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Evaluating the Effectiveness of Machine Learning and Computer Vision Techniques for the Early Detection of Maize Plant Disease

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ABSTRACT

Monitoring plant growth is a crucial agricultural duty. In addition, the prevention of plant diseases is an essential component of the agricultural infrastructure. This technique must be automated to keep up with the rising food demand caused by increasing population expansion. This work evaluates this business, specifically the production of maize, which is a significant source of food worldwide. Ensure that Mazie's yields are not damaged is a crucial endeavour. Diseases affecting maize plants, such as Common Rust and Blight, are a significant production deterrent. To reduce waste and boost production and disease detection efficiencies, the automation of disease detection is a crucial strategy for the agricultural sector. The optimal solution is a self-diagnosing system that employs machine learning and computer vision to distinguish between damaged and healthy plants. The workflow for machine learning consists of data collection, data preprocessing, model selection, model training and testing, and evaluation.

1. INTRODUCTION

India is a country notable for its generations of horticulture. The vast majority of the 'country's population rely on Agriculture [1]. Farmers use very technical approaches to get the best yield, and then technology can enhance quality. Agriculture Plays a pivotal role in the global economy. Pressure on agricultural systems will increase with population growth [2]. Plant productivity is the bedrock of Agriculture. This process involves ensuring that the right plants are grown, nurtured, and maintained in them. environment. Disease detection, prevention and diagnosis is the key aspect here [3]. Crop diseases are a major threat to food security, and disease identification is a complex task in regions due to the limited infrastructure [2]. Machine Learning is an aspect of artificial intelligence that teaches computers how to learn and understand input [1] [4]. Machine Learning makes it possible to use a computational model that use several layers to learn and represent data in multiple forms. Machine learning and artificial intelligence are used in a great many applications today. In order to have a successful machine-learning session, an appropriate algorithm must be used to achieve the expected result [5]. Computer vision is a very crucial component when it comes to disease detection. Computer Vision is a form of artificial intelligence that uses computers to understand and

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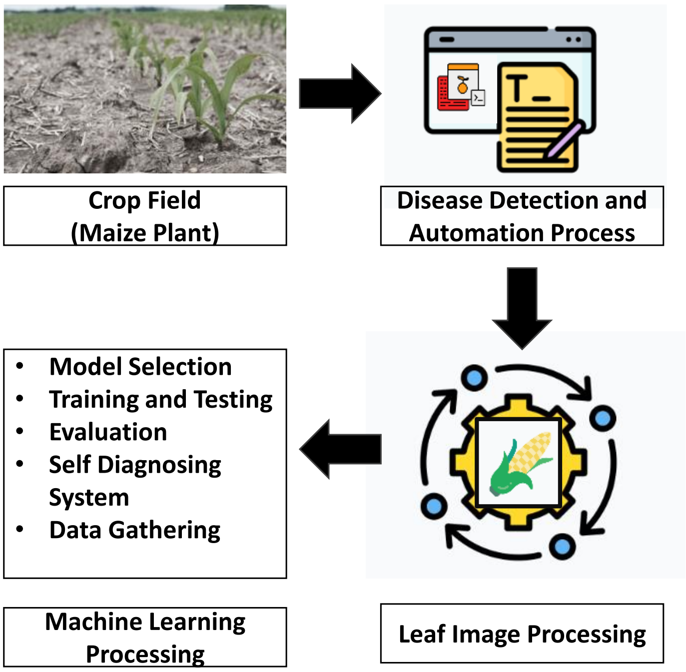

Fig. 1. Automated Disease Detection in Maize Plants using Machine Learning and Computer Vision

identify objects [6]. Major applications of Machine learning and computer vision have been applied in agriculture [7], healthcare [8] and robotics [9].

This objective of this work is to detect plant diseases quickly, specifically common rust caused by Puccina sorghi [2]. Puccina sorghi is a fungus that affects maize species. It was one of the most commonly occurring diseases that affected maize. Many diseases cause maize plants harm, but Common Rust is the most prevalent.s. Early detection is usually the most excellent method to preventing illness development. The work helps by automating detection. Machine vision is an effective way to monitor plant growth. Outdoors, though, the changing light and various backgrounds can make this problematic [3] to detect and alert people participating in the maize plant. Figure 1 indicates the automated disease detection in maize plants using Machine Learning and Computer Vision.

2. Organisation of This Work

This article is organised into sections to provide a clear understanding on the paper's contents. The following is an organisation of the paper, detailing the contents of each section:

2.1 Introduction

The introduction provides an overview of the importance of monitoring plant growth in the field, the challenges faced, and the need for an intelligent gadget to automate the process.

2.2 Literature Review

This section discusses the existing literature on plant growth monitoring and the use of intelligent gadgets to address the challenges faced. It highlights the need for a sreal-time system to detect common rust on maize plants.

2.3 Existing Systems

This section describes two existing systems for plant disease detection. The first system is a real-time monitoring system developed by Mishra, Sachan, and Rajpal that uses a deep convolutional neural network (CNN) to detect corn plant disease. The second system is a CNN-based computational procedure developed by Sibiya and Sumbwanyambe for the recognition and classification of maize leaf diseases.

2.4 Proposed System

This section presents the proposed system for detecting common rust on maize plants. It details the dataset used, the model architecture, the training process, and the visualisation technique.

2.41 Dataset

The section discusses the dataset used, which includes 4188 images of maize leaf diseases and healthy leaves collected under controlled settings.

2.42 Model Architecture

The section details the model architecture used for the proposed system, which involves a deep CNN.

2.43 Train Model

The section describes the training process used for the model.

2.44 Visualization Technique

The section explains the visualisation technique used to interpret the results.

2.5 Result and Discussion

This section presents the results obtained from the proposed system and discusses the model's accuracy in detecting common rust on maize plants.

2.6 Conclusion

The conclusion summarises the paper's contents and highlights the significance of the proposed system in automating the plant growth monitoring process.

This article is provided in the way shown below. Section 1 discusses the introduction of the project, which touches on agriculture activities, plant diseases, machine learning and the project's overall development. Section 2 describes the organisation of this paper. Section 3 describes the literature overview for this paper that correlates with agriculture, expert systems, machine learning and maize disease; Section 4 discusses existing systems used for plant disease detection. Section 5 discusses the proposed system that will be applied to this project which details the dataset used, the model architecture, the training process, and the visualisation technique. In addition, Section 6 describes the results and discussion of susing machine learning algorithms in detecting maize disease. Lastly, Section 7 concludes the paper's’s contents and addresses the significance of plant growth monitoring progress on agricultural activities.

3. Literature Review

Plant growth in the field is now monitored by human workers using visualisations. In certain cases, these visualisations are false positives due to a lack of automation and photo processing, making them ineffective. Because of this, a particular foundry may make a bad investment. Using an intelligent gadget to keep tabs on this procedure is a wise decision. Thanks to this device, an individual will be able to respond appropriately when they are notified by the development of common rust on maize plants. This aims to reduce the time between symptom development and identification.

Agriculture plays a pivotal role in the global economy. Pressure in agricultural systems will increase with the expansion of the population [2]. Thus, integrating technology in this sector will be very valuable and beneficial for the future. Maize is one of the world's most popular food grains, and due to diseases leading to crop loss, the economy can be affected and threaten food availability. The recent evolution of smart devices will enable them to automatically diagnose maize diseases and prevent severe crop losses [3]. This work's goal is to detect plant diseases quickly, especially the major significant forms plaguing the industry: Common Rust, Blight and Gray Leaf Spots. Various diseases harm maize, but common rust is one of the most common. Early detection is usually the greatest method to preventing illness development. The work helps by automating detection and the cultivation of Maize is possible in almost any climate. The importance of this plant is due to its high usage in human and livestock nutrition. In other industries, maize is used in various materials like ethanol and fibre [5]. Countries like India have Maize as their third most important food crop, here, they cares plagued by Blight and Common Rust, and they cause substantial economic losses to maize crops in India [3]. Using technology to identify these types of disease early on and the right remedial steps are taken, a rise in crop yield and grain quality could be seen.

The use of expert systems in agriculture is not as straightforward as it could be due to a lack of a template to follow. However, these systems that target crop plant recognition, especially in robotics, have a huge potential to increase agricultural tasks [5]. Machine learning offers data-driven predictions and analysis in various applications. Machine Learning can accelerate and automate image analysis, improving throughput when dealing with labour-intensive work [1]. Many different approaches are used for plant disease and detection. The common ones are logistic regression, K-nearest neighbours (K-NN), support vector machine, deep convolutional networks (CNN) and decision trees. Each has its benefits and cabins with image pre-processing methods feature extraction can be enhanced [6]. Traditional image processing and convolutional neural network (CNN) approaches are used to automatically detect plant diseases [5]. Machine learning has successfully classified and identified a wide array of maize illnesses from plant leaf images. Input deep convolutional neural networks automatically learn most significant features [1]. Computer vision that can extract useful information form plant images and videos is becoming quite rapidly an essential technique in plant phenomics [10], maintenance and growth. To be able accurately detect maize leaf lesions is a vital step in automatic identification of maize leaf diseases but, the identification of these can be quite complex due appearance of maize leaves, such as growth, shape, size, texture, and posture, it all can vary quite significantly between maize varieties and growth stages [11].

Image acquisition, pre-processing of images, extraction of features, recognition of maize plant infections are the essential steps to be able to recognise diseases using computer vision [12]. Convolutional neural networks are different kind of multiplayer neural networks, they are designed to recognise visual patterns directly from a pixel image with limited pre-processing [13]. The inputs are passed through these layers and certain features will be extracted from layer to layer to learn the object class and be able to tell it from the other classes [14]. The philosophy behind the dense convolutional neural networks is that if deep neural networks contain shorter connections between layers close to the input and those close to the output, it can be far more efficient, accurate, and more profound. In a CNN, every layer is connected to every other layer in a feed-forward manner. Deep CNNs do require a large data quantity to get the best outcomes. When there is insufficient data, then image augmentation plays a role. Image augmentation artificiality produces training images using several processing methods like image flipping, gamma correction, noise reduction or injection, colour augmentation, rotation, and scaling [6].

Computer vision is a form of artificial intelligence that uses computers to understand and identify objects [15]. Computer Vision works in enabling computers to see, identify and process images in a similar way that the human eye does. The objective is not just for the computer to see but to understand what it sees. This is critical in relation to the work focus, i.e., identifying diseased plants. At an abstract level, computer vision uses observed data and makes an inference about the environment of that data. Computer vision implores the automatic extraction of information from images. Using a library allows for this image manipulation in preparation for training the model. OpenCV represents Computer Vision Open Source. It contains the library of programming capacities for AI programming. Open CV is required for picture handling applications continuously [12]. An area in which computer vision has helped the most is detecting the disease's severity [15].

Advancements in the field of Machine Learning and Computer Vision have vastly improved the capabilities of what can be achieved within computing. It takes a combination of image processing and machine learning algorithms to build an intelligent system for disease recognition. The model used in this work will be the ResNet50 model that has been modified for this instance. ResNet is a deep CNN integrated with images, auto-encoding and classification and it won the 2015 ImageNet Large Scale Visual Recognition Challenge [16]. It uses a much deeper network than most, which can be more powerful than a shallow one. Using transfer learning makes it an effective choice for disease recognition.

Crop production has increased rapidly over the past several decades, but at different rates plant wide. These increases have been spurred on mainly due to technological developments, infrastructure improvements, investment increases [17] and better ways to monitor plant production and growth. Maize is one of the most important cereal crops based on total production worldwide. Compared to the other cereals, maize is the most widespread crop next to wheat and rice in the world and is ranked fourth right after rice, sorghum and wheat. Maize is the single largest source of calories and protein for the poor in about 20 countries and the primary weaning food for babies. In countries like Kenya, Maize is an important food crop and is susceptible to a wide range of diseases [18]. Over the last few years, there has been a progressive increase in the demand for maize grain in use for value-added products like glucose, sorbitol and dextrose.

Diseases are the primary disaster that affects maize production and the annual loss caused by disease is estimated to be about 6-10% [11]. Plant diseases affect the growth of maize plants; therefore, their early identification is very important [19]. In maize the leaf can be affected by bacterial and fungal diseases. Northern leaf blight and grey leaf spot are bacterial diseases, whereas common rust is a fungal disease [13].

Common Rust is incited by Puccinia sorghi and is the most destructive fungal foliar disease of maize worldwide. It is estimated that common rust diseases reduce grain yield of maize in susceptible genotypes by 40% on an average. This pathogen favours cool temperatures ranging (16-23 °C) and high relative humidity (100%) [20].

3.1 Content of Maize Diseases

Maize is a widely cultivated cereal crop that is susceptible to a range of diseases caused by various pathogens such as fungi, bacteria, viruses, and nematodes [21]. This article will discuss the common diseases affecting maize plants, their symptoms, causes, and management strategies. Maize streak disease is caused by a virus called Maize streak virus (MSV). The disease is transmitted by the leafhopper vector, Cicadulina mbila. The virus causes stunted growth, yellowing of leaves, and the development of streaks on the leaves. Infected plants may also produce small cobs with poor kernel development. The disease can be managed through resistant maize varieties, cultural practices such as crop rotation and sanitation, and chemical control of the vector.

The Northern Corn Leaf Blight (NCLB) look like if it affected a maize plant. Northern corn leaf blight is caused by the fungus Exserohilum turcicum [22]. The disease is characterised by the development of cigar-shaped lesions on the leaves, which may merge to form large necrotic areas. Severe infections can cause premature death of the plant. The disease can be managed by planting resistant maize varieties, crop rotation, and the use of fungicides.

The Gray Leaf Spot (GLS) if it affects a maize plant [23]. Gray leaf spot is caused by the fungus Cercospora zeae-maydis. The disease is characterised by the development of rectangular lesions with gray centers and dark margins on the leaves. The lesions may coalesce to form large necrotic areas, which can lead to the premature death of the plant. The disease can be managed by planting resistant maize varieties, crop rotation, and the use of fungicides.

The Maize Dwarf Mosaic Disease (MDM) look like if it affects a maize plant. Maize dwarf mosaic disease is caused by a virus called Maize dwarf mosaic virus (MDMV) [24]. The disease is transmitted by aphids and leafhoppers. Infected plants may exhibit stunted growth, yellowing of leaves, and the development of mosaic patterns on the leaves. Furthermore, the disease can be managed using resistant maize varieties and vector control.

4. EXISTING SYSTEM

4.1 Detection of Real-Time Corn Plant Disease Using a Deep Convulational Neural Network

This system was built by Researchers S.Mishra, R Sachan and D Rajpal [3]. They are based in India and designed a system that was to help aid the issue of crop loss prevalent in the area. The paper presented a real time monitoring system. The proposed system had a multilayer CNN that had 11 layers that had been trained on a GPU. They utilised a Raspberry pi to process an image or smart phone that would capture the images of the maize/corn plants. The image below shows the model accuracy stabilising to 99% after 24 epochs worth of training. The trend is confirmed with the loss curve shown below, which becomes more consistent after 18 epochs. When evaluated on test data, the model had an accuracy of 98.04% [3]. These results clearly showcase a model very capable at predicting that achieved outstanding results immediately after 20 epochs of training. The results do showcase unstable validation results. The inconsistent validation results could be a sign of overfitting.

Table 1. Accuracy results of the CNN ion the Classification and recognition of maize leaf diseases and healthy leaves [20].

Type of Maize Disease	Total Percentage of Images	Total Percentage of Testing Images	CNN Classifier Accuracy
Northern Corn Leaf Blight	70%	30%	99.9%
Gray Leaf Spot	70%	30%	91%
Common Rust	70%	30%	87%
Healthy	70%	30%	93.5%

Table 2. Table of system diagram description

Name	Function
Camera	Used to obtain image, the camera will be attached to the Raspberry Pi by USB and will capture the image
Capture	The camera will periodically capture, and that image is stored for it to be tested can checked. It is rare for disease to just appear, and it takes time to do so, so when monitoring it is logical to capture images periodical as opposed to continuously
Raspberry Pi	This is a small PC like module that has the function necessary to do basic processing and can be portable
Disease Detection Algorithm	Here the image is run the prediction model to test if it shows markers of any of the Maize plant disease
Monitor	This is simple to showcase to the user the results or name of the identified infection

Table 3. Libraries and Languages

Name	Function
Python	Python is becoming one of the most popular high level programming languages. it has grown in popularity especially in Machine Learning. It was the language of choice for the work [8]. Python support packages and modules; it has a built-in interpreter. It is a multi-platform language.
OpenCV	This is the Computer Vision Library. It houses the programming capacities for all for its AI programming. This library is needed for image handling applications [8]. It is mainly aimed at Computer Vision, this library was used in the work to resize images, load them into the model and output those images. It is written in C++, but it has bindings for Python, Java and MATLAB
MATPLOT LIB	This is library used to plot images and form graphs. One can use it to show images and curves in a graphed format. It is vital when plotting to see the image dimensions or the training rate of a model
PyTorch	This is an open-source machine learning library that can be used to develop and train machine learning models. It can be used to create deep neural networks and implement image classification algorithms. PyTorch is known for its ease of use and is often used for research purposes. It could be used in this research to train the machine vision algorithms to detect the growth patterns of Maize plants
ImageJ	This is a software package used for image analysis. It can be used to process and analyse images and extract features from them. In this research, it could be used to preprocess the images captured by the Raspberry Pi camera and extract features that could be used to training the machine vision algorithm
LiDAR	Light Detection and Ranging (LiDAR) is a remote sensing technology that uses laser pulses to measure distances to objects. I could be used in this research to create 3D models of the maize plants and monitor their growth in real-time. LiDAR could provide additional information that could be used to supplement the machine vision algorithm

Table 4. Trained Model

Epoch	Accuracy (%)	
	Train	Test
0	0.95	99
10	0.97	0.98
20	0.97	0.98
30	94	0.89
40	0.97	0.98
50	0.96	0.97
60	0.97	0.97

Table 5. Trained Model

Epoch	Accuracy (%)	
	Train	Test
0	0.9	1.0
5	0.10	0.11
10	0.10	0.11
15	0.10	0.2
20	0.0	0.10
25	0.0	0.0
0	0.9	1.0

The graph, Table 2 and Table 3 show the results of the trained model made by Mishra et al. Fig 1 shows how the accuracy evolved and developed with each epoch. Before 10 epochs, there is an exponential growth to the high mid-90s of accuracy. The graphs showcase that the system designed by Mishra et al, can take an image of a diseased healthy corn plant leaf as the input of the convolutional neural network and be able to identify whether its state is healthy or diseased. The system proposed by this paper can take the image of the diseased or healthy maize plant leaf as the input of the CNN and identify the plant as healthy or suffering from diseases like blight or rust.

4.2 *The Use of CNNs in a Computation Procedure for the Recognition and Classification of Maize Leaf Diseases Out of Healthy Leaves*

Sibiya and Sumbwanyambe proposed a system that is capable of Classifying Maize Leaf Diseases from healthy Leaves using a Convolutional Neural Networks (CNN) [20]. The paper explores how they utilised Neuroph Studio Framework IDE to build a deeply facilitated CNN in which the convolution and pooling features extractions were embedded in that library. They built a CNN that had 50 hidden layers for the recognition and classification of maize leaf diseases out pf the healthy leaves. They utilised the Neuroph framework. Neuroph flameworking being a Neural Network framework built of Java it is flexible and lightweight. They trained this network with the use of 100 colour images that represented each disease and healthy. Of those 100 images available, 70% were utilised for training, the remainder for testing CNN.

Below is the individual success in classifying each.

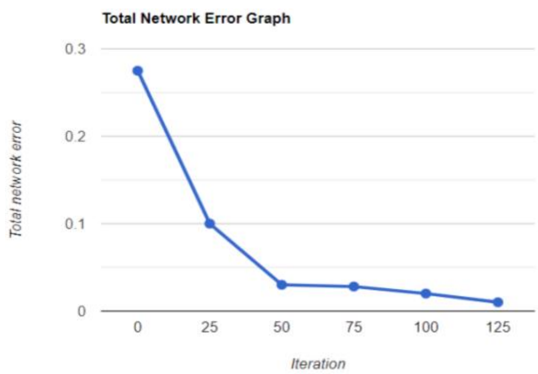

Fig. 2. Total network error graph during and after training of the CNN network on Neuroph framework [20].

Figure 2 showcases the evolution of the model with each iteration. This graph shows that the error rate of the CNN made by Sibiya et al., dropped from its initial 0.275 to 0.01. Below is the individual success in classifying each category for the model. The table shows which class tends to be classified with the best accuracy and which does not. From this data, it can surmise that. Overfitting may occur with this algorithm in that it will be capable of predicting Blight with high-level accuracy and it could lead it to deduce that what it is see is Blight most of the time when that may not be the case. The table also shows that the model may always struggle to identify Common Rust.

From this data, the final accuracy becomes 92.85% [20]. The results show that the model would achieve between 87% and 99.9% in each class but averaged to 92.85%. These results showcase that the CNN can recognise and classy the maize leaf diseases at an overall accuracy of 92.85% with the model trained in 150 iterations giving a minimal error of 0.01 [20]. This showed that the Sibiya et al model could learn quickly from its data and produce results.

4.3 Multi-Pathway Activation Function Module Provides High Accuracy Detection of Maize Leaf Diseases

Y. Zhang et. al did an experiment in which they tested multiple neural networks looking for variations to see which would achieve the best prediction accuracies and over how many epochs [11]. The experiment was based on the Pytorch framework. The models they used were the VGG series, ResNet series and DenseNet series to detect Maize leaf diseases. Each model had a sub model created with variations to see which would be the most effect to just as the main model but as a sub model as well.

Table 6. Experiment results of VGGNet Series [11].

Epoch	**Accuracy**			
	VGG11	**VGG13**	**VGG16**	**VGG19**
0	0.52	0.54	0.6	0.62
5	0.58	0.62	0.66	0.72
10	0.64	0.7	0.75	0.8
15	0.68	0.76	0.82	0.94
20	0.8	0.77	0.88	0.92
25	0.78	0.82	0.9	0.96
30	0.82	0.86	0.9	0.98
35	0.86	0.88	0.92	0.96
40	0.88	0.89	0.92	0.96
45	0.91	0.9	0.92	0.96
50	0.91	0.91	0.94	0.96

Table 7. Experiment results of ResNet Series [11]

Epoch	**Accuracy**				
	ResNet18	ResNet34	ResNet50	ResNet101	ResNet152
0	0.58	0.48	0.5	0.46	0.48
5	0.56	0.58	0.56	0.56	0.54
10	0.62	0.65	0.64	0.66	0.62
15	0.74	0.74	0.76	0.68	0.7
20	0.82	0.8	0.78	0.68	0.74
25	0.9	0.9	0.88	0.78	0.78
30	0.94	0.94	0.96	0.86	0.9
35	0.94	0.94	0.96	0.92	0.88
40	0.92	0.94	0.94	0.94	0.88
45	0.94	0.96	0.96	0.94	0.88
50	0.92	0.95	0.96	0.96	0.9

Table 8. Experiment results of DenseNet Series [11].

Epoch	**Accuracy**			
	DenseNet121	**DenseNet161**	**DenseNet169**	**DenseNet201**
0	0.52	0.66	0.55	0.56
5	0.68	0.72	0.68	0.68
10	0.78	0.82	0.76	0.78
15	0.84	0.9	0.82	0.82
20	0.86	0.94	0.86	0.86
25	0.92	0.94	0.88	0.9
30	0.92	0.96	0.92	0.96
35	0.92	0.96	0.9	0.92
40	0.94	0.96	0.94	0.94
45	0.94	0.96	0.92	0.94
50	0.96	0.96	0.94	0.96

Table 6,7 and 8 above showcase the results of the experiment after testing multiple models. The images lead to believe that the VGG19, ResNet50 and DenseNet161 were the best performers among the network models [11]. They used training model parameters established by Pytorch based on the ImageNet dataset. From the images one can get excellent results from whichever model they go with after the 50 epochs, but learning rate and consistency will tell the best model among the sub-models. The product is a simple raspberry pi with a camera attached that will capture images and analyse that image.

Figure 3 presents a visual representation of the Deep Learning algorithm in the form of a flowchart. The provided visual representation illustrates the essential steps required to achieve a high level of deep learning proficiency, specifically in the context of classification tasks. These stages involve: amassing the dataset, model training, which leads to performance metrics that indicate the 'model's capacity and finally, visualisations techniques are used to classify the images as healthy and non-healthy [3]. The system will use transfer learning than, with some fine-tuning and feature setting it will be able to identify maize leaf disease.

5. Proposed System

5.1 Methodology

The algorithm chosen was a CNN based on the ResNet model. ResNet50 model is 50 layers deep and has been trained on pre-set images on the ImageNet dataset. The ResNet model has pretrained values and weights [20]. The idea is to use transfer learning and adapt this model to this specific maize leaf disease detection case. A regular neural network is not equipped to manage these images. If a normal Neural network was utilised this would require each neuron to be connected to each pixel and the resultant computational model would be very massive and require a substantial number of computational resources to computer, the model [20]. A Convolutional Neural Network however can handle images in various ways and at the same time. ResNet50 models can be simpler to train and optimise and can gain high accuracy with an increase in depth [25].

Figure 4 shows the structure of a Convolution Neural Networks (CNN) as depicted in Figure 9 implemented in the system. The proposed algorithm had one input layer attached to the ResNet Model to make transfer learning applicable in this instance. The image below shows this structure.

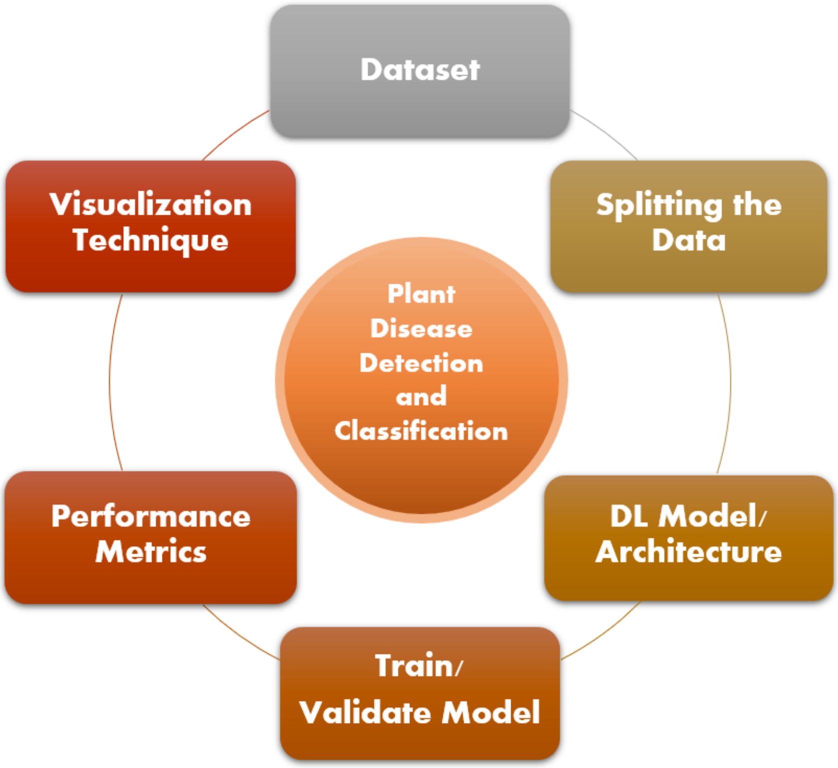

Fig. 3. The Structure of the proposed ResNet algorithm.

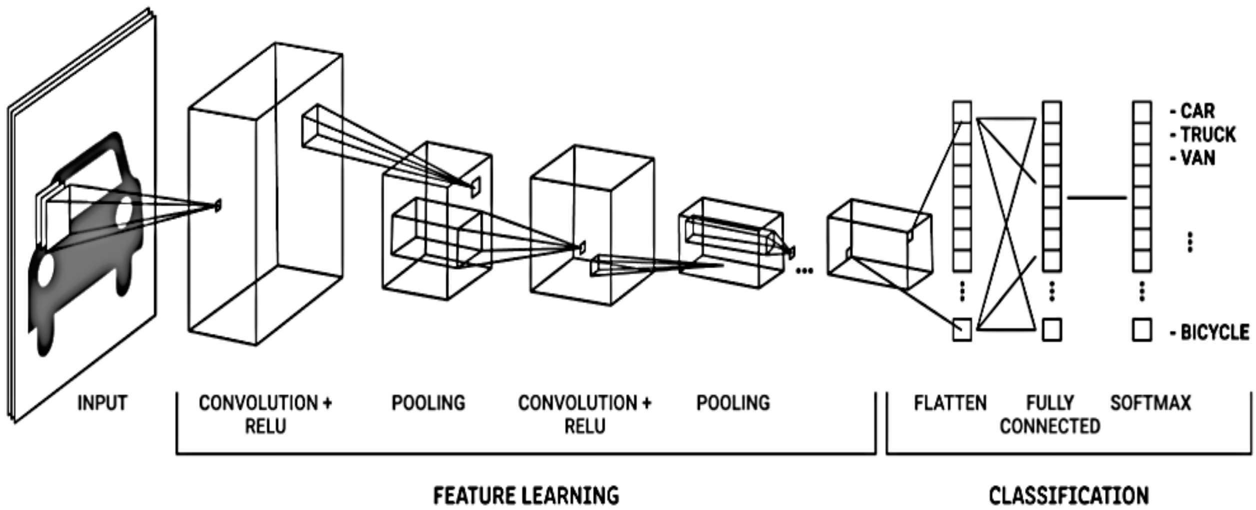

Fig. 4. Example structure of a CNN [20].

Input_1: InputLayer	***Input***	***(None, 224, 224, 3)***
	Output	***(None, 224, 224, 3)***
	↓	
Resnet50: Model	***Input***	***(None, 224, 224, 3)***
	Output	***(None, 4)***

Fig. 5. Layers of Model (image obtained from code base output)

Figure 5 shows the model layers derived from the code base output. This model uses the adaptative momentum (Adam) optimiser and the loss function that used here is the categorical cross entropy due to the fact that more than 2 classes were used. The model would be trained for 15 epochs to make certain that model will be fully trained.

5.2 Dataset

The first stage in building the model for this work was to obtain the dataset that fits the situation. Using Kaggle dataset was found. It is a Mazie leaf Disease detection dataset of 4188 images. Common Rust Images were 1306, Gray Leaf Spot images were 574, Blight images were 1146 and finally, the healthy images were 1162. This dataset was made using the popular Plant doc and Plant village datasets. These datasets have images that were collected under controlled settings. It is one of the few if not the only public dataset on disease detection [26].

The next stage, pre-processing, is the step to ensure that the data selected is useable for training. Pre-processing helps improve model performance by performing model enhancements and resizing to increase classifier accuracy and decrease training time [25].

These two datasets have images of various plants, but this dataset had to be made specific for this work. In order to prevent overfitting or mispredictions the dataset has to be equal on all accounts which means reducing the images to 500 images so that the classifier does not get too good at predicting common rust because it is the most common image it will see. The model needs to know each disease and equal number of times. For this work, each class was reduced to 500 images.

The next stage of data splitting involved integrating that while establishing the model itself. The dataset was an 80/20 split. This meant that 80% of all images involved were used for training. The remaining 20% was used for the testing/validation of the model.

5.3 Model Architecture:

5.3.1 Train Model

This stage involves combining the ResNet50 model with a final layer that complements the dataset present. The proposed algorithm had one input layer attached to the ResNet Model to make transfer learning applicable in this instance. The model would be trained for 15 epochs to make certain that model will be fully trained.

5.3.2 Visualization

Using Tensorboard, training visualisations can be generated that can be analysed and checked to see in graph form how the model trained over each epoch. This pplication can showcase more than one trained model. Each model can be trained and compared looking for the best trained.

5.3.3 System Diagram

Figure 6 showcases tbe diagram of plant disease detection system that was created and used for the research.

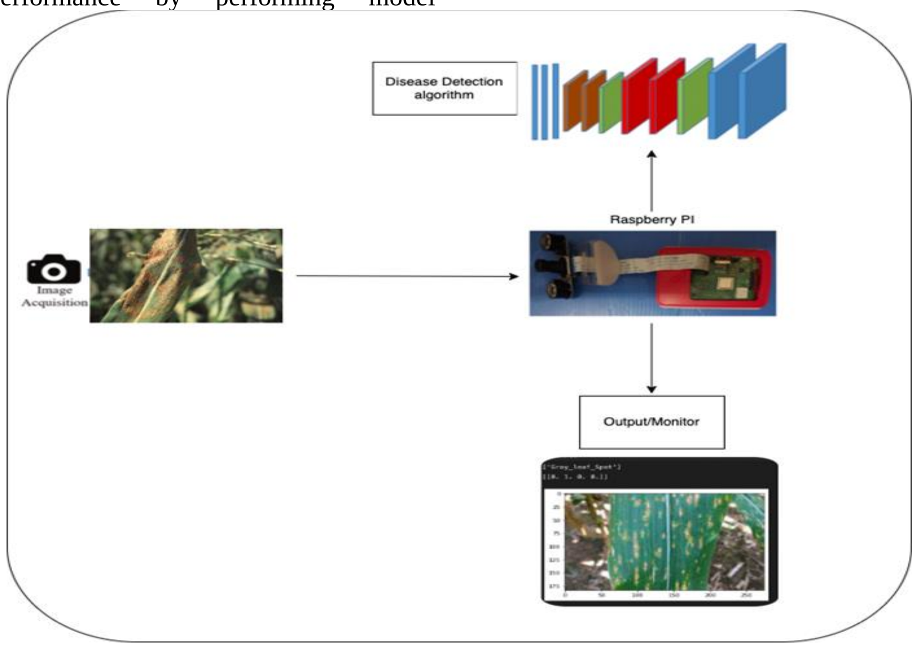

Fig. 6. Diagram of plant disease detection system

6. RESULTS AND DISCUSSIONS

This stage involved feeding into the model images of a shape (224, 224). A batch size of 64 was chosen. The graphs below showcase the results post training of the model.

Fig. 7. Comparison of all tested models (image obtained from tensorboard)

Name	Smoothed	Value
ResNET50-CNN-MLDD-1643972766/train	0.8601	0.8766
ResNET50-CNN-MLDD-1643972766/validation	0.6145	0.7684
ResNET50-CNN-MLDD-1644079551/train	0.8816	0.8941
ResNET50-CNN-MLDD-1644079551/validation	0.6033	0.5483
ResNET50-CNN-MLDD-1644129973/train	0.9045	0.9123
ResNET50-CNN-MLDD-1644129973/validation	0.7914	0.8445
ResNET50-CNN-MLDD-1644175444/train	0.9196	0.9263
ResNET50-CNN-MLDD-1644175444/validation	0.7802	0.8708
ResNET50-CNN-MLDD-1644577711/validation	0.2734	0.278

Fig. 8. Accuracy of model.

Figure 7 represents the results of all tested models, which are named in Figure 8. Using Tensorboard a summary of all trained models could be made to find the most effect model and the number of epochs. Figure 8 shows the names and information of each model that was trained for the test. The legend indicates the number of epochs allotted to each model. In addition, the'model's accuracy and the model's name were denoted by the various colours.. From these results, it shows that the most effect model would be the “ResNET50-CNN-MLDD-1644175444/train” model, which was the final model selected and the results can be seen in Figure 9.

The 15 epochs represent the 15 times that learning algorithm went through and worked through the training data and the same for the validation data. The Blue in the graphs represent Training data and the yellow is the validation data (testing data).

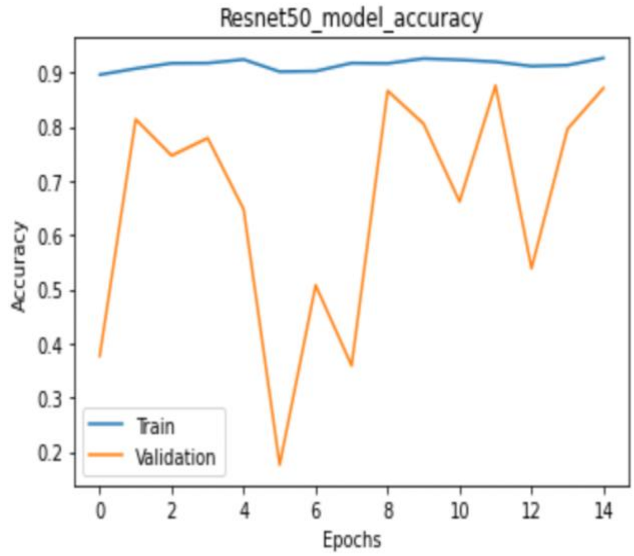

Fig. 9. Model accuracy over each epoch (image obtained from training).

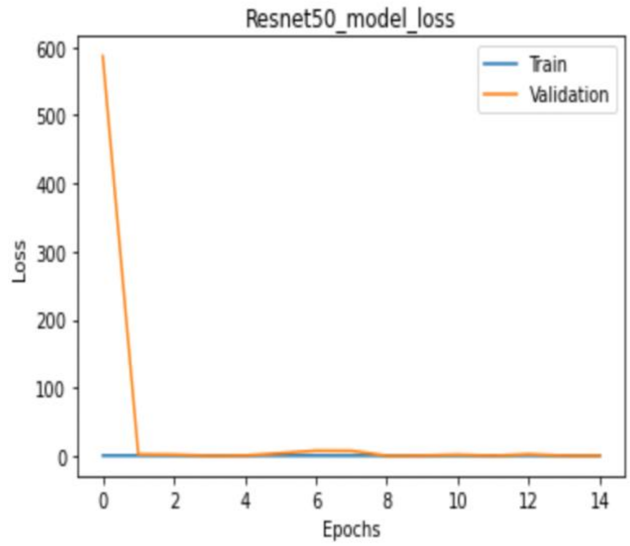

Fig. 10. Model loss over each epoch (image obtained from training).

Figure 10 the model loss after the first initial epoch stays consistently low and finally completes at 0.1804. The validation starts very high but rapidly improves.

Fig. 11. Image 1 test results.

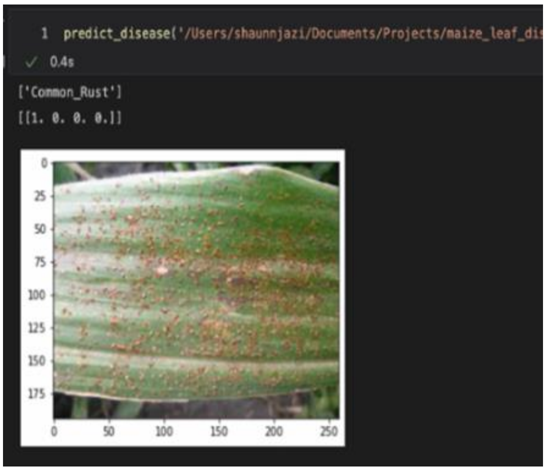

Fig. 12. Image 2 test results.

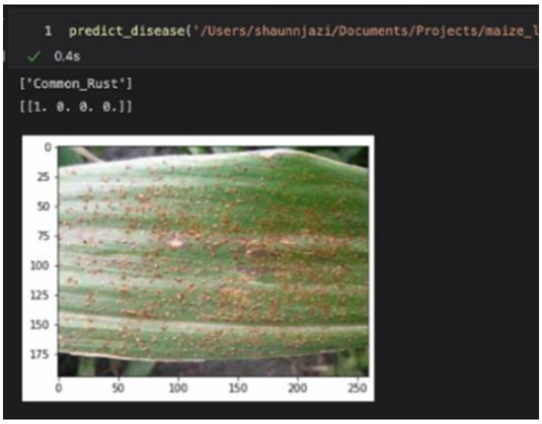

Fig. 13. Image 3 test results.

Figure 11 shows that the mode after training achieved an accuracy of 92.63% After 15 epochs worth of training. With each epoch taking approximately 50 mins to elapse. With a dataset of 1724 images, 25% were used for validation and the rest for training. The graph shows that the model is consistent at the 90% accuracy rate with little deviation, whereas the validation offers erratic results. This most likely due to overfitting the model. Figures 11, 12, and 13 depict the practical application of the model's forecast and the outcomes it yielded. Figure 11 demonstrates the predictive capacity of the model in identifying the presence of the Grey Leaf Spot illness in the given image. The figure in Figure 12 demonstrates the precise forecasting of common rust. The model's classification in Figure 13 inaccurately identified the observed disease as Common Rust instead of correctly detecting it as Corn Blight. This demonstrates that while the model may have detected an illness, there is still progress to be made before achieving complete accuracy.

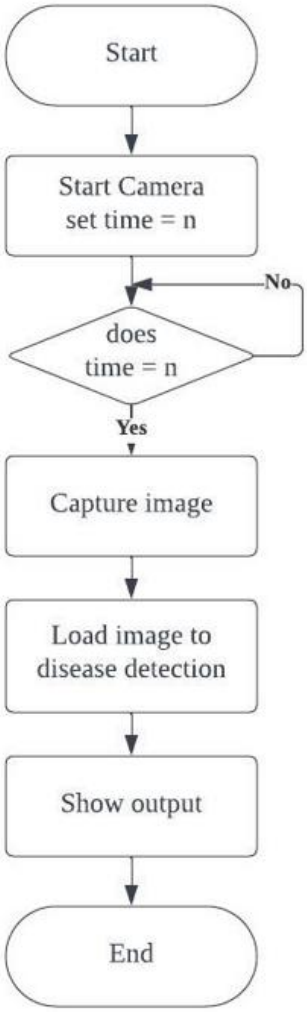

Fig. 12. Flow diagram of disease detection.

Figure 12 shows the flow of diagram of disease detection in the system for the maize plant. The flow diagram here showcases the process and the stages for the system. When the system is started, the camera will be turned on. At the stage an interval time will be set. This interval time is the period between each image. This means that camera will not be continuously capturing images. For example, after every 12 hours an image is captured for the sole purpose of checking if diseases or not. This is an idle stage for most of the time. The interval is due to the fact that these diseases do not rapidly change maize 'plants' appearance. Symptoms of diseases like Common Rust take about 7 days post infection to show any physical signs [5], thus it is not advisable to continuously capture images. When the interval does elapse then an image can be taken by the camera attached to Pi. This image will be stored in a location from which disease detection algorithm can import the image for analysis. When analysis is done the system should be able to output the results that is either Diseased or still healthy. Then the physical workers can react in the appropriate manner to solve the issue if one is present. Table 9 provides a comprehensive overview of the comparisons made between established systems and proposed solutions.

7. CONCLUSION

Agriculture is the backbone of many a country and crop loss due to plant disease is a major factor that leads to reduction in crop yield all over the world. Using Neural Networks and Computer Vision for plant disease identification are the methods needed to reduce severity of losses and minimise crop health issues. The benefit here is the reusable nature of the work, in that it can be applied to more plants than just maize. With the appropriate data set it can be applied in many areas. Several maize diseases exist that vary in symptoms, most of which are fungal, bacterial, and viral. Diagnosing maize diseases quickly and accurately and being able to take corresponding control measures is of great significance to maize production. If monitoring is to be only done by a human visual acuity, then the possibility of misdiagnosis can be very high. The work of monitoring these plants can be time-consuming and laborious, due to this it is possible that maize diseases like common rust might not be diagnosed and treated in time. With this research, the biggest benefit will be the increased early detection which will affect yields and costs. This is a very important thing since many rely on this plant's success, it being a very common and popular plant worldwide. The results achieved are decent and promising. The recognition accuracy can be improved by further fine tuning and optimising the hyper parameters furthermore data augmentation may be used. In future research adding even more diseases can reduce the limitations of the model.

Table 9. Comparisons among establish systems and Proposed Systems

Author	Purpose	Model	Accuracy	Loss	Dataset
Mishra, Sachan & Rajpal	Mazie Leaf disease detection	11-layer CNN	98.04%	0.109	Images from MaizePlantations in Raebareli and Sultampur district & Plant Village
Sibiya & Sumbwanyambe	Mazie Leaf disease detection	50 hidden layers	92.85%	-	Self-collected Images
This work	**Maize disease detection**	**51 hidden layers**	**92.63%**	**0.1804**	**Plant Village Dataset**
Zhang, Wa, Liu, Zhou, Sun, & Ma	Mazie Leaf disease detection	DenseNet161	97.01%	-	ImageNet Dataset
Gyires-Toth, Osvath, Papp, Szucs	Plant Detection	AlexNet	69.565%	0.051	PlantCELF
Kurtlmus, Kavdir	Corn/ maize tassels detection	Support Vector Machine (Scikit-Learn-2014)	81.6%	-	Self-Collected Uludag university Research farm, Bursa, Turkey
Geetharami, Pandian	Pleat Leaf Disease detection	9-layer CNN	96.46%	-	Plant Village Dataset
Pryadharshini, Arivazhagen, Arun, Mirnalini	Maize leaf Disease detection	5-layer CNN (LeNet)	97.89%	-	Plant Village Dataset

Image Acquisition: In order to identify and diagnose plant diseases, it is necessary to obtain photographs of plants. Various technological tools, including digital cameras, drones, and sensors, have the capability to acquire visual representations of maize plants. Image pre-processing involves the necessary manipulation of acquired pictures to eliminate any undesirable noise or distortion. Image processing and computer vision techniques have the potential to be employed for the purpose of enhancing and normalising images. Feature extraction is a crucial step in the training of machine learning models, as it involves the extraction of relevant information from pre-processed images. Computer vision algorithms have the capability to detect and analyse several characteristics, including colour, texture, and shape, which can serve as indicators of plant disease. Machine learning techniques can be employed to acquire knowledge of patterns and correlations between extracted data and the occurrence of diseases. Subsequently, these algorithms can be employed for the purpose of categorising photographs into two distinct groups: healthy or diseased.

Disease Diagnosis: Following the completion of training, a machine learning model can be effectively employed for the purpose of diagnosing diseases in novel photos of maize plants. Enhancement of Plant Productivity: Through the early detection and diagnosis of diseases, farmers are able to implement suitable interventions to mitigate disease propagation and reduce potential crop yield reduction. This phenomenon has the potential to enhance plant production and increase crop harvests. The utilisation of machine vision proves to be a highly efficient method for the surveillance and assessment of plant growth. However, the dynamic lighting conditions and diverse backgrounds present outside can provide challenges in this regard [3]. In this study, a cost-effective camera system and a Raspberry Pi module are employed to identify and notify individuals engaged in the cultivation of maize plants.

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