proposed by Liu et al, the SSD algorithm works in 3 stages:

1. Feature extraction, where all crucial feature maps are selected. It uses only convolutional layers here.
2. Detecting heads, which involves creating the most appropriate bounding maps for all the feature maps. This stage also uses only convolutional layers
3. Reducing error rate caused by repeated bounding boxes, using non-maximum suppression layers

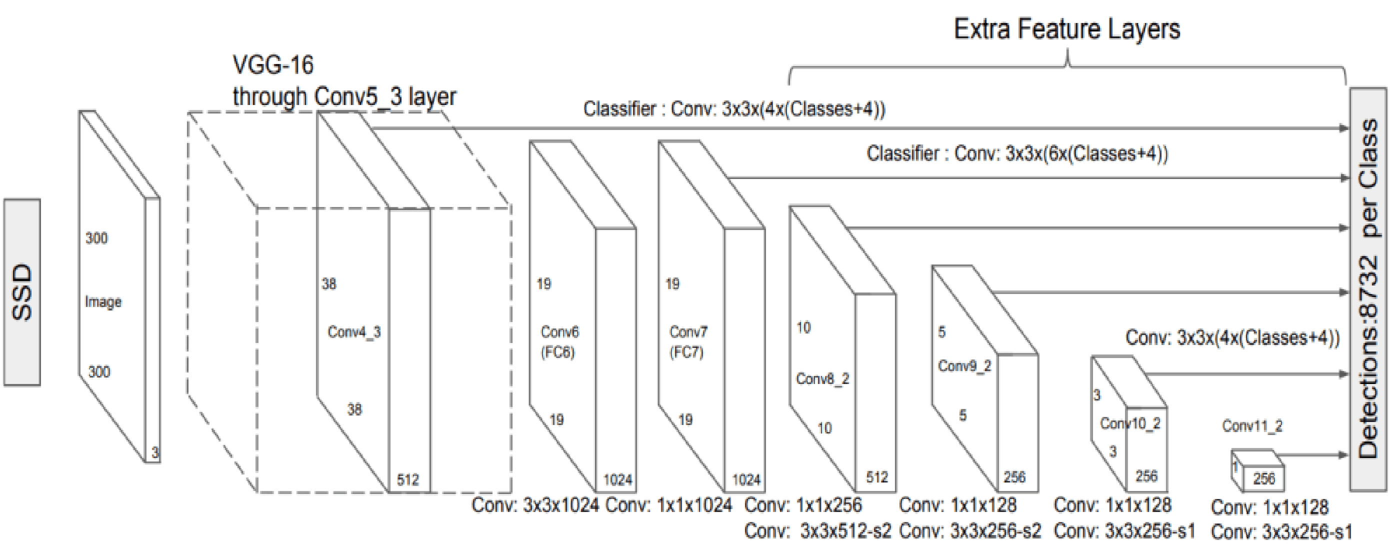


**Figure 13:** SSD Algorithm Architecture [28]

The SSD Algorithm Architecture is shown in Figure 13 above. The SSD Mobilenet model is re-trained using the Tensorflow and Keras Preprocessing algorithm as shown in Algorithm 1 below:

Algorithm 1: Model Training using Tensorflow and Keras Preprocessing

1. **annotate** *images* **into** *annotationData*
2. **using** *XMLTFRecordConverter()*
3. transform *annotationData* into *TFRecord*
4. **initialize** *imageDataAugmentation()*
5. **create** *labelMap*
6. **select** *pretrainedModel*
7. **input** *modelConfigParams*
8. **train** *model*

Algorithm 2 below shows how image data augmentation is implemented using Keras.

Algorithm 2: Image Data Augmentation using Keras

1. **initialize** *imageDataGenerator()*

2. **open** *imageFolder*
3. **create** *augmentFolder*
4. **do**
5. **select** *image* **from** *imageFolder*
6. **using** *keras.preprocessing*:
7. **resize** *image*
8. **rescale** *image*
9. **select** *kerasAugmentationMethod*
10. **augment** ***image***
11. **save** *image* **in** *augmentFolder*
12. **while** *imageFolder.next()* ← *true*

### 3.2 *System Implementation*

#### 3.2.1 *Environment Setup Steps*

The packages for the needed environment can be replicated following the steps outlined below.

- **Anaconda Installation**
  - The Anaconda Python 3.9 64-Bit installer is used in this project. Run the executable file, follow the setup instruction to the end to complete the installation process. Add Anaconda3 to my PATH environment variable. This ensures anaconda is universally available by other editors and on the cmd.
  - Create a new Anaconda virtual environment. Open Command Prompt/Terminal, enter.

```
1. conda create -n tensorflow pip python=3.8
```

  - Activate the new environment using the following command:

```
2. activate tensorflow
```

- **Install the required items**
  - Install the jupyter environment with the following command

```
3. conda install -c conda-forge jupyterlab
```

  - The libraries can be installed by running

```
4. pip install -r requirements.txt
```

#### 3.2.2 *Data preparation*

For the purpose of balancing, 5,000 images from each class were used. This filtered dataset was divided into 3 parts; train data, validation data and training data in the ratio 8:1:1.

#### 3.2.3 *Data pre-processing*

The images were scaled to convert them from integers to float in a range acceptable and usable by the neural network. The snapshot of the parameters used in data augmentation and scaling is shown in the snapshot below. Data augmentation was carried out to improve the data representation. Data preprocessing was carried out in a similar fashion as reported in the mobilenet paper. Dimensions of the images were tuned until a good representation was found. The current image dimension being used is like what was reported in the MobileNet paper [29]. For this project, the Random shifts, flips and zoom Image Data Augmentation were utilized.

#### 3.2.4 *Model Training*

Pretrained MobileNetV2 model loaded from Keras was used in its traditional state. The top of the model was popped off and a new fully connected layer representing the number of classes in this project was added to the model. Table 7 below shows the parameter used in the training of the model.

**Table 7:** Parameters for the Model Training

| Model | MobileNetV2 |
|---|---|
| Total params | 301,123 |
| Trainable params | 301,123 |
| Non-trainable params | 0 |
| Regularization | L2 |

| | |
|---|---|
| Optimizers | Adam |
| Loss | Binary Cross Entropy |
| Epoch | 20 |
| Callbacks | Early Stopping, Tensorboard, Checkpoint |

**Figure 14:** Best practice Nutrient-rich sample

**Figure 15:** Nitrogen-deficient maize in very early days

## 4.0 EXPERIMENTAL EVALUATIONS, ANALYSIS AND EXPERIMENTS

### *4.1 Model performance analysis and Improvement*

The model achieved a training and validation accuracy of 81% after 20 epochs. The graph below in Figure 16 shows the details of performance during training and validation.

The model loss for the training dataset is 0.52 while for the test dataset, it has a model loss of 0.49. Model loss measures how well (or bad) a model is doing. With a lower model loss, it shows that our model is doing well.

### *4.2 Benchmarking the Proposed Model with Popular Methods*

The SSD Mobilenet model that this proposed model is built on has an accuracy of 79.83% when implemented using the Caffe framework for Object Detection [30]. The proposed model comes out better with an accuracy of 81% using the framework highlighted in this paper.

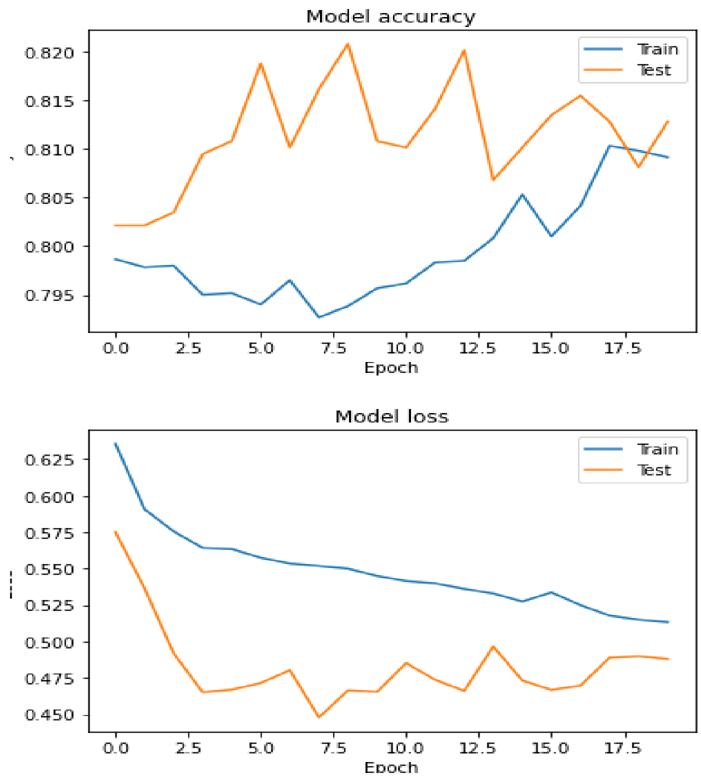


**Figure 16:** Model Accuracy and Loss

### *4.3 Implementation of TFLite Model on Android Device*

To implement the TFLite version of the model on an Android device, the Jetbrains Android Studio IDE was used. An implementation of the Tensorflow Lite library (AAR) was added using MavenCentral to the build.gradle file. The TFLite model file exported from the training was then added to the assets folder in the Android project, alongside a label text file for classification of the images streamed from the camera. To call the TFLite model in the Android code, methods from the Tensorflow Lite Library including the Tensor Flow Image Classifier (TFIC) and associated data structures in the library were used.

## 5.0 CONCLUDING REMARKS

The model and mobile application produced from this research is directly usable by smallholder farmers to identify nitrogen deficiency and bad soil health in maize plants. The smallholder farmers can also use the mobile app on low-end cheap Android phones in English, Yoruba and Hausa languages. The methods also proposed in this research is directly usable by other researchers in making existing machine learning models for agriculture usable for smallholder farmers in remote areas of Nigeria and beyond. This will allow better solutions to be developed and for more usage of machine learning in agriculture.

The paper was limited by the number of images that could be obtained. A higher accuracy of the machine learning model implemented could have been gotten with a more robust dataset. The project could also have been extended to iOS devices but for some difficulties with the TensorFlow library.

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