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IMPROVING RICE PRODUCTION BY DETECTING DISEASES USING IoT IN NORTH WEST NIGERIA

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Abstract
This paper presents an automated rice plant disease prediction which is the key in preventing the losses incurred during rice production and farming in Northern Nigeria. Because of the tedious methods involved in traditional agricultural method of identifying rice diseases, it has become imperative to have an automated method of classifying and predicting rice plant diseases. The steps to follow for the Rice plant diseases prediction and detection in this research work are image capture, pre-processing, segmentation, feature extraction and classification. Diseases that attacked rice plant in northern Nigeria are microbial in nature. In order to prevent this from happening, a sensor node is attached with a health maintenance system to capture the image of the rice plant and perform an analysis using the four classification techniques of K- Nearest Neighbor (KNN), Back Propagation Network (BPN), Support Vector Machine (SVM) and Convolutional Neural Network (CNN). Among the four techniques employed, Convolutional Neural Network (CNN) was found to perform better with an accuracy of 99.34%.

KEYWORDS: Internet of Things, classification Technique, wireless Sensor Network

1. Background

Rice is one of the most important food crops in the world and likewise in Nigeria where its consumption has increased considerably. To meet the demand of the ever increasing population, technology has to be introduced in order to increase yield and production. It has become necessary to meet the demand of the world's current population growth rate, and the least costly means for achieving this aim is to increase rice yield and production, wherever possible.

According to Agricultural Data Statisticians Gro Intelligence, "Nigeria produced 4.9 million tons of rice in 2019, this is an increase of up to 60% in 2013". But, it is far below the local annual consumption of 7 million tons. Also, the U.S. Department of Agriculture, predicts that, Nigeria's rice imports will rise by 9% to 2.4 million tonnes in this year, this is due to the high cost of unprocessed paddy rice which is caused by pest and diseases and high operating costs at mills.

Rice production in northern Nigeria is used both as a cash and food crop has many challenges, among which are the effect of pest, weeds, birds and diseases (S. Mohammed, 2016).

Materne, N., & Inoue, M. (2018), in their work cited that one of the major challenges facing farmers in Africa as other part of the world is the threat of pest and diseases. This is not only to the farmers but, also affect the economy of the country. They also suggested that weather, environment and climate are very important in determining the type of diseases and if the disease will develop further or not. Majority of our farmers are local farmers and rely heavily on traditional method of diseases control, that is, use of spray pesticide, only when they noticed that the plant is showing some kind of symptoms.

Research Objective

The Objective of this research is to develop a smart agricultural solution based on IoT technology that will alert farmers of different types of rice diseases and their possible medications via a mobile phone. Other objectives that the research work will aim to achieve are as follows:

I. To explore different types of rice diseases that are peculiar to northern part of Nigeria.
II. To use at least use four types of classification techniques, for more accurate prediction and choose the best among them.
III. To develop a bird scaring system that will drive away bird as well as human intruders.
IV. To develop a mobile application to provide information to rice farmers about the diseases that will affect their rice crops.

Research Scope and Limitation

This research work will focus on developing smart agricultural solution to rice farmers by sending SMS to their mobile phones on different types of diseases that may have an adverse effect to the growth of their plants.

The rice plant diseases prediction will be performed using image processing technique. Four types of classification technique will be used, out of which one will be chosen based on the performance and accuracy of its prediction. The four classification techniques are:

i. K- Nearest Neighbor (KNN)
ii. Back Propagation Network (BPN)
iii. Support Vector Machine (SVM)

iv. Convolutional Neural Network (CNN)

2.0 Review of related Literature

The literature Reviews here will be on existing research using the same method and also on other research using same method but different applications.

2.1 Plant Disease Detection Using Image Processing

Gavhale, K. R., & Gawande, U. (2014) summarized and reviewed image processing techniques for identifying and detecting diseases on different species of plant. The techniques used for detection are; Back propagation Neural Network (BPNN,) support Vector Machine (SVM), K- means clustering and Spatial gray-level dependence matrices (SGDM) which are used for both healthy and infected plants. It was found out that these techniques have a very good potential ability to detect plant diseases but with some limitations.

In one of their paper, Kumar, S., & Kaur, R. (2015) suggested that BPNN is the easiest non-linear technique to be implemented among SGDM, SVM, and K- means in terms of plant diseases detection.

Different types of classification techniques were studied by Savita, N.et al (2015), in order to find which technique works best for a particular method. It was found that K- Nearest Neighbor is a simple algorithm to test for classification but is complex while making predictions. Neural Network can tolerate noise input but understanding its algorithm structure is a complex issue. Accordingly, Support vector machine SVM is found to be the best machine learning algorithm for classifying dimensional dataset, but its inability to find optimal parameter for training nonlinear dataset makes it difficult to implement.

Pramod and S. landge (2013) developed an image processing technique system that will detect and classify plant diseases. This system sends information via an SMS to farmers to notify them if there is any outbreak of plant diseases. They suggested that if the system be implemented, it will enhance productivity and reduce overhead cost.

Chandra Karmokar, B, Samawat Ullah, M, Kibria S, et al, (2015) developed a system called tea leaf diseases Recognizer (TLDR). It is an easy and cost effective way of identifying diseases of the tea leaf which can also be extended to other leaf plants. Neural Network Ensemble (NNE) was used for recognition and 91% accuracy was achieved. Several advantages were given by the authors on why they used the combination of feature Extraction and Neural Network Ensemble for training.

An overview of plant diseases detection using image processing was given by Khirade, S. D, Patil, A, B (2015), where they started by highlighting the basic steps for diseases detection using image processing, and discussed fully each step. They concluded by affirming that image processing can be used to accurately detect and classify plant diseases. This can be done by the use of artificial neural network ANN methods such as back propagation algorithm, SVM, self-organization feature map, etc.

Another study conducted by Ashourloo, D., Aghighi, H., Matkan, A. A, et al. (2016), investigates the use of machine learning regression technique to detect leaf rust diseases by using hyperspectral measurement. They use partial least square regression (PLSR), v support vector regression (v- SVR) and Gaussian process regression (GPR) to detect diseases on wheat leaf rust diseases.

In order to have a meaningful dataset, the study used a non-imaging spectro radiometer in the region of 350 to 2500nm to measure the infected and non-infected leaves. It was found that Gaussian process regression (GPR) has a better performance than the other methods when using small training sample size. In comparison to machine learning technique and spectral vegetation indices (SVIs), the result shows that machine learning technique although reliable is not sensitive to different disease symptoms.

Artificial neural network concept in Image processing was used in one study undertaken by Jhuria, M., Kum, A. (2014), conducted on ninety-two images used for learning database on two fruits, by which three diseases of grape and two diseases of apple were considered. The features that are taken for feature extraction are morphology, color and texture. It was found out that morphology feature extraction gave a more reliable result of 90 percent than the other two features of color and texture. Matlab was used for the implementation of the Artificial Neural Network.

Anand H. Kulkarni et al. (2013) proposed a methodology of detecting plant diseases using different types of image processing techniques accurately and in its early stage. Gobar filter was used for feature extraction and artificial neural network was used for the classification. The result gave a 91 percent recognition rate.

A software solution was proposed and experimentally carried out by Landge, P.S., Patil, S.A., Khot, D.S, (2013) to detect and classify plant diseases using image processing. The solution employed the use of neural network algorithms. An SMS will be sent to farmers indicating the type of diseases and possible solution.

A new approach of using deep learning method to classify and detect plant diseases was explored by S. Sladojevic, M. Arsenovic, A. Anderla, et al. (2016). They developed a model using deep convolutional Neural Network to detect the presence of diseases in plants from leaf images. An overall accuracy of 96.3% was achieved by the training model.

Data mining technique and wireless sensor nodes technology were proposed by Kumar, N. (2017), to predict plant diseases. Sensors were deployed to farm land to sense the environmental parameters, and the sensed data from the sensors earlier deployed will be compared with the existing threshold value of the soil and plants. The sensed data is fed to the microprocessor via the wireless module. The data received will be analyse using data mining such as Markov to detect possible plant diseases. The user can access the result of the analysis via an android smart phone displayed on the user interface.

2.2 Comparison of classification techniques

Although, there are many classification techniques that can be used for feature extraction to help in predicting plant diseases, a summary of some classification technique were compared in terms of their advantages and disadvantages by Gavhale, K. R., Gawande, U. (2014) as shown in table 2.1.

S/N	Classification technique	Advantages	Disadvantages
1	Probabilistic Neural Network (PNN)	1. Tolerate noise inputs 2. Adopt to data modification 3. Classification instances for more than one output	1. training time takes longer 2. large complex network structure 3. A lot of memory is required for training dataset
2	k-Nearest Neighbor(KNN)	1. simple classifier irrespective of training process 2. Applicable to a small untrained data set	1. the numbers available in the training samples can increase the speed of computing distance 2. sensitive to irrelevant input and expensive in testing each instances
3	Radial Basis Function (RBF)	1. faster training phase 2. easier to interpret hidden layer	1. slower execution time
4	Back Propagation Network (BPN)	1. easy implementation 2. applicable to wide variety of problems 3. can form complex nonlinear mapping	1. it's slow in learning 2. difficult to know the number of neurons and layers required
5	Support vector machine (SVM)	1. it can be robust even if the training data has some bias 2. simple geometric and sparse solution	1. Has complex algorithm 2. Can be slow training 3.

Table 2.1

2.3 Limitations on some related works on plant disease prediction

Diseases prediction methods depend on the solution of the accuracy of the methods used. The table below summarizes drawbacks on some methods used to predict plant diseases. The limitations were clearly stated and it's because of that this research work will consider a mix solution in order to achieve the objective of the research work.

S/N	Authors	Year	Title	Methods	Limitations
1	S. Kaur, S. Pandey, S. Goel	2018	"Development of semi-automatic leaf disease prediction and classification for soya bean"	Three types of diseases were considered and trained on SVM for different features	1. Required high computation 2. Changing parameters for every task
2	W.-L. Chen, Y.-B. Lin, F.-L. Ng, et al	2019	"RiceTalk: Rice Blast Detection using Internet of Things and Artificial Intelligence Technologies"	CNN, SVM, KNN and Decision Tree were used	Accuracy of prediction is low
3	M. Al-Amin, T. A. Bushra, M. N. Hoq,	2019	"Prediction of Potato Disease from Leaves using Deep CNN towards a Digital Agricultural System"	Deep Convolutional Network	Accuracy of prediction is low. Requires high computation and parameters
4	N. Materne, M. Inoue	2018	"IoT Monitoring System for Early Detection of Agricultural Pests and Diseases"	(LR) logistic Regression, (RF) random forest, and (KNN) K-Nearest Neighbor	1. Linear dependency cannot be removed 2. Accuracy of prediction is low.
5	D. Ashourloo, H. Aghighi, A. A. Matkan, M. R. Mobasheri, et al	2016	"An Investigation into Machine Learning Regression Techniques for the Leaf Rust Disease Detection Using Hyperspectral Measurement"	Regression algorithms methods	Linear dependency cannot be removed
6	Pramod S. l, Sushil A. P, Dhanashree S. K., et al	2013	Automatic Detection and Classification of Plant Disease through Image Processing	Neural Network	Slow rate of disease detection and severity of the disease

Table 2.2

3.0 PROPOSED NOVEL CNN MODEL FOR AUTOMATIC PLANT DISEASE PREDICTION

The IoAT app has the capability of Disease Prediction, which are explained as follows.
This module notifies the farmer of the crop disease, if any, by using the computational power of the smart phone.

7

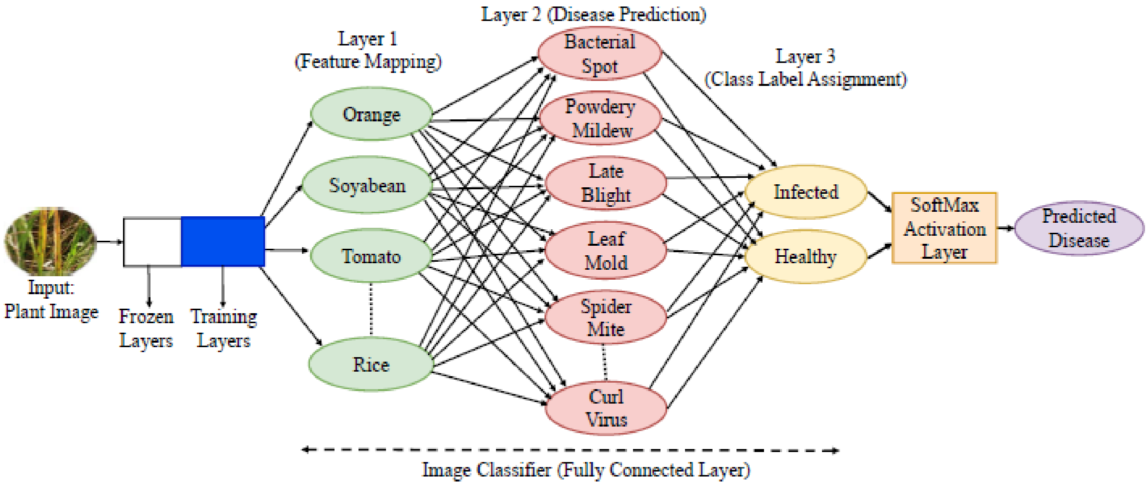

Fig. 1 proposed CNN model

The basis of plant disease prediction depends on the deep learning model created using Convolutional Neural Networks (CNN). In spite of a plethora of classification techniques being available, CNN is best suited for image classification because:

1. CNN is a very efficient feature extractor. It uses adjacent pixel information and then uses different convolution layers to down sample the image without losing any crucial information and then performing a prediction at the end layer.
2. The final features obtained from CNN are invariant to occlusions. This is achieved because the system does feature extraction by convoluting the image and filters to generate invariant features which are passed into the next layer.
3. CNN is found to perform better with unstructured data such as images in comparison with other classifiers such as Support Vector Machines (SVM), etc.
4. In other classification algorithms such as; Nearest Neighbors (KNN), SVM, and logistic regression.

The final efficiency is lesser compared to CNNs because the latter employs transfer learning.
Disease prediction takes place in simple steps, as represented in Fig. 2, which can be summarized as:

- Firstly, the crop leaf image present in the cloud is retrieved by the app.
- Secondly, the retrieved image is given as an input to the trained Deep Learning model which extracts the features. The extracted features are given to feature mapping, disease prediction and class label assignment layers to test for the infection in the crop, along with the confidence percentage using the Softmax activation layer.
- Lastly, the prediction results from the trained model are shown as the final information regarding the health of the crop on the User Interface. And the same process is repeated after 24 hours

:

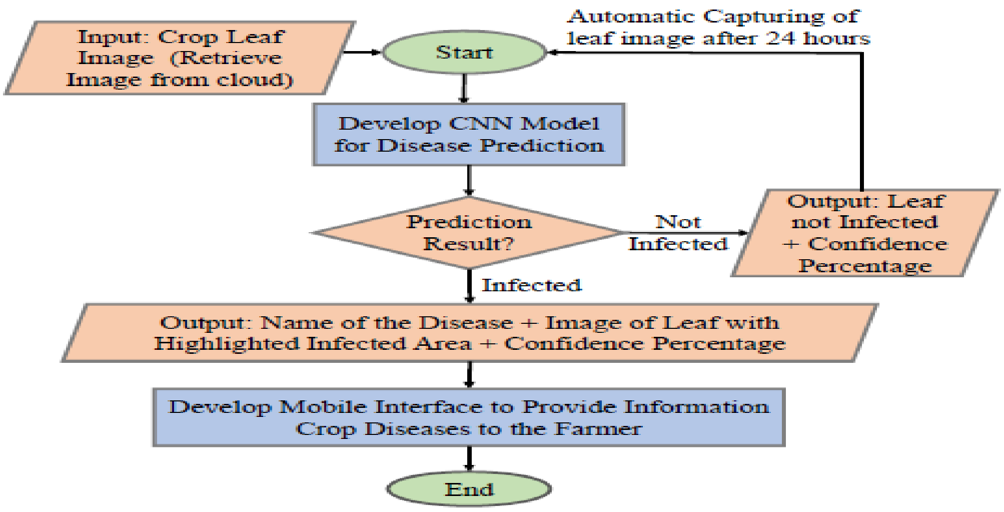

Fig.2 proposed method for diseases prediction using IoT

Dataset is the most critical factor which affects the performance of the DL model. The Plant Village dataset consists of 54,306 images of healthy and non-healthy crop's leaf, which can identify 38 different diseases. This dataset is used to train the DL model. The dataset is annotated by classifying all the 54,306 images into different folders consisting of pictures of the leaf of a particular disease, and folder's name the same as that of the disease.

The training set consists of examples from the dataset which are used for learning to fit the parameters for training the image classifier model. The training set is used to find the optimal weights using the back propagation rule. The validation set is used to fine-tune the parameter of the classifier being trained. It helps in finding the end-point for the back propagation algorithm. For testing the trained model, we use image sets of both healthy and diseased crop diseases.

The training aims to fit a model that best suits our dataset. The advantages of using CNN lies in the capability of capturing and learning relevant features from the image, which is calculated by the following expressions:

$$G[m,n] = (f * h)[m,n] \quad (1)$$

$$= \sum_j \sum_k h[j,k]\, f[m-j, n-k]. \quad (2)$$

In the above expressions, the input image is denoted by f, and the kernel or filter (small matrix of numbers) is denoted by h. The indexes of rows and columns of the result matrix are denoted by m and n.

The model is trained with three different architectures, namely, ResNet50, ResNet 34 and AlexNet with the same dataset. Better performance has been achieved with ResNet 50. The basic building block of ResNet 50 is the convolution block and identity block. It allows skipping connections, which helps in designing deeper CNN (up to 150 layers) and uses batch normalization. Therefore, ResNet 50 architecture is used transfer learning and the architecture designed for IoAT is given in Fig. 2. In spite of the availability of several state-of-the-art architectures, ResNet outperforms, each of them because of the following reasons:

- It can go deeper without degradation in the accuracy and increase in error rate. This is achieved through" identity shortcut connections".

- It can learn the residuals so that the predictions are close to the real.
- Through the pre-activation variant of the residual block, a deeper ResNet can also outperform its shallower counterpart.

To further add on to the advantages of ResNet 50 and increase the prediction accuracy of IoAT, an additional three fully connected layers with a softmax activation function is added. When we give the crop image as input to the ResNet 50, where it passes through batch normalization, and conv and identity blocks. After which it acts as input to the fully connected layers, after which by using the Softmax Activation layer it is classified as Healthy / Infected or Diseased crop, along with the name of the disease.

The advantage of training the model for a specific application on top of an existing pre-trained model is adding to the current knowledge. This is known as Transfer Learning and makes the model more intelligent. The network is represented using the following expressions:

$$H(x) = F(x) + x \tag{3}$$

$$F(x) = W2\ \_\ \mathrm{relu}(W1\ \_\ x + b1) + b2: \tag{4}$$

In the above expressions, H(x) is a mapping function, F(x) and x simultaneously represent the stacked non-linear layers and the identity function. W2 and W1 represent the weight matrices, and b1 and b2 are the bias terms. During the training period, the ResNet learns the weights of its layers, during which F(x) learns to adjust the predictions to match the actual values. Once the model is created, the weights need to be saved for later use.

Requires: *Crop's Leaf Image input from cloud*
Ensures: *Disease prediction result*
Notions: CI: Crop Image, OUTPUT_CI: Crop image from previous layer processing, **: Data flow is happening between the cloud database.

```
while TRUE do
    ReadFromCameraModule(CI)**;
    SendCloud(CI)**;
    ReadCloudtoMobileApp(CI)**;
    IntializeInputLayer(Pre-Processed(CI));
    Input(OUTPUT_CI, conv block);
    Input(OUTPUT_CI, max pool);
end
SaveIntoFile(ExtractedFeatures);
TrainedCNNModel;
```

Algorithm for the proposed rice plant disease prediction

3.1 Hardware requirement

ESP8266 Node Microcontroller Unit (MCU) is interfaced with a camera module is also interfaced with the solar node for further usage of predicting the health of the crop.

OV7670 Camera Module: The OV7670 Camera Module is used to capture photos of the plant leaf. It has a high sensitivity for low light applications. The module is used due to its low cost and pre-processed image output.

3.2 Software Requirements

In this section, various software such as Arduino Integrated Development Environment (IDE), ThingSpeak cloud database, Kaggle Kernel and Django are all used in order to develop the application.

4.0 Validation of Results

Here we talked about the performance measures of the trained image classifier. The deep learning model is trained using three different architectures to compare and select the best performing architecture.

The accuracy produced by using each of the three architectures, i.e., ResNet 50, ResNet 34, and AlexNet, is described in Table 4. Different architectures are used to show that the model used to train is better performing than the existing models.

Architecture	Accuracy for epochs = 4
IoAT	99.24%
ResNet 34	94.97%
AlexNet	90.63%

Table 4: comparison of accuracy of model architecture

As ResNet 50 provides the best accuracy, it has been chosen as the pre-trained model architecture for production. Since the accuracy achieved is taxing, there arises a demand for performing a check on the overfitting of data. To accomplish this analysis, the dataset is split into varying percentages of training and validation, which is presented in Table 5.

Train Split (%)	Validation Split (%)	Accuracry for epochs = 4
80%	20%	99.24%
60%	40%	96.19%
40%	60%	95.27%
20%	80%	93.37%

TABLE 5: Test for overfitting of data.

5.0 Conclusion and frontiers for further research

As the accuracy is consistently above 90% even when the train split is just 20%, it can be concluded that there has been no over-fitting. The confusion matrix, as shown in Fig. 4, is used as an evaluation metric for the performance of the trained model on the test data. It is calculated between the different class labels of the actual and predicted values of the test dataset. The number of correctly classified disease labels is given at a cell [i; i]. This cell will have the highest value for that column and row of the given matrix for a well-trained model. Value of the cell [i; j] greater than one states that the class I is wrongly classified as class j, where j is the predicted label and i is the actual label of for the image and vice-versa. The number of misclassifications in predicting the actual class label for various diseased images can be seen in red circles in Fig. 4. From the figure, a total of 72 images among the complete dataset are found to have been misclassified, whereas a total of 7580 images have been tested and classified correctly.

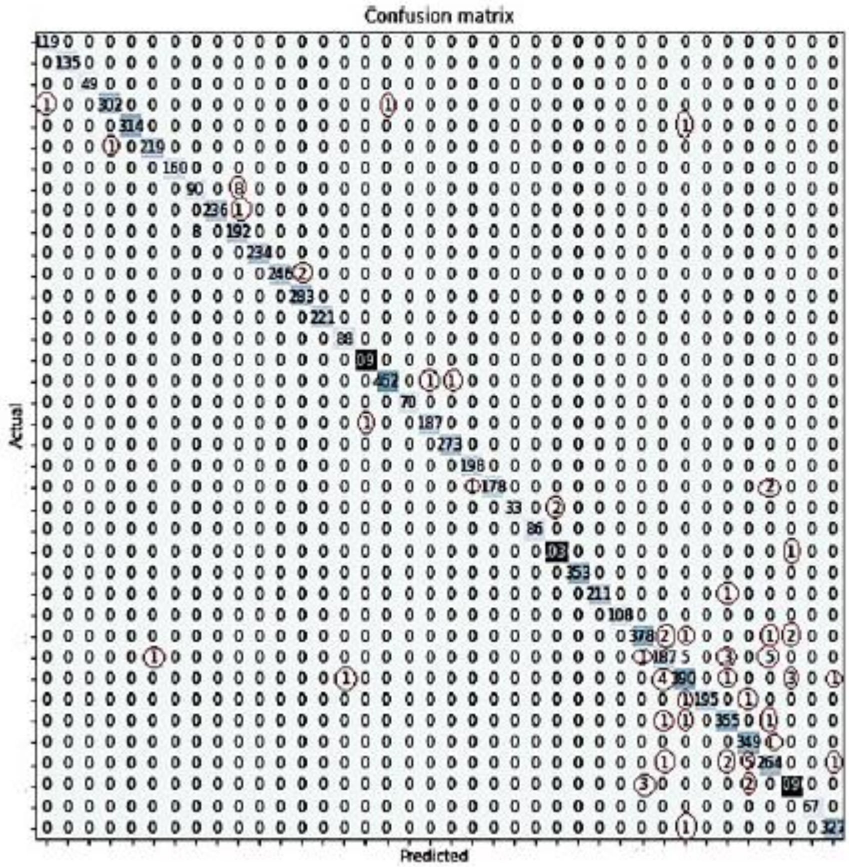

Fig.4: confusion Matrix for the trained Model

A total of 200 images belonging to 14 different crops is tested using the developed mobile app. From 28 diseases 5 images each and the rest 10 diseases 6 images each were taken to test the solution for 14 different types of crops. 36 diseases were identified correctly out of 38 different diseases. 197 images were identified correctly with the developed mobile app, out of 200 different disease images. The results are shown in Table 6.

	Correctly Classified	Misclassified
200 images	197	3
38 diseases	36	2

Table 6: Results with real Dataset

Finally, in this paper, a rice disease prediction system is proposed to aid the farmer in making agriculture more profitable and less arduous. The deployment of the proposed method is demonstrated in real-time.

In future, the proposed solution of the developed mobile app can be made available for usage in various regional languages like Hausa, Yoruba and Igbo for the ease of use by the farmer and a multi-platform app can also be developed enabling app usage in Android and iOS. A database for various other crop diseases can be built and used to train the model, increasing the efficiency of the solution and enabling coverage of more number of crops and their diseases.

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