

Maize (Corn) Leaf Disease Detection System Using Convolutional Neural Network (CNN)

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Abstract. Crop disease prevention is essential for global food security, and early detection of crop illnesses is a critical component of disease protection. Manual approaches require specialist knowledge, which takes longer time depending on the perimeter of the field or farmland, incurs more money, and can still be inaccurate, hence AI is touted as the ideal answer. In this study, three common maize leaf diseases (Leaf Blight, Common Rust, and Leaf Spot) and their healthy counterparts were classified using a deep learning - convolutional neural network (CNN) based model, Keras on TensorFlow. The CNN model does not require any preprocessing or explicit feature extraction, and it takes a 224 × 224 pixel images of corn leaf of any class at random as input. The four classes were correctly identified with an accuracy of 98.56%. These and other performance metrics have values that allow for the development and deployment of programs that help farmers and plant pathologists diagnose sickness and administer suitable remedies more quickly and correctly. Consequently, farmers who identify plant disease manually can save time and reduce their concerns about incorrect detection.

Keywords: Convolutional Neural Network (CNN) · Keras · TensorFlow · Maize leaf · Disease detection

1 Introduction

According to [1], Maize also known as corn, is a grain cereal that was first made fit for domestic life and human consumption around 10,000 years ago, by native people in southern Mexico. According to [2], maize output has surpassed that of wheat and rice, making it a staple crop all throughout the world. In addition, he added, it is used to make corn ethanol, animal feed, and a few other maize products, such corn starch and corn syrup, besides being consumed by people. Dent corn, flint corn, flour corn, pod corn, popcorn, and sweet corn are the six primary varieties of maize that are now grown [3].

Maize is cultivated more frequently than any other grain each year, because of its vast cultivation across the world, uses for maize include making cornmeal, oil, alcoholic drinks such bourbon whiskey, feedstock for the chemical sector, and alcoholic beverages through fermentation and distillation. Moreover, ethanol and other biofuels are produced using it. [4].

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Plant diseases are unfavorable factors that drastically lower crop output and quality. There is little to no question that pests, diseases, and other unfavorable elements in crops may significantly reduce agricultural output. Therefore, detection and identification of crop leaf disease is highly important if we are concerned about improving the quality of crop cultivation.

Zea mays L., sometimes known as maize, occupies a special place in global agriculture as a source of food, feed, and other industrially significant goods. Over 100 million hectares of land are used to grow maize in poor nations, and roughly 70% of the world's total maize output comes from low- and lower-middle-income nations [5]. It offers food and money to more than 300 million households in sub-Saharan Africa [6, 7]. From research it was known that being a staple meal, a raw material for breweries, and a component of livestock feed, maize is in great demand in Nigeria. It is used to make corn syrup, corn oil, custard, corn flour, and corn flakes in the confectionery and food industries, even golden morn and so on, some of which includes baby foods for healthy growth. Nigerians consume maize in a variety of ways. In order to make pap, it is ground, fermented, and regionally processed. In the Southwest, Ogi, Akamu, and Koko are some of the regional names for this pap. As a staple cuisine, corn on the cob is also cooked or grilled.

In 2018, 7.5% of the world's maize crop, or around 75 million tons, was produced in Africa. The greatest producer in Africa, Nigeria, produces about 33 million tons of maize annually, followed by South Africa, Egypt, and Ethiopia. Maize accounts for around 24 percent of cropland in Africa, with an average output of about 2 tons/hectare/year [8].

According to [8] recent research, about sixty percent of the maize produced in Nigeria is used to manufacture poultry feeds. Maize is reported to be responsible for 50–70% of feeds for poultry farming in Nigeria, this was disclosed in a statement by the chairman of the Poultry Association of Nigeria (PAN) in 2020. The association also attributed the high cost of egg and other poultry products in the country recently to an increase in the price of maize. Beverage companies utilize another twenty-five percent. In comparison, about 15% percent is consumed locally in homes. Nigeria's agricultural sector accounts for a sizable portion of the country's GDP. Agriculture's share of the overall GDP between January and March 2021 was 22.35 percent, up almost one percentage point from the corresponding period in 2020. 5.88 percent of Nigeria's agricultural GDP is accounted for by maize alone. [8].

Leaf blight, gray spot and rust are the most prevalent disease that causes substantial economical loses to maize crop, thus, it is essential to have a system that can detect maize disease through the leafs at an early stage.

2 Literature Review

One of the most important crops, maize, often known as corn, is remarkably adaptable to a variety of environmental conditions [9]. The maize disease can affect many different sections, including the panicle, leaf, or stem. But only leaf-related diseases are taken into account in this area. Agriculture is now using computer vision technologies, and there has been a lot of development in recent years in the exploration of picture segmentation based on the location of the crop and the sickness, which has been a huge help to agriculture.

[10] This section reviews the previous works on classifying maize leaf disease using different algorithms.

In their paper, [11] utilized an image supplied by a system user as an input, and the uploaded image was analyzed using CNN Classifier. The K closest neighbors (KNN) method is then used to choose the best mix of elements to validate the illness. The K closest neighbors (KNN) method is a simple algorithm that maintains all available examples and classifies new cases using a similarity metric (e.g., distance functions). This technology is used to determine and anticipate an automated system for the user to properly detect maize leaf diseases. To validate the illness, the CNN classifier (Convolutional Neural Network) technique is utilized to extract features from photos, and the KNN algorithm is used to store all known instances and classify new cases based on a similarity measure.

Furthermore, [12] suggested a unique DenseNet architecture-based approach for recognizing and classifying three maize leaf diseases. In selecting appropriate hyper parameter values, the authors employed a grid search to discover optimal values. Unfortunately, this poses a plague of dimensionality, which is a project restriction. DenseNet employs much less parameters than the other CNN architectures tested in their experiment. The experiment findings indicated that the DenseNet utilized in the experiment obtained an accuracy of 98:06% while using less parameters and training time.

To identify maize leaf disease, some researchers developed a convolutional neural network (CNN) optimized by a Multi-Activation Function (MAF) module, with the goal of improving the accuracy of standard artificial intelligence approaches. Because they were unable to get adequate dataset, they used image pre-processing methods to extend and supplement the illness samples. To expedite the training, transfer learning and the warm-up approach were applied. As a consequence, three types of maize illnesses (maculopathy, rust, and blight) were reliably and effectively recognized. In the validation set, their method's accuracy reached 97.41%, and they performed a baseline test to validate its efficacy. Secondly, they chose three groups of CNNs based on their performance. They then performed ablation trials on five CNNs. The findings revealed that adding the MAF module increased the performance of CNNs. Furthermore, the multiplexing of Sigmoid, ReLU, and Mish performed best on ResNet50, as the accuracy could be enhanced by 2.33%, demonstrating that their proposal is suitable for agricultural output [13].

In the study, [14] suggested an upgraded ResNet50 maize disease diagnosis model to address the issue of disease identification accuracy and speed in real-time spraying operations in maize fields. First, the Adam algorithm is used to optimize the model. It then adopts an exit strategy and a Rectified Linear Activation Unit (ReLU) incentive function, modifies the learning strategy using an inclined triangle learning rate, and increases Ridge Regression (L2 regularization) to reduce overfitting. Second, three 3x3 tiny convolution kernels were added to the ResNet50 model's initial convolution kernel. Last but not least, the training set to verification set ratio was 3:1. In an experimental comparison, [14] suggested's maize disease recognition model outperformed other models in terms of accuracy. Their achievement was great because unlike Sumita et al., whose model achieved an average accuracy of 98:40%, but reduced to 88:66% when deployed, their model accuracy in the dataset is 98.52%, and 97.826% in the farmland. Also, the average

identification speed is 204 ms, which offers technical assistance for the investigation of maize field spraying equipment while also meeting the accuracy and speed needs of maize field spraying operations.

Nevertheless, [15] used datasets from Kaggle on three major leaf disease: big spot, gray leaf spot and rust. VGG and ResNet were used to build a two-channel CNN. Using maize leaf illnesses as study objectives, a data collection on maize leaf diseases was created and preprocessed using the composition and features of AlexNet, VGG, and ResNet, respectively. According to their study, the grouping findings on those three categories of maize leaf diseases reveal that the two-channel CNN model outperforms the single AlexNet model.

Public dataset from Plant Village and some taken by Smartphones in natural environment which accumulates to a total of 7,701 images were used by [16]. To reduce the computation efforts, all the images were resized to 224 × 224 pixels before training the model. Separately, certain data augmentation techniques were used to the picture to improve the model's generalization capabilities and prevent it from overfitting. Their model consists of three steps. Stage one gathers information from small parts of an image and encodes it into tokens, stage two is the main computational network that conducts self-attention, and stage three maps the classification token into four classes to finish the final classification. The model's total accuracy was 97.87%.

A network-based maize leaf disease detection approach based on wavelet threshold-guided bilateral filtering, multi-channel ResNet, and attenuation factor (WG-MARNet) is suggested. The difficulties of noise, interference from the backdrop, and low detection accuracy of maize leaf disease photos are solved using this approach. Firstly, the capacity to feature extract and the environmental interference resistance of the input picture were improved using the Wavelet threshold guided bilateral filtering (WT-GBF) processing layer based on the WG-MARNet model. WT-GBF was used to decompose the input image into its high- and low-frequency components and decrease image noise. Secondly, by utilizing the multiscale feature fusion approach, the feature representation was improved and the danger of overfitting was reduced. Then, an attenuation factor is added to high- and low-frequency multi-channel to enhance performance instability during deep network training. After comparing convergence and correctness, PRelu and Adabound are employed in place of the ReLU activation function and the Adam optimizer. The experiment's findings showed that the approach had an average identification accuracy of 97.96% and a detection time of 0.278 s for a single image [10].

3 Methods and Materials

To develop the CNN-based maize leaf detection model, data were collected, trained, evaluated and made available in a format deploy-able for real life application. The flow chart in Fig. 1 shows the overview of the system.

The remaining section of the work is divided as follows:

- Datasets collection & analysis
- System Specification
- The CNN Model Architecture
- Model development
- Summary

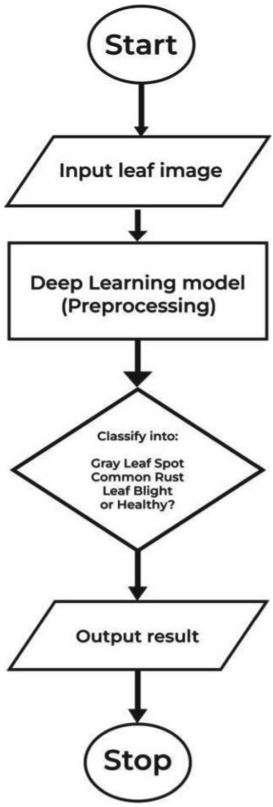

Fig. 1. Flow chart of overall system

3.1 Dataset Collection and Analysis

For every research work, gathering and processing as many data as possible is primary because datasets contribute vital action. For the purpose of this research work, a maize leaf disease dataset was collect from Kaggle which include leaf blight, gray spot, rust and healthy containing 4,109 images [17].

Due to limited training system resources, a subset of the collected dataset was made to reduce the total number of data from 4,109 images that was collected to 1,600 images in total with 400 for each class respectively. See Table 1 below for analysis.

Table 1. Subset of the datasets collected from Kaggle

s/n	Type	Amount	Training	Testing
1	Gray Leaf Spot	400	80%	20%
2	Common Rust	400	80%	20%
3	Leaf Blight	400	80%	20%
4	Healthy	400	80%	20%

The sample in each label were divided in the ratio 80:20 of training to the testing.

Training Datasets (80%) for :

$$\text{Gray Leaf Spot} = 80\% \text{ of } 400$$
$$400 = 320 \text{ samples}$$
$$\text{Common Rust} = 80\% \text{ of } 400$$
$$400 = 320 \text{ samples}$$
$$\text{Leaf Blight} = 80\% \text{ of } 400$$
$$400 = 320 \text{ samples}$$
$$\text{Healthy} = 80\% \text{ of } 400$$
$$400 = 320 \text{ samples}$$

Testing Datasets(20%) for :

$$\text{Gray Leaf Spot} = \text{total} - \text{train}$$
$$= 400 - 320 = 80$$
$$\text{Common Rust} = \text{total} - \text{train}$$
$$= 400 - 320 = 80$$
$$\text{Leaf Blight} = \text{total} - \text{train}$$
$$= 400 - 320 = 80$$
$$\text{Healthy} = \text{total} - \text{train}$$
$$= 400 - 320 = 80$$

The total train dataset is 1200 while the total test datasets is 320

Furthermore, the data in each folder are separated into sub-folder labeled train and test with ratio 80:20 respectively as illustrated in Table 1. Also, Fig. 2 showed example of datasets collected.

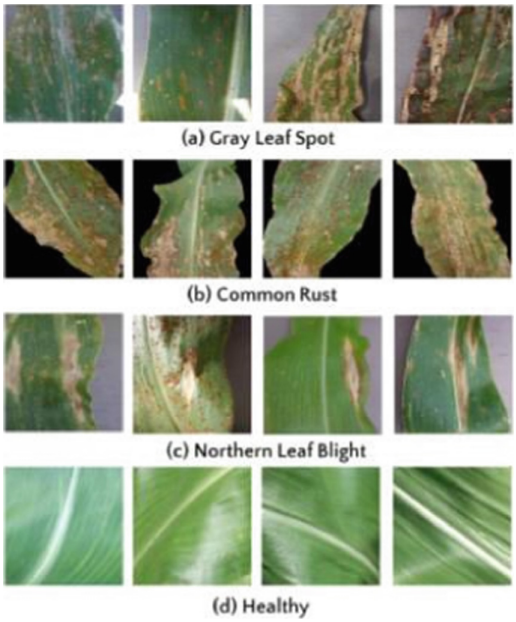

Fig. 2. Dataset sample

Table 2. Summary of the system employed

S/N	NAME	TYPE/SPEC
1	System Model	Lenovo T460 - ThinkPad
2	CPU	Intel i5-6300U (4) @ 3.000GHz
3	GPU (Graphics)	Intel Skylake GT2 [HD Graphics 520]
4	RAM	8 GB
5	HDD	500 GB
6	Operating System	Linux Mint 21.1 × 86_64
7	Virtual Machine	Google Colab

3.2 System Specification Model

TensorFlow, the software used to create machine learning models, and Python's Keras are tightly linked neural network Application Programming Interfaces (APIs). A neural network may be easily defined using Keras' models, and TensorFlow will then construct the network. [18]. Google created the high-level, deep learning API called Keras for using neural networks. It is used to make neural network implementation simple and is built in Python. Moreover, it allows different neural network computing backends [19]. The Keras API was developed with people, not machines, in mind. Keras adheres to best practices for reducing cognitive load by providing consistent & straightforward APIs,

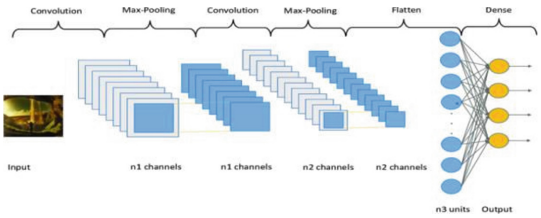

Fig. 3. Keras (TensorFlow) Architecture Model

minimizing the number of user interactions required for typical use cases, and providing clear & responsive error signals. It also has a ton of documentation and development instructions [20]. Figure 3 shows Keras architectural model.

3.3 Model Development

This model was developed on a virtual machine, the popular Google Colab was used due to the system's resources. Table 2 described the system information employed. The Google TensorFLow library was used for development of this project, a process called transfer learning. Keras API was used for enhancement of the training. The inputs to the CNN are 224 × 224 image sizes for each classes of the disease. The details of the model and the dimensions of each layer are shown in Table 3.

Table 3. Model summary

Model: "Sequential"		
Layer (type)	Output Shape	Parameters (params) #
conv2d (Conv2D)	(None, 222, 222, 32)	896
conv2d_1 (Conv2D)	(None, 220, 220, 64)	18496
max_pooling2d (MaxPooling2D)	(None, 110, 110, 64)	0
dropout (Dropout)	(None, 110, 110, 64)	0
flatten (Flatten)	(None, 774400)	0
dense (Dense)	(None, 128)	99123328
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 4)	516
Total params: 99,143,236 ‖ Trainable params: 99,143,236 ‖ Non-trainable params: 0		

3.4 Summary of Methodology

The summary of the methodology presented in this section is explained in chronological form of the above sub-sections. Accordingly, a flow chart overview of the system was

shown. Datasets was collected from Kaggle and no preprocessing was performed on them as the model used accepts RGB images as input. To avoid over-fitting, the datasets were augmented and re-sized to 224 x 224 which is the Keras input image size. The datasets were then trained using the Keras, a Tensorflow machine learning model. The results for training, validation, and evaluation were recorded, explained, and presented in the subsequent chapter.

4 Result and Discussion

4.1 Result

The final training accuracy is 0.9859 and the test loss is 0.0830, while the validation accuracy is 0.8031 and the test loss is 0.6843. The results and discussion of results in this section are arranged in chronological order as presented below.

4.2 Results Obtained After Training

The results obtained from the model fitting for 20 epochs with a batch size of 64 using Adam optimizer is shown in Table 4. The figure also shows the training accuracy and loss, and the validatiom accuracy and loss after every epoch.

Table 4. Model fitting

EPOCH [20 = = = 20]	TRAINING LOSS	TRAINING ACCURACY	VALIDATION LOSS	VALIDATION ACCURACY
Epoch 1/20	8.4309	0.4258	0.9721	0.5531
Epoch 2/20	0.8091	0.6445	0.6507	0.7281
Epoch 3/20	0.6399	0.7117	0.6111	0.6938
Epoch 4/20	0.5711	0.7406	0.5768	0.7281
Epoch 5/20	0.5211	0.7680	0.4965	0.7750
Epoch 6/20	0.4745	0.7828	0.4797	0.8062
Epoch 7/20	0.4239	0.8148	0.4509	0.7937
Epoch 8/20	0.3812	0.8320	0.5331	0.7688
Epoch 9/20	0.3029	0.8680	0.4489	0.7875
Epoch 10/20	0.2426	0.9250	0.4811	0.8156
Epoch 11/20	0.2380	0.9062	0.7147	0.7875
Epoch 12/20	0.2735	0.9055	0.5249	0.8125
Epoch 13/20	0.1761	0.9320	0.5466	0.8031

(*continued*)

Table 4. (*continued*)

EPOCH [20 = = = 20]	TRAINING LOSS	TRAINING ACCURACY	VALIDATION LOSS	VALIDATION ACCURACY
Epoch 14/20	0.1335	0.9539	0.5993	0.7844
Epoch 15/20	0.1477	0.9523	0.5450	0.8062
Epoch 16/20	0.1062	0.9734	0.5195	0.8125
Epoch 17/20	0.0874	0.9766	0.6439	0.8188
Epoch 18/20	0.0663	0.9867	0.6604	0.8313
Epoch 19/20	0.0720	0.9758	0.6161	0.8375
Epoch 20/20	0.0830	0.9859	0.6843	0.8031

The training and loss percentage accuracy, and corresponding confusion matrix for the model are shown in Fig. 4, 5 and 6 and Table 5 shows the classification report for maize (corn) leaf disease detection system.

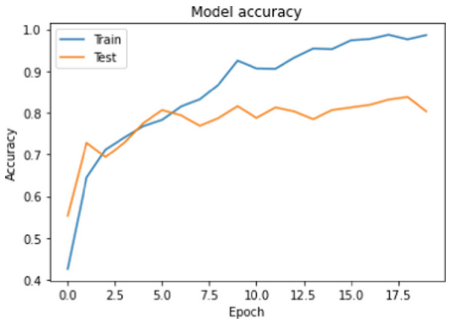

Fig. 4. Model accuracy graph for Maize (Corn) Leaf Disease Detection System

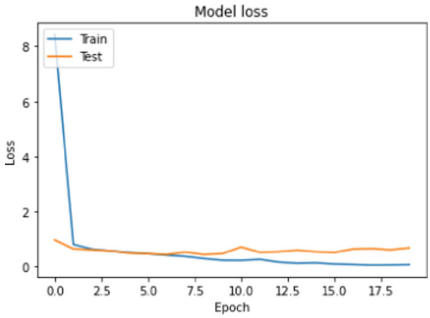

Fig. 5. Model loss graph for Maize (Corn) Leaf Disease Detection System

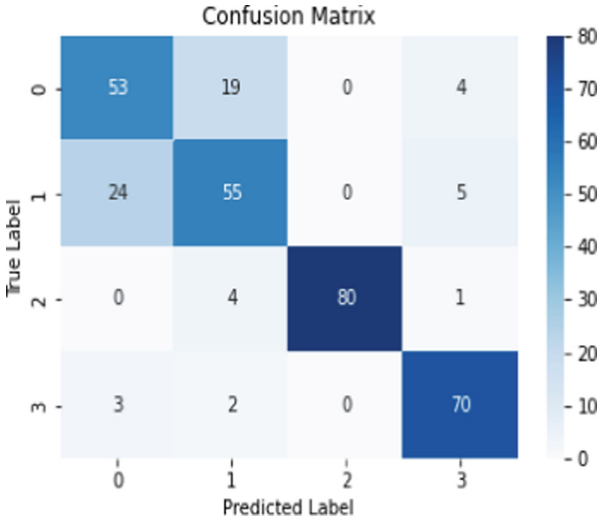

Fig. 6. Confusion Matrix for Maize (Corn) Leaf Disease Detection System

Table 5. Classification report for Maize (Corn) Leaf Disease Detection System

Labels	Precision	Recall	F1-score	Support
0	0.50	0.73	0.59	55
1	0.79	0.64	0.71	98
2	0.99	1.00	0.99	79
3	0.94	0.85	0.89	88
accuracy			0.80	320
macro avg	0.80	0.81	0.80	320
weighted avg	0.83	0.80	0.81	320

4.3 Discussion of Result for Datasets

Considering the fact that only three common classes of disease were considered in this work and with a forth class being the healthy ones, datasets were collected from Kaggle which includes; leaf blight, gray spot, rust and healthy containing of 4,109 images. Chronologically, each classes contains 1,146 images, 1,306 images, 574 images, and 1,162 images from which a subset of the datasets was extracted reducing the total amount of data from 4,109 images to 1,600 images, 400 for each class respectively due to limited training system resources. Before training, the datasets were re-sized and augmented to avoid over-fitting and improve accuracy.

The training uses 20 epoch and 64 batch size. Input images of size 224 $\times$224 are fed to the network. Based on the result presented above, the model achieved an overall accuracy of 98.58%. As illustrated in the classification report in Table 5, the trained

model is assessed by calculating its accuracy, precision, recall, and F1-score values for maize (corn) leaf disease detection system. Initially, these results may be explained by indicating which of the following four categories the on the test model predictions belong into:

5 Conclusion and Recommendation

5.1 Conclusion

The prevention of crop diseases is crucial for ensuring the security of the world's food supply, and its main component is the early detection of crop illnesses. Manual methods of doing this involves expertise knowledge which will take a longer detection time depending on the area of the farmland, incur more cost and can still be inaccurate, hence AI is presented as the best solution. The model achieved an accuracy of 98.59%. In this study, four most common maize leaf diseases were detected for using Keras on Tensorflow. Using the CNN model, the transited region of the leaf is readily divided and analyzed, and the best results are immediately produced. As a consequence, farmers who identify plant diseases by hand can save time and reduce the likelihood of making a mistaken identification.

5.2 Recommendations

This model can be further worked on and improved in the following ways:

i. Live images should be strictly used as the datasets and maybe with a few.
ii. Deploying the model to a plant watering drone to be able get a real-time plant monitoring system where disease can be detected during irrigation process.
iii. The model can be improved to a detect as many maize diseases as possible
iv. Step by step solution to the detected disease can be included to the model to suggest what action is to be taken after a disease is detected.
v. Bayesian hyper-parameter optimization can be used to improve the model's accuracy by tweaking some hyper-parameter and fine-tuning the model.

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