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# Prospect of Smart Agriculture Using IoT and Data Analytics: A Perspective of Kebbi State, Northwestern Nigeria

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**ABSTRACT**

Nigeria is an agricultural nation, with majority of its citizenry predominantly relied on it for survival. Recently, the sector is receiving a lot of attention due to the need to diversify and a bit away from an oil-driven economy. The sector is one among the most contributing to the nations` Gross Domestic Product (GDP), recording 21% in the previous year. However, one of the causes of low crop yield is diseases caused by agents such as fungi, bacteria, and viruses. The advent of technology has led to its influence in the agricultural sector. The recent evolution and fusion of IOT, ML and Data Analytics has brought succour for especially plant monitoring and management. This research work investigated the capability of IOT, ML and DA in tomato plant disease classification in Yauri Emirate, Northwestern Nigeria. We further conduct a survey with a view to understanding the knowledge, acceptability or otherwise of the mentioned techniques. The result of our classification using CNN, a DL model achieves a near-optimal accuracy of 98.6% with a loss of 0.03% while recording over 98.3 % for both precision and recall on the predicted labels. We also observed that our target audience for the survey lacks near total knowledge of smart farming, hence the need for the stakeholders in the domain to embark on sensitization and awareness towards reaping its numerous advantages.

**Keywords**: CNN, Data Analytics, Internet of Things (IOT), Machine Learning (ML), Yauri

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## I. INTRODUCTION

The most common source of livelihood and employment in Nigeria is agriculture. The survival of its citizenry is based mainly on agriculture. The development of the country`s economy is highly dependent on it, as it is the most important source of food. According to [33], the sector contributed about 24.17% in the 4$^{th}$ quarter of 2021 and over 21% to nominal GDP in the second quarter of 2023. The largest contribution was from crop production amounting to nearly 19 percent of the GDP. In the same vein, there is the need for Nigeria to diversify her economy from oil based to agriculture due to the uncertainties associated with the global prices of crude oil [20, 32] and the alarming population currently estimated at about over 220 million with an annual growth rate of 2.53% [34]. The Nigeria agricultural sector is receiving a lot of attention in recent times mainly due to the reason for diversity with an increasing total budget allocation of 28% for the 2024 fiscal year [38]. Based on this, two key gaps facing the agriculture sector have been identified. They include the inability to meet domestic food requirements and the inability to export at quality levels required for a competitive market [20].

However, Crop diseases result in considerably low throughput. The studies in [35] outline yield depletion between 20% and 40% of global agricultural production caused by insects, pests, viruses, animals, and weeds, hence the need for pest control. In addition, they have several facets, some with short-term, and others with long-term consequences for global food security [36]. Crop production losses due to pests and diseases are quite substantial, particularly in the semi-arid conditions [37] which Northern Nigeria forms part of. Therefore, it is imperative to detect diseases in plants well in advance to avoid crop destruction [29]. Currently, farmers and growers must spend 70% of their time monitoring and understanding the status of the crops rather than performing actual farm work, especially in the region under study mainly due to pest attack, theft, or fear of animal invasion.

To increase agricultural production with limited resources, major technological advancement is crucial [26]. The applications of the Internet of Things (IOT) have the potential to optimize both the operational efficiency of farmers and the yield of the land. The Internet of things is a promising technology which provides efficient and reliable solutions towards modernization of several sectors. On one hand, IoT based solutions are being developed to automatically maintain and monitor agricultural farms with minimal human involvement [11, 21]. On the other hand, the use of Data Analytics (DA) can enable targeted application of resources such as fertilizer, thus reducing cost and increasing yields. It will provide the competitive edge needed by farmers in terms of reliable decision making and improved productivity [20]. Even though, efforts are ongoing through Public Private Partnerships (PPP), where both governments, industry and funding agencies are setting up large, commercialized farms at the same time trying to persuade farmers of the need for technology adoption. However, the acceptance has been worrisome [3]. Considering this, The Nigeria Government, Kebbi State Government and Dangote Group (leading African Entrepreneur) has setup a tomato processing plant in the region under study [39]. Tomato, also known as Solanum Lycopersicon [34], is among the most crucial fruit in every household globally. This plant is severely affected by several fungal, bacterial, and viral diseases [13, 28], with symptoms visible in different parts of the plant viz. leaf, stem, fruit etc. Fig 4 depicts a few of the diseases in Tomato crops, taken from the processed image of our experimentation. Early and late blight are two diseases which pose a high risk to tomato crops and make farmers run at a loss. On one hand, prompt recognition and classification of diseases is very crucial for ensuring both the quality and quantity of tomatoes [7]. On the other hand, the proliferation of smartphones and the recent advancements in Deep Learning (DL) has paved the way for smartphone-assisted disease detection [28].

In the agricultural domain, IoT is used in various aspects of the sector. The major applications of IoT in agriculture are weather monitoring, disease monitoring and detection, irrigation monitoring and control, animal monitoring and tracking, theft monitoring and tracking etc**.,** Fig 1 depicts major application of IOT bedeviling agricultural sector in the domain under study. All these applications are accomplished with the aid of different IoT-based sensors/devices by using Wireless Sensor Networks (WSNs) that help the farmers collect relevant data through sensing devices [8].

Researchers in the field of IOT, Machine learning and particularly deep learning have proposed different IoT-based solutions in the sector capable of increasing production with less human effort. Some of the relevant techniques have been identified [23-32] and summarized in the next section.

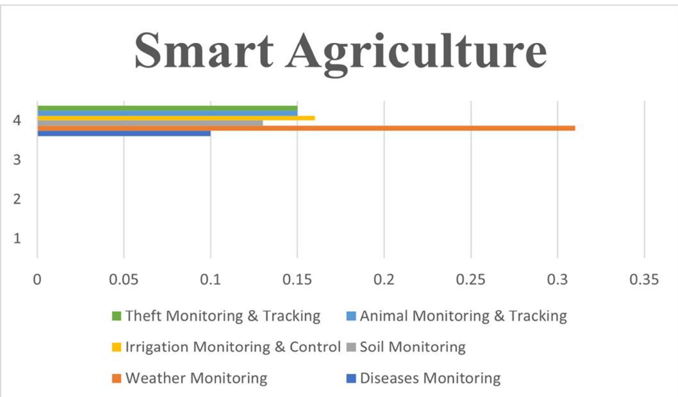


**Figure 1: Application of IOT & Data Analytics in Agriculture, Adapted from [4 & 8]**

## II. RELATED WORKS

We wish to acknowledge the wealth of contemporary literature works in IOT and data analytics for the prediction and classification of crop diseases. This section is subdivided into two sections: 1) Crop Diseases Monitoring 2) Crop Disease Prediction/Classification using Deep Learning Models.

### a. Crop Disease Monitoring

We observed from the literature [21] that agricultural sector of many countries world over suffers from revenue and production problems due to low yield. So, various diseases diminish the required quantity and quality of these plants. However, due to technology advancement, agricultural system has drastically changed and can help farmers with informed decision. The IOT paradigm is fast evolving which seeks to connect several different cyber-physical components for multi-domain modernization [11] whose aim is to autonomically monitor and track agricultural lands with little or no human intervention. These applications were depicted in fig 1. The term Precision/Smart Farming was coined following rapid advances in the fusion of IOT and DL just as earlier mentioned in agricultural domain [11] thereby allowing farmers to upgrade their operations for sustainable food supply.

Crop raiding in Africa, especially Nigeria is a huge challenge, which even aggravates to communal clashes, in addition to animal invasion. The authors in [40] deployed an IOT based monitoring system to manage wheat diseases, pest, and weeds. Similarly, a monitoring and repelling system for the protection of crops against animal attacks has also been presented [41]. In view of the above, it's now evidently clear that it's both saver and economical for farmers to leverage on the technology under study. It saves time and resources as well as increasing improved yields. Additionally, automatic crop disease detection is quite cheaper and accurate compared to employing an expert. Hence, the following section provides the role of machine learning and deep learning models for the prediction and classification of various crop diseases.

### b. **Crop Disease Prediction/Classification Using Deep Learning Models**.

Early detection of leaf disease reduces the spreading of diseases [7] and it's a major challenge. Ordinary visual assessments in a large farm by expert is two-fold strained, inaccurate and resource intensive [22]. In recent times, the fusion of IOT and ML paradigm have become very useful in the diagnosis of leaf disease. Fig 2 depicts such a vital relationship. This study reported some of the relevant ML and DL techniques employed for leaf disease detection/classification. Table 1 summarized a few of them.
Recently, Deep Learning models, particularly Convolutional Neural Networks have gained more ground in image detection/classification [22]. The work in [19, 23, 28, 32] equally aligned with preceding assertions that several ML and DL models in the literature attempted to

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identify leaf diseases but some challenges remain unaddressed. The authors further acknowledged the prowess of the existing pre-trained models such as GoogleNet, AlexNet, ResNet and VGGNet and reiterated that CNN trained on the popular PlantVillage dataset [14] suffice. This further motivated our choice on leveraging CNN alongside the PlantVillage Dataset.

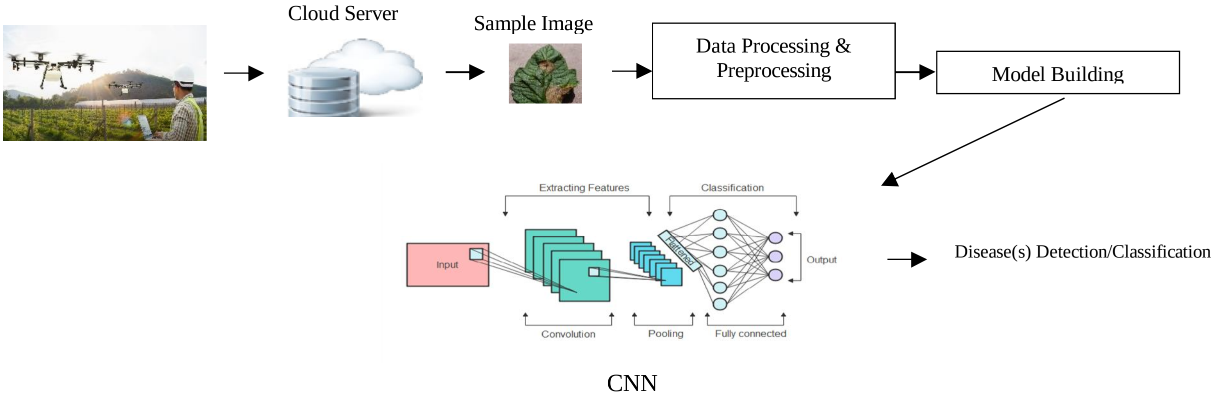


**Figure 2: Fusion of the Internet of Things and Data Analytics**

The main reason behind CNN-based models` popularity in this context is the appropriate automatic feature extraction from the dataset. The authors in [23] proposed a lightweight model based on CNN, it can be conveniently deployed in mobile scenarios. The model was implemented on a plant disease dataset consisting of 38 classes with a total of 87, 867 images. The model achieved an accuracy of 97% which rivals some of the popular pretrained deep learning models. Similarly, a Custom CNN-based model to classify various tomato plant diseases was proposed [28]. Compared to state-of-the-art models like Alex net and VGG-16. The proposed outperforms in terms of both computational cost and accuracy [28]. In line with the above, a ResNet-9 model which detects the blight disease in both tomato and potato leaf images was employed [31]. The popular “Plant Village Dataset” was utilized with the 3,990 initial training data samples after augmentation, the model was trained with these hyperparameter values, and examined on the test set containing 1,331 images, achieving an accuracy of 99.25%. while the authors in [32] proposed a CNN based model to classify tomato leaf diseases using a public dataset. To avoid overfitting, the authors employed GAN to generate samples with the same features as the training data. The results showed a high performance in the classification of diseases in tomato leaves with an accuracy greater than 99% in both the training and the test dataset.

In another way, the authors in [27] employed Multivariate Normal Deep Learning Neural Network (MNDLNN) classifier. In addition, they equally used Rectifier K-Means Clustering for image segmentation of unhealthy regions after which Random Motion Squirrel Search Optimization (RMSSO) was used for feature extraction. Thereafter, the proposed MNDLNN effectively detects and classifies the disease types with an accuracy of 95.2%. Similarly, the work in [29] proposed a framework containing 40 different hybrid DL models which contains a combination of 8 variants of pre-trained DL architectures, viz., EfficientNet (B0–B7) as feature extractors and five machine learning techniques, i.e., K-Nearest Neighbors (KNN), AdaBoost, Random Forest (RF), Logistic Regression (LR), and Stochastic Gradient Boosting as classifiers. A real-time image dataset of tomato early blight was collected. The validation of the proposed model was done using the public plantvillage dataset. The proposed model achieved an accuracy of 87.55%. While the authors in [30] present a novel hybrid of Principal Component Analysis (PCA) with a customized Deep Neural Network which has been named PCA-DeepNet. It also consists of Generative Adversarial Network (GAN) for obtaining a good mixture of datasets. Image detection was carried out using the Faster Region-Based Convolutional Neural Network (F-RCNN) with an overall accuracy of 99.60%.

## III. ADOPTION OF IOT AND DATA ANALYTICS IN THE TRADITIONAL FARMING SYSTEM OF THE NORTHWESTERN NIGERIA FOR PREDICTION OF TOMATOES DISEASES.

Tomato is one among the most cultivated crops in the Northwestern Nigeria by our rural farmers, accounting for 3,816,000 t/year and is a major food consumed in every household [1]. It grows mostly in the semi-arid regions which described our case study. In Yauri Emirate[1] where most of the inhabitants of the two Local Government Areas (LGA) are predominantly farmers, being the only source of their livelihood. The people produce different varieties of tomatoes amongst other perishables. The farming industry in the region is worth thousands of hectares and the production capacity as per district wise in the selected farms are depicted in Table 2. However, we lose both quality and quantity of this crop due to various kind of diseases, wide range of pest and lack of technology in the fields. Tomato diseases like early blight and late blight [23] are troublesome for our traditional farmers who majorly

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lacks basic education and/or access to agricultural extension services. This disease is caused by a fungus [6] that infects both leaves and the fruits. This infected fruits lacks market value, thereby heavily impacting on the economic wellbeing of these farmers.

The major aim of this study was to be able to predict tomatoes` s early and late blight which happened to be the most common bedevilling disease of tomato plant. In this regard, we wanted to collect real data from the field but due to circumstances, we resort to using a public dataset [14]. The ideal framework consists of several IOT nodes routed around the tomato orchards with a gateway for data collection from the assumed mesh nodes. The procedure is shown in Fig 2. After deploying the sensory nodes in the target orchard for data collection, a network is established between the nodes, data acquisition is done by nearby gateway. After which real-time data analysis would be carried out location wise for prompt action if need be. The same model is used in all the target orchards.

In precision farming, IOT plays a critical role for their ability to autonomously sense, capture and share desired data in real time from any location and at any time [22, 42]. In agriculture, there exist a diverse range of sensors such as environmental sensors, soil sensors, plant sensors etc., for real time data collection [21].
This collected data is very helpful for crop disease prediction.

In our proposed model, we only require plant images as input, **Algorithm 1** provides a pseudocode of the prediction model. After sensor deployment and data collection, then the next step is to find a suitable prediction model fitting the captured data [19] with a view to analyse and make an inference. Lines 1-8 explains the said procedure with the timing condition at line 6. Normally, the data is prepared in .CSV format, the captured data would then be pre-processed for model fitting, thereafter, the cleaned data is fed into the proposed model for necessary analysis according to lines 10-13. As earlier mentioned, we wish to state that during field data acquisition, we encounter some issues beyond our control, hence the decision of utilizing a public dataset [14].

ALGORITHM 1: PROPOSED TOMATO PREDICTION MODEL USING IOT AND DATA ANALYTICS

***Input**: Realtime Image Dataset*
***Output**: Tomato Disease Prediction*

```
1   x ◄——— 1 to n;
2   Deploy WSN_x in the tomato orchard
3   for WSN_x do:
4   |  Deploy 4 Cameras C_1, C_2, C_3, C_4:
5   |  Deploy Gateway G_x;
6   |  while 10<=Time< 16 do:
7   |  |  Collect Dataset_x in the SQLSever DB;
8   |  |  Time +=1;
9   |  End
10  |  for i in Dataset_x do:
11  |  |  Apply Data Proprocessing;
12  |  |  Perform Data Analysis;
13  |  |  Get results;
14  |  End
```

**Table 1: Deep Learning Based Plant Disease Prediction/Classification**

| Reference | Approach | Image Dataset | Disease(s) | Measured Metrics | Result |
|---|---|---|---|---|---|
| [9] | DNN | - | Early blight, Late blight, Healthy | Accuracy | 97% |
| [17] | DCNN | 54, 306 | 26 diseases, 14 crops | Accuracy | 99.35% |
| [19] | VGG16, VGG19, CNN | 5838 | Early blight, late blight, Healthy | Accuracy | 92.08% |
| [22] | CNN | 2658 | Early blight, late blight | Accuracy | 76.59 |
| [23] | CNN | 87,867 | Multi Class | Accuracy | 97% |
| [27] | MNDLNN | - | Multi Class | Accuracy | 95.2% |
| [28] | CCNN | 16,012 | Multi Class | Accuracy | 98.44% |
| [29] | Framework | 2591 | Early blight, late blight | Accuracy | 87.55% |
| [30] | PCA-Deepnet | 56000 | Multi class | Accuracy | 99.60% |
| [31] | ResNet-9 | 1331 | Early blight, late blight | Accuracy | 99.25% |
| [32] | CNN | 15000 | Multi Class | Accuracy | 99% |

**Table 2. District production capacity of Tomatoes in Yauri Emirate**.

| **District** | | **Sub-District** | **Production Capacity (in metric tonnes)** |
|---|---|---|---|
| Yauri | | *Shanga* | 350.76 |
| | | *Tondi* | 280.6 |
| | Ngaski | *Gafara A* | 480.5 |
| | | *Gafara B* | 180.9 |

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**Table 3: Farmers Survey**

| Date | Sub-District | | | Selected farmers | Respondents |
|---|---|---|---|---|---|
| 20th – 30th April, 2023 | Yauri Emirate | Yauri | *Shanga* | 300: M=200, F=100 | 100: M=80, F=20 |
| | | | *Tondi* | 200: M=150, F=50 | 80: M= 60, F=20 |
| 2nd -9th June, 2023 | | Ngaski | *Gafara A* | 150: M=120, F=30 | 70: M=50, F=20 |
| | | | *Gafara B* | 150: M=110, F=40 | 50: M=40, F=10 |
| Total | | | | 800 | 300 |


**Figure 3: Classes in the image's dataset**

**Table 4: Interview Questions and Answers**

| Attributes in the interview | Parameters | Response % |
|---|---|---|
| Age of Farmer | < 40 years | 40 |
| | 40 -65 years | 45 |
| | >65 years | 15 |
| Education | Secondary | 20 |
| | Higher | 5 |
| | Others | 65 |
| Cultivated Land | <10 | 60 |
| | 10-20 | 28 |
| | >20 | 12 |
| Knowledge of IOT, ML, DA | YES | 98 |
| | NO | 2 |

**Table 5: Dataset Statistics**

| Class Label | Training Set | Testing Set | Total |
|---|---|---|---|
| Early Blight | 1536 | 192 | 1728 |
| Late Blight | 1480 | 185 | 1665 |
| Healthy | 1540 | 193 | 1733 |
| Total | 4,556 | 570 | 5126 |

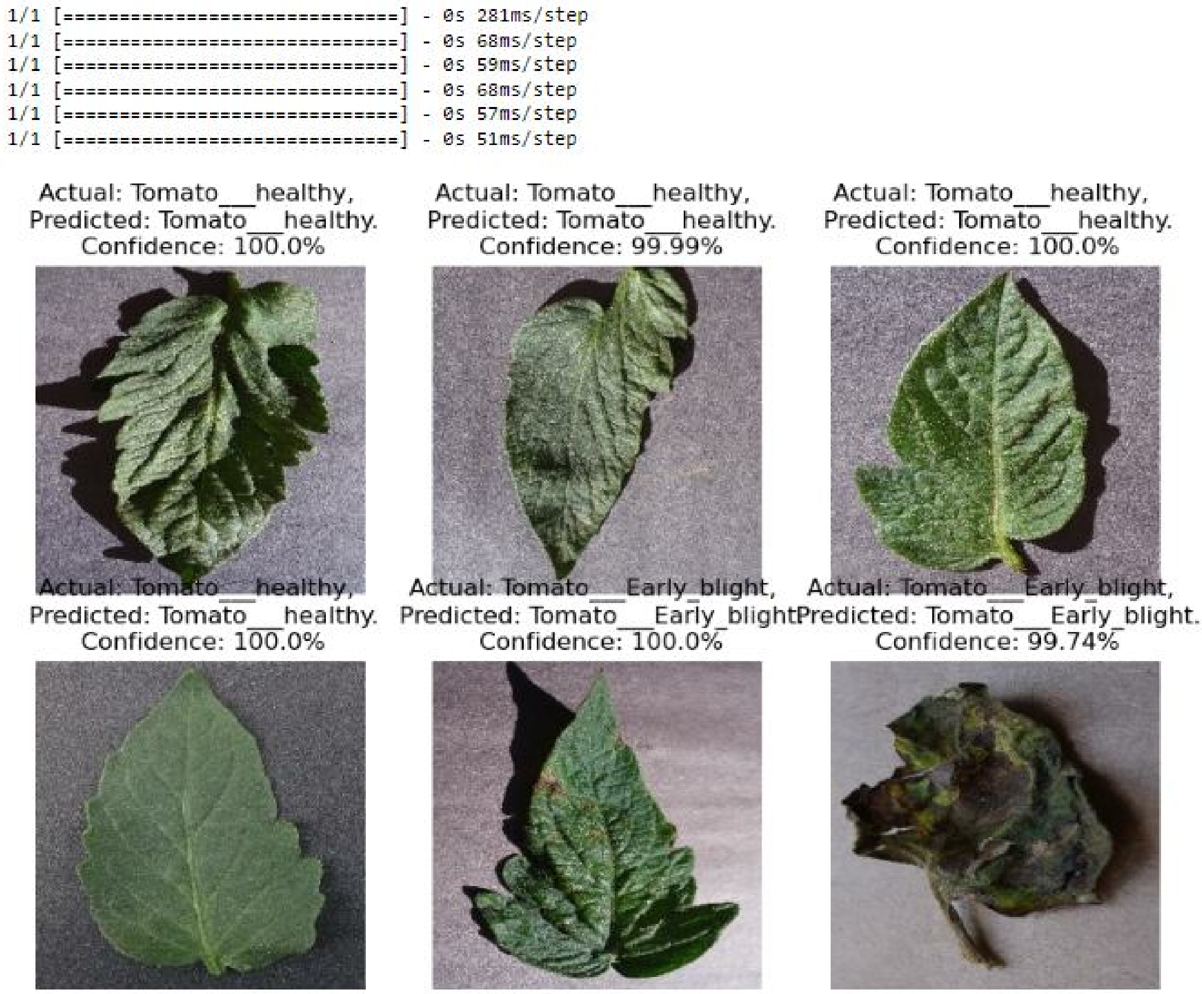


**Figure 4: Prediction confidence of the class labels**

**Table 6: Proposed CNN Model**

| No | Layer | Parameter |
|---|---|---|
| 1 | Convolutional layer | Filters=32, kernel_size= (3,3), activation=" Relu", and input_shape= (256, 256, 3) |
| 2. | Max pooling layer | Pool_size= (2, 2) |
| 3 | Convolutional layer | Filters=64, kernel_size= (3,3), and activation=" Relu" |
| 4 | Max pooling layer | Pool_size= (2, 2) |
| 5 | Convolutional layer | Filters=128, kernel_size= (3,3), and activation=" Relu" |
| 6 | Max pooling layer | Pool_size= (2, 2) |
| 7. | Convolutional layer | Filters=256, kernel_size= (3,3), and activation=" Relu" |
| 8 | Max pooling layer | Pool_size= (2, 2) |
| 9 | Flatten layer | () |
| 10 | Dense layer | Units=64 and activation=" Relu" |
| 11 | Dropout Layer | Rate=0,2 |
| 12 | Dense layer | Units=3 and activation=" Softmax" |

**a. Challenges of Accepting IOT/Data Analytics for Traditional Farmers in Yauri Emirate.**

Precision Farming (PF) is a term currently on the wild throughout the agricultural industry. The study of PF comes in several ways, it is regarded as the system for meeting the increasing challenges of needs from scarce resources, from its technical connotation of a farm management system that uses information technology for decision making to the dissection of the factors involved in the complex scenario of

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adopting relevant tools [3]. Besides the numerous advantages that comes with the technology, there exist a few challenges faced by the domain players, including farmers, researchers, and agriculturist [4]. Most importantly is the incompatibility of the technology in our target domain, as farmers greatly vary in knowledge, skills, and attitude towards innovations, as well as farm size alongside financial capacity [5]. However, Due to neglect or lack of counselling support by way of rural extension services, the process of the adoption of new technology is uncertain. Hence, the idea of conducting a local survey on the knowledge and perception of precision farming in the study area.

Even though, the Nigerian government has recently shown commitment towards making more investment into the sector as well keying into the technology advancement, we wish to state that currently the usage of technology in the farming sector of the region under study remains a mirage. This and more led to deepening more effort by researchers towards unravelling the fundamental reason for the slow or lack of acceptance of the technology.

### b. Survey Description

***Domain Mapping***: Yauri and Ngaski districts belong to Kebbi state, Northwestern Nigeria, the region is inhabiting a land area of about 1,306 square miles (3,380 $km^2$) and scattered over six major districts, including one of the sites under investigation (Yauri Emirate) [2]. Yauri lies within latitudes 10.74°E and 10.44°N and longitudes 4.77°N and 4.46°E [6]. Rain begins in May/June and lasts till October/November after which winter period sets with lowest temperature of the year. Cultivation of Rice, Maize, Millet. Onions, Pepper, and Tomatoes alongside fishing is the major occupation of the people under study. Onions, Pepper, and Tomato are considered cash crops while other varieties are for family consumption.

In Nigeria, crop yield is hampered by many factors but the most worrisome is disease and pest management which ultimately affect the post-harvest outcome. We did a local survey in the target region with a view to ascertaining the level of knowledge, acceptance, and the prospect of adopting the usage of precision farming using technologies like IOT, Machine Learning and Data Analytics (DA).

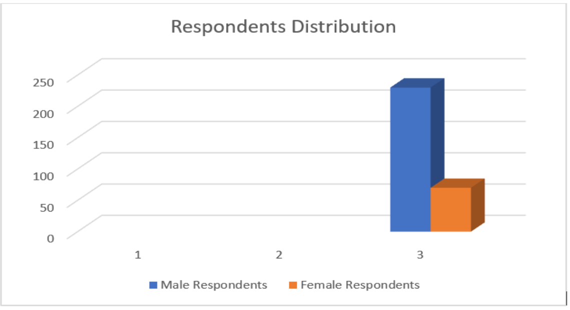


**Figure 5: Respondents Demographic Chart**

The sampled population of this study comprises of small-scale farmers (subsistence) to large scale farmers (commercial) with a gender sensitive distribution as depicted in Fig 5. The main idea is to understand the level of knowledge and awareness of the contribution and prospect of ICT in agriculture within our target audience. The information extracted would contribute to the guiding principles for the relevant stakeholders. In view of the above, we decided to question our audience through an interview. The total of 800 farmers were carefully selected across the two zones, then a random sampling technique was employed where 300 respondents were interviewed corresponding to 37% from the total frame based on their population density. Table 2 describes the survey parameter distribution. Having observed the nature of our respondents, we interviewed them with questions mostly requiring “YES” or “NO” answers. Over 60% of our respondents lack a basic school certificate while the remaining number were either totally unaware of the technology or were aware of it but had never been used. This revelation poses a serious challenge to the relevant stakeholders. Table 3 depicts the nature of our questions during the interview as well as the corresponding responses. The end results demonstrate an urgent need for the relevant bodies to consider immediate action.

## IV. METHODOLOGY

### a. Dataset

The dataset for the experimentation was taken from [14]. The dataset has a total of 5697 images, containing 3 classes (‘tomato_early_blight’, ‘tomato_late_blight’, ‘healthy’). Fig 3 depicts the given classes as detailed in Table 5

### b. Experimental Settings

We performed the experiment on a laptop computer, core i5, NVIDIA GEFORCE, running windows 10 education edition equipped with 64-bit operating systems having 12GB RAM. Both the training and testing were executed in Jupyter Notebook.

### c. The Proposed CNN Model

The hyper-parameters used in the proposed CNN model are depicted in Table 6 designed for the classification of tomato diseases. The layers of the model were based on theory, trial, and error. The model consists of convolutional, pooling, and fully connected layers. These layers performed the main task of feature extraction and classification. We split the dataset into 80% for training, 10% for testing and 10% for validation in 32 batches. We used Adam as our optimization algorithm with a learning rate of 0.001. For fast training we shuffle the training dataset in the cache 1000 times and autotuned the buffer size. Thereafter, we performed some resizing and rescaling (1.0/255). Fig 5 depicts a sample predictive label indicating confidence percentage.

### d. Model Evaluation

The evaluation is twofold, firstly, training and validation, secondly, testing as can be depicted in fig 6 after 50 EPOCHS. For getting the accuracy during training and validation, we used keras library from the sklearn.metrics

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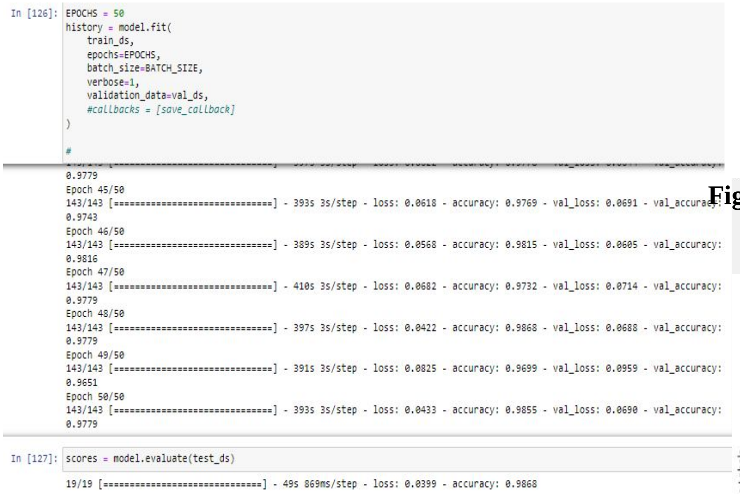
as per equation 1. while the loss function is the difference between the model prediction and the actual labels in the training set.

$$\boldsymbol{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Then, during the testing phase, we calculated precision and recall as per equations 2 and 3 based on our confusion matrix (fig 8). Fig 7 depicts the chart for the precision and recall.



```
In [126]: EPOCHS = 50
          history = model.fit(
              train_ds,
              epochs=EPOCHS,
              batch_size=BATCH_SIZE,
              verbose=1,
              validation_data=val_ds,
              #callbacks = [save_callback]
          )

          #
0.9779
Epoch 45/50
143/143 [==============================] - 393s 3s/step - loss: 0.0618 - accuracy: 0.9769 - val_loss: 0.0691 - val_accuracy:
0.9743
Epoch 46/50
143/143 [==============================] - 389s 3s/step - loss: 0.0568 - accuracy: 0.9815 - val_loss: 0.0605 - val_accuracy:
0.9816
Epoch 47/50
143/143 [==============================] - 410s 3s/step - loss: 0.0682 - accuracy: 0.9732 - val_loss: 0.0714 - val_accuracy:
0.9779
Epoch 48/50
143/143 [==============================] - 397s 3s/step - loss: 0.0422 - accuracy: 0.9868 - val_loss: 0.0688 - val_accuracy:
0.9779
Epoch 49/50
143/143 [==============================] - 391s 3s/step - loss: 0.0825 - accuracy: 0.9699 - val_loss: 0.0959 - val_accuracy:
0.9651
Epoch 50/50
143/143 [==============================] - 393s 3s/step - loss: 0.0433 - accuracy: 0.9855 - val_loss: 0.0690 - val_accuracy:
0.9779

In [127]: scores = model.evaluate(test_ds)
19/19 [==============================] - 49s 869ms/step - loss: 0.0399 - accuracy: 0.9868
```

**Figure 6: CNN Testing after 50 EPOCHS**

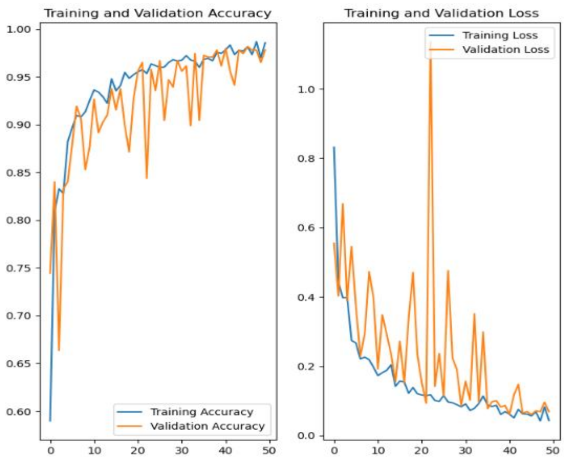



**Figure 7: Training Accuracy of the Proposed CNN Model**

$$\boldsymbol{Precision} = \frac{TP}{TP+FP} \qquad (2)$$

$$\boldsymbol{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

Where Positive Predictions = True Positive ($TP$) + False Positive ($FP$)

Negative Predictions = False Negative ($FN$) + True Negative ($TN$)

$TP$ is the number of correctly predicted positive label, $FP$ is the number of negative labels incorrectly predicted as positive, $TN$ is the number of negative labels that is correctly predicted, $FN$ is the number of positive labels incorrectly predicted as negative.

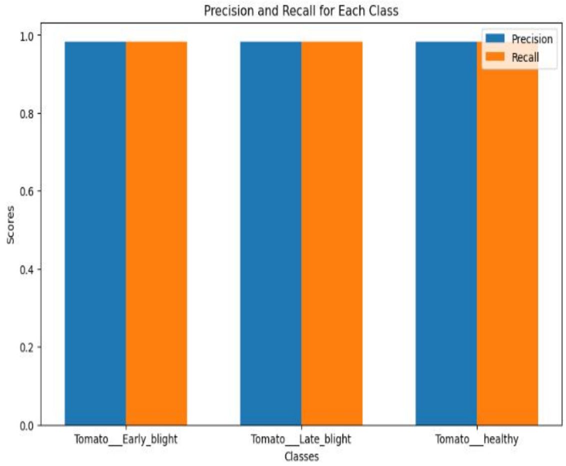



**Figure 8: Precision and Recall for each class from our Confusion Matrix**

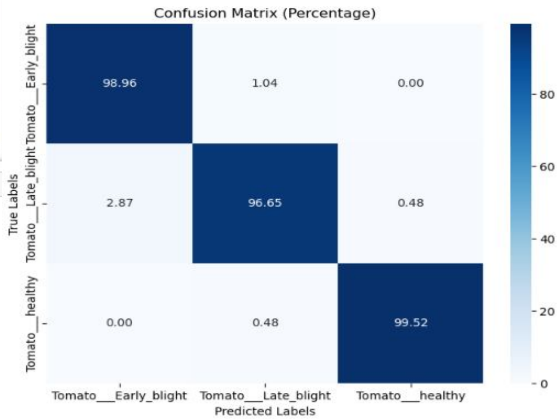



**Figure 9: Confusion Matrix of the Predicted Labels**

**e. Discussion of Results.**

We have trained and evaluated our proposed model with the testing, achieving a near-optimal accuracy of 98.6% with a loss of 0.03% while recording over 98.3 % for both precision and recall on the predicted labels. We also observed that our target audience for the survey lacks near total knowledge of smart farming, hence the need for the stakeholders in the domain to embark on sensitization and awareness towards reaping its numerous advantages. Its worthy of note to state that some of key challenges hampering the lack of knowledge of acceptance of the technology ranges from lack of education, awareness, funding to policies from the government.

## V. CONCLUSION

This research underscores the critical role of technology, particularly the integration of Internet of Things (IOT), Machine Learning (ML), and Data Analytics (DA), in addressing the challenges faced by the agricultural sector, particularly in disease management for tomato plants in Yauri Emirate, Northwestern Nigeria. The study demonstrates the effectiveness of Convolutional Neural Network (CNN), a deep learning model, in accurately classifying tomato plant diseases with a near-optimal accuracy of 98.6% and minimal loss. Furthermore, the survey conducted highlights a significant lack of knowledge among the target audience regarding smart farming technologies, indicating a pressing need for stakeholders to prioritize sensitization and awareness campaigns to maximize the benefits of these innovative approaches in agriculture. We wish to extend the work to other crop diseases and equally develop a mobile application for our target audience.

**Authors Contribution**

We equally wish to state that the Conceptualization of this work was done by Shuaibu Yau, Methodology was provided by Aminu Aliyu and Saidu Yahaya, Draft writing was carried out by Shuaibu Yau and Abdulhakeem Ibrahim while Farouk Musa Aliyu reviewed and edit the manuscript.

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