Towards Leveraging AI Deep Learning Technology as a means to Smart Farming In Developing Countries: A case of Zambia

Barbara Chalwe Kunda
Computer Science Department
university of Zambia
Lusaka, Zambia
musondabarbara@gmail.com

Jackson Phiri
Computer Science Department
university of Zambia
Lusaka, Zambia
Jackson.phiri@unza.co.zm

***Abstract*— Despite Plants being a major source of food for the world population, they continue being ravaged by plant diseases, a situation that greatly contributes to significant decline in production, which ultimately adversely impacts on food Security. Owing to the fact that manual plant disease monitoring is both laborious and error-prone, there has been a heightened need for farming practices that are sustainable, efficient, reliable and cost effective, necessitated by the need to adopt cutting edge technologies such as Artificial intelligence. Smart farming as an innovative approach to agriculture, offers farmers in developing countries a means to effectively diagnose and proactively manage plant diseases. Innovative smart farming solutions through the use of technology makes precision in agriculture possible, by enabling farmers to adopt practices that are optimized based on real-time data and analytics. The increased precision in dealing with problems such as crop disease detection help reduce consumables during disease maintenance, thereby increasing profitability and enhancing food security. This study aims to leverage technology as a means to smart farming in Zambia, a developing country in the sub-Saharan region of Africa, by employing a Convolutional Neural Network (CNN) model for the detection of tomato leaf diseases. Tomato production in Zambia faces significant challenges due to the prevalence of diseases such as early blight, late blight, and leaf mold, which can potentially lead to substantial crop losses. Nonetheless, Early and accurate detection of these diseases is crucial for effective management and increased productivity. This study proposes the use of Automated tomato leaf disease detection through the use of a convolutional neural network model. The plant village dataset which is one of the largest open access repository of expertly curated leaf images for disease diagnosis is used in this study. The CNN model is trained using this dataset, enabling it to learn discriminative features and patterns associated with different disease classes. This system offers an opportunity to empower farmers with timely and accurate information regarding disease occurrence and severity, enabling them to take proactive measures for disease management. By leveraging technology as a means to smart farming, the study aims to improve the efficiency, productivity, and sustainability of tomato farming in Zambia. The Convolutional neural network for the detection of tomato leaf disease was built, successfully trained and deployed. The accuracy of the CNN Model was at 95.8%**

Keywords— Smart agriculture, automatic plant disease detection, Artificial intelligence, CNN Model, Food security

I. INTRODUCTION

Zambia, a landlocked country spanning approximately 752,614 square kilometers, possesses considerable untapped potential in the agricultural sector. This can be deduced from the fact that, of the 58% of its total land area, equivalent to 42 million hectares, which is arable land for agricultural purposes, only a mere 15% of this viable land is currently under cultivation [24]. Additionally, Zambia boasts extensive forests and woodlands, covering around 71% of its land, equivalent to 535,000 square kilometers [24]. These statistics highlight the significant untapped opportunities that remain within the Zambian agricultural sector. Although agriculture is vital for the well-being and food security of the population, it continues to occupy a secondary position in the country's economic development agenda, following mining. According to the 8th national development plan, more than 70 percent of Zambia's population relies on the agricultural sector for their livelihoods. However, the ten-year period from 2011 to 2020, agricultural growth averaged at 0.4 %, contributing 5.8 % to the GDP [26]. Despite agriculture being the mainstay of the larger proportion of the population, its growth has lagged behind the annual national population growth rate of 2.8 % [26]. Approximately 61% of the population live below the poverty line with majority being found in rural areas [25]. To achieve equitable growth and effectively tackle ongoing issues related to poverty, as well as food and nutrition security, it is imperative to provide solutions that will help upsurge farming activities to levels that will help maximize the untapped potential in terms of arable land that remains underutilized. Despite agriculture playing a pivotal role in creating employment opportunities for over 50 % of the workforce, the Zambian economy remains mainly dependent on copper [27]. Most small holder farmers who happen to be in the majority continue facing a number of challenges, such as limitedness to accessing of resources, unpredictability in weather patterns which mostly exacerbates the widespread of crop diseases, among other challenges [22]. Crop diseases, if poorly managed, have the potential of causing significant crop losses and ultimately, food insecurity [23]. The use of Smart farming, also known as precision agriculture, presents a probable solution to curb these challenges. By leveraging AI deep learning technology, and using technologies such as Convolutional Neural Networks (CNNs), smart farming strives to improve agricultural practices, thereby enhancing resource management, as well as improved crop yields [23]. The Integration of AI deep learning into traditional farming practices could potentially transform agriculture in developing countries like Zambia. This research study therefore focuses on exploring the benefit of leveraging AI deep learning technology as a means to smart farming in Zambia. The specific objectives include developing a convolutional neural network model for tomato leaf disease, which includes early blight, late blight and leaf mold. For training purposes, the plant village dataset which is one of the largest open access repository of expertly curated leaf images for disease diagnosis, was used. The system also involves integrating real-time environmental data from sensor networks and IoT devices, so as to establishing an early warning system to alert farmers about potential disease outbreaks. The outcomes of this research is expected contribute to the body of knowledge on more proactive modes of farming which involves smart farming applications in developing countries, using Zambia as a case study. The study demonstrates how AI deep learning technology can be used as a tool to empower smallholder farmers, while improving their decision-making, and ultimately promoting sustainable agricultural practices [22].

A. BACKGROUND

TOMATO, Solanum lycopersicum, is a Vegetable that is commonly cultivated worldwide. Recent statistics show that around 180.64 million metric tons of tomatoes are grown worldwide which amounts to an export value of 8.81 billion US Dollars [1] [2]. Zambia Tomato Consumption is set to reach 23.63 Thousand Metric Tons by 2026 from 24 Thousand Metric Tons [27], which shows no remarkable progress. Despite the foregoing, the production of tomatoes had over the years been declining due to the crop being Susceptible to various diseases [2]. More often than not, traditional disease detection approaches have a significant reliance on manual inspection of diseased leaves mostly done through visual cues or chemical analysis of infected areas, which can be prone to low detection efficiency as well as poor reliability due to human error. Additionally, the lack of professional knowledge of the farmers and the unavailability of agricultural experts who can detect the diseases in remote areas also hamper the overall harvest production [2]. The highlighted problems and many others tend to pose an adverse effect of on food security world- wide while causing great losses for the stakeholders involved in tomato production. The need for early detection and classification of diseases implemented using tools and technologies available to the farmers to alleviate the effects of pests in tomato farming, cannot therefore be overemphasized [3]. By incorporating AI in farming practices towards smart farming in Zambia, Farmers can optimize agricultural operations such as irrigation, fertilization, and pest control. AI algorithms can also be to analyze sensor data, weather patterns, and crop conditions to provide precise recommendations on resource allocation, reducing waste and maximizing efficiency. Farmers in Zambia can also make significant strides towards smart farming by using AI can enable smart families to monitor and manage crops more effectively. For instance, AI-powered image recognition algorithms can analyze images of crops to detect diseases, pests, or nutrient deficiencies at an early stage. This allows for targeted interventions and timely treatment, minimizing crop losses and ensuring healthier yields.

II. RELATED WORK

Machine learning is a subfield of artificial intelligence that allows a system to intelligently learn from input data and uses it to make decisions as well as find patterns and relations without necessarily having to explicitly perform programming. Machine learning, as opposed to traditional statistical-based models, is a “black-box” with sophisticated functions that can handle complex interactions between predictors and the target values [10]. The use of machine learning in agriculture is essential to help improve the efficient use of resources for agricultural cultivation and harvesting, as well as livestock production [10]. In a related research Kirange D, carried out a research on Machine learning approach towards leaf disease classification [4]. In this research, the performance for different feature extraction techniques for tomato leaf disease detection were evaluated using three techniques namely, GLCM, Gabor and SURF. Additionally, the classification techniques that were used included decision trees, SVM, KNN and Naïve Bayes. The experimental results for this research validated that Gabor features effectively recognized the different types of tomato leaf disease. Further, in terms of classification techniques used, the SVM was found to be better as compared to other classification techniques [4]. Another research on Early real-time detection algorithm of tomato diseases and pests in the natural environment was done in china. This research was aimed at the complex background of early period of tomato diseases and pests image objects in the natural environment an object detection algorithm based on Yolo v 3 for early real-time detection of tomato diseases and pests was used. The test results show that the method is suitable for early detection of tomato diseases and pests using large-scale video images collected by the agricultural Internet of Things The conclusion of the research was that at present, most of the object detection of diseases and pests based on computer vision needs to be carried out in a specific environment. The was concluded that Most object detection of diseases and pastes based on computer vision needs to be carried out in a specific environment [5]. Another related research was carried out in Tanzania at university of Dar es Salam by Lilian Mkoyi ,et al on the early identification of Tuta absoluta in tomato plants using deep learning [6] . This research was conducted to help solve tomato plant pest Tuta absoluta devastation at early tomato growth stages. Deep learning approach was used to identify tomato leaf miner pest (Tuta absoluta) invasion. The Convolutional Neural Network architectures (VGG16, VGG19, and ResNet50) were used in training classifiers on tomato image dataset captured from the field containing healthy and infested tomato leaves. The performance of each classifier was then evaluated by considering accuracy of classifying the tomato canopy into correct category. Experimental results show that VGG16 attained the highest accuracy of 91.9% in classifying tomato plant leaves into correct categories. It was concluded that the model may be used to establish methods for early detection of Tuta absoluta pest invasion at early tomato growth stages, hence assisting farmers overcome yield losses. [6].Sabbir A et, al [11] suggest that Current research trends on tomato leaf disease classification have also involved the development of solutions using Deep Neural Architectures, simplifying networks for faster computation targeting embedded systems, real-time disease detection, etc. Sabbir A et,al further assert [11] that the use of such intelligent systems incorporating these solutions could Significantly reduce crop yield loss and avert the tedious effects of manual monitoring tasks, while minimizing human efforts. Additionally, Sabir A et, al affirms that the recent past, approaches in tomato leaf disease classification mainly involved different image-based hand-crafted feature extraction techniques that were usually fed into machine learning-based classifiers. These works mainly focused on only a few diseases with extreme feature engineering and were often limited to constrained environments [11]. They argue that, owing to their sensitivity to the surroundings of leaf images, machine learning approaches mostly relied on rigorous preprocessing steps like manual cropping of region of interest RoI, color space transformation, resizing, background removal, and image filtering for successful feature extraction. This meant that the complexity was increased due to preprocessing limited the traditional machine learning approaches to classify a handful of diseases from a small dataset, thus failing to generalize on larger ones [11]. According to Sabbir A et, al, the use of self-curated small datasets meant that performances of a significant prior works were not comparable. Hence, the introduction of the plant village data set saw the alleviation of challenge challenges that were faced through the use of small self- curated datasets data sets [11]. Sabbir A et, al further suggest that the plant village availed the usage of 54,309 images of 14 different crop species and 26 diseases [18], a subset of which contains nine tomato leaf diseases. This according to Nguni et,al has necessitated the recent trends on several works on tomato leaf diseases to be able to segment leaves from complex backgrounds [12], real-time localization of diseases [13], detection of leaf disease in early-stage [14], visualizing the learned features of different layers of CNN model [15], [16], combining leaf segmentation and classification [17], and so on. These works mostly address the challenges posed by lighting conditions and complex backgrounds lighting conditions and uniformity of complex backgrounds. In a related research on Tomato leaf disease detection using deep learning techniques done in india by Nagamani and Sarojadevi, a more consolidated approach was used, as the study looked at how to identify tomato plant leaf disease using machine learning techniques, including the Fuzzy Support Vector Machine (Fuzzy-SVM), Convolution Neural Network (CNN), and Region-based Convolution Neural Network (R-CNN). The findings were confirmed using images of tomato leaves with six diseases and healthy samples The classification methods of Fuzzy SVM and CNN were analyzed and compared with R-CNN to determine the most accurate model for plant disease prediction. It was concluded that the R-CNN-based classifier had the most remarkable accuracy of 96.735% compared to the other classification approaches [7]. Ananda and Vandana also undertook a research, based on the disease detection and classification of different crops using Transfer learning [8]. The main objective of research with was to make on-going improvements in the performance of the model. The Convolutional Neural Network (CNN) methods were used for detecting Multi-Crops Leaf Disease (MCLD). The features extraction of images was done using a deep learning-based model to classify the sick and healthy leaves. The CNN based Visual Geometry Group (VGG) model was used for the purpose of monitoring the performance measures. The performance measure parameters which were taken to be accuracy, sensitivity, specificity precision were monitored and measured. The designed model was able to classify disease-affected leaves with greater accuracy. In the experiment proposed research achieved an accuracy of 98.40% of grapes and 95.71% of tomatoes [8]. Another research was done in china at Shandong University of Technology by Xiaojie et al [9] to gain insight into the state-of-the-art of IoT applications in protected agriculture and to identify the system structure and key technologies and the use of integrated application. Therefore, a systematic literature review of IoT research and deployments in protected agriculture over the past 10 years was evaluated as well as the contributions made by different academicians and organizations Selected references were clustered into three application domains corresponding to plant management, animal farming and food/agricultural product supply traceability. Furthermore, the challenges along with future research prospects were, to help new researchers of this domain understand the current research progress of IoT in protected agriculture and to propose more novel and innovative ideas in the future. Some of the challenges were device heterogeneity and data heterogeneity, it was sited that device heterogeneity problems affects scalability of IoT in protected agriculture and the data heterogeneity problem hinders the use of fusion information by models. The cost has always been a barrier to the large-scale application of IoT to ordinary farmers, especially in developing countries like China and India [9]. Another related research using Agricultural decision system based on advanced machine learning models for yield prediction in east Africa, was done by Rubby Aworka et al [10]. In this research, three crop prediction models namely Crop Random Forest, Crop Gradient Boosting Machine and Crop Support Vector Machine were used. Further a combination of climate data, crop production and pesticide data was used to develop a decision system based on advanced machine learning models. A decision system was used to predict the crop yield at the country level in fourteen East African countries. The experimental results showed that the three proposed machine learning models fit well the crop data with a high accuracy and the proposed models were reliable and generalized well the agricultural predictions in East Africa.

III. MATERIALS AND METHODS

In this section, the methods used materials used to build the model are briefly discussed.To build a deep learning Convolutional Neural Network (CNN) model for tomato leaf disease detection, the following materials and methods are required:

a. MATERIALS

Dataset: A large dataset of labeled tomato leaf images containing different types of diseases such as early blight, late blight, and leaf mold.

Programming Language and Libraries: Python, along with deep learning Library called TensorFlow was .

Hardware: Sufficient computational resources, including a powerful CPU or GPU, to train the deep learning model efficiently.

b. METHODS:

Data Preprocessing: Loading the tomato leaf image dataset and divide it into training and testing sets. As well as Augment the training dataset by applying random transformations like rotation, flipping, and zooming to increase its variability.

Model Architecture:

The CNN architecture was using for image classification tasks.

c. **Model Training**:

Thi**s** involved the Initialization of the CNN model with random weights. The training of the model on the preprocessed training dataset using the compiled settings was then done. The training was done as an iterative process over multiple epochs, adjusting the model's weights through backpropagation to minimize the loss on the training data.

d. Model Evaluation:

Evaluation of the trained model was then done on the test dataset which in this case was the plant village dataset to measure its accuracy, precision, recall, and F1-score for each disease class. After which the results were analyzed and interpreted to assess the effectiveness of the CNN model for tomato leaf disease detection.

e. DEEP LEARNING

Deep learning is a subfield of machine learning that involves the use of artificial neural networks with multiple layers to model and solve complex problems. It's a type of machine learning that is capable of learning and extracting high-level features from large datasets, which enables the development of sophisticated models that can perform tasks such as image recognition, natural language processing, and speech recognition [20]. Deep learning models are composed of multiple layers of artificial neurons that are connected to each other in a hierarchical manner. Each layer processes the input data and passes it to the next layer until the output is produced. These layers are typically composed of simple mathematical functions, such as linear transformations and nonlinear activation functions. Deep learning algorithms can learn directly from raw data, which eliminates the need for feature engineering. The learning process involves the optimization of the model's parameters using backpropagation, a method that calculates the gradients of the model's performance with respect to the weights and biases of the neurons. One of the key advantages of deep learning is its ability to learn hierarchical representations of data. The lower layers of the model extract simple features, such as edges and corners, while the higher layers learn more complex features, such as object shapes and textures. This allows deep learning models to learn features that are useful for solving complex problems. The purpose of building the model, deep learning was used because of its capabilities to extract high level features from a large data set such as plant village that was used to train the model [20].

f. A NUERAL NETWORK

A neural network is a computational model inspired by the structure and functioning of the human brain. It is a collection of interconnected nodes, known as artificial neurons or simply neurons, organized in layers. Neural networks are designed to process and learn from input data to make predictions or perform specific tasks [21].

Some of the key components and concepts of the neural network includes the following:

Neurons: Neurons are the basic building blocks of a neural network. Each neuron receives input signals, performs a computation, and produces an output signal. In artificial neural networks, neurons are mathematical functions that apply weights to the input signals, sum them up, and pass the result through an activation function to produce an output.

Layers: Neurons are organized into layers in a neural network. Typically, a neural network consists of an input layer, one or more hidden layers, and an output layer. The input layer receives the input data, and the output layer provides the final output or predictions. The hidden layers are intermediate layers that process and transform the input to capture meaningful representations.

Weights and Biases: Each connection between neurons in adjacent layers is associated with a weight and a bias. The weights determine the strength or

. Figure2 shows the diagram of the biological neural network.

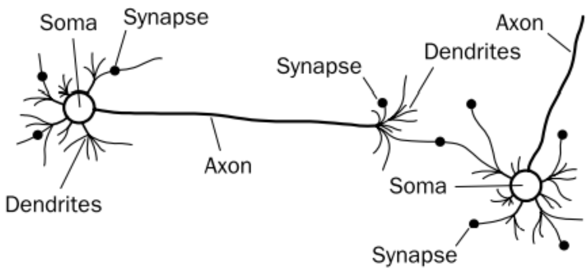

Figure 2 Biological neural network

c. CONVOLUTION NUERAL NETWORK

A convolutional neural network (CNN) is a specialized type of deep learning model that is designed to process and analyze structured grid-like data, such as images, video frames, and audio spectrograms [21]. CNNs are particularly effective in computer vision tasks, including image classification, object detection, and image segmentation. During the process of building the model the model, the was utilized by employing convolutional layers and hierarchical feature extraction. The CNN was best suited for this task due to its ability to effectively learn and recognize patterns and structures in visual data, making them powerful tools for various computer vision tasks. Figure 3 below shows the architecture of the convolutional neural network [21].

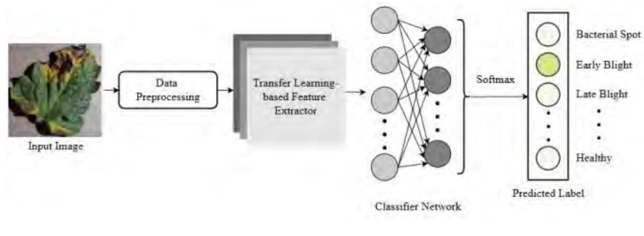

Figure 3: over view of the Tomato classification architecture

d. DATA SET

Recent studies show that, the Plant Village Dataset is the largest open access repository of expertly curated leaf images for disease diagnosis [19]. The dataset comprises 54,309 images of healthy and infected leaves belonging to 14 crops, labeled by plant pathology experts. Among them, 18,160 images are of tomato leaves, divided into one healthy and nine disease classes. This dataset offers a wide variety of diseases and contains samples of leaves being infected by various diseases to different extents [19]. A sample image from some classes of tomato can be seen in figure 4

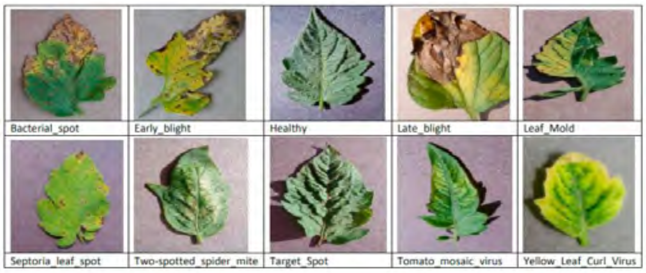

Figure 4 plant images from the plant village data set

The plant village dataset mainly contains nine types of tomato diseases in as shown in figure 4 namely, Target Spot, Mosaic virus, Bacterial spot, Late blight, Leaf Mold, Yellow Leaf Curl Virus, Spider mites: Two-spotted spider mite, Early blight and Septoria leaf spot.

e. STEPS FOR TRAINING THE MODEL

The following steps were taken to train the model:

Dataset Preparation: The Plant Village dataset was downloaded from the Kaggle website. This dataset includes the labeled images of plants and their corresponding disease classes.

Splitting of the dataset: The dataset was then spit into training and validation sets to evaluate the model's performance during training.

Data Preprocessing: Preprocessing was done to prepare images for training. Preprocessing steps included resizing the images to a consistent size, normalizing the pixel values to a suitable range (e.g., 0-1), and applying data augmentation techniques like random rotations, flips, or zooms to increase the diversity of the training data and improve generalization.

Model Architecture Selection: In the CNN architecture that was selected, three convolution and max pooling layers were used. In each layer various number of filters were applied. The architecture of CNN model is illustrated in figure 5 below.

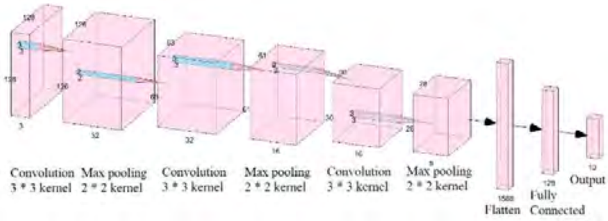

Figure 5: an illustration of the CNN architecture

Model Creation: This involved Implementation of the chosen CNN architecture using a deep learning framework which in this case was TensorFlow .

Model Training: The model was then rained using the plant village dataset by feeding the training images through the model in batches. Multiple epoch, while monitoring the training loss and validation accuracy.

Fine tuning: Fine tuning was done to the model refers to the trained model. This was done to ensure the model is best suited for the task of disease detection.

IV. RESULTS AND DISCUSSION

The model was run for 1000 Epoch iterations, the validation and training accuracy is presented in figure 6 below

For the calculation of loss, the categorical cross entropy method was applied. The formula applied is as follows:

$$loss = -\sum_{c=1}^{M} log(p_{o,c})$$

where M - number of classes, y - binary indicator (0 or 1) if class label c is the correct classification for observation o and predicted probability observation o is of class c. After analyzing the performance of the model, the testing was done. For testing purposes, a total 500 sample was used and for the various classes testing accuracy is different and it is ranging from 75% to 100% and the average accuracy of the proposed model is 95.8%

EPOCH ITERATIONS

Table 1 below shows a snippet of the iterations that were done. Each epoch consists of several iterations or batches, where a subset of the training data was fed to the model for training.

Model: "sequential_3"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(32, 256, 256, 3)	0
conv2d_6 (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d_6 (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_7 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_7 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_8 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_8 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_9 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_9 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_10 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_10 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_11 (Conv2D)	(32, 4, 4, 64)	36928
max_pooling2d_11 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten_1 (Flatten)	(32, 256)	0
dense_2 (Dense)	(32, 64)	16448
dense_3 (Dense)	(32, 3)	195
conv2d_7 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_7 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_8 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_8 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_9 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_9 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_10 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_10 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_11 (Conv2D)	(32, 4, 4, 64)	36928
max_pooling2d_11 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten_1 (Flatten)	(32, 256)	0
dense_2 (Dense)	(32, 64)	16448
dense_3 (Dense)	(32, 3)	195

Total params: 183,747
Trainable params: 183,747
Non-trainable params: 0

Table 1 showing the number of epoch iterations

a. INTEPRETATION OF ITERATION RESULTS

The results of the table are interpreted as follows:

During the training process, the model was built and defined using the sequential layer type. The table shows that Convolutional layers (Conv2D) and pooling layers (MaxPooling2D) were added one after another, forming the convolutional part of the model. The feature maps were then flattened using Flatten, and fully connected layers (Dense) were added for classification. Finally, the model was compiled with an optimizer, loss function, and metrics for evaluation.

During deep learning training of a CNN model, there were three key parameters that were considered, these included total params, trainable params, and non-trainable params. These parameters provide insights into the overall size and composition of the model.

Total Params: Total params refers to the total number of parameters in the model, including both trainable and non-trainable parameters. It represents the overall size and complexity of the model. Parameters include the weights and biases associated with the model's layers. In table 1, the results show that the total parameters were 183,747

Trainable Params: Trainable params are the parameters that are updated and learned during the training process. They are the weights and biases that the model adjusts to minimize the loss function and improve its performance. Trainable params contribute to the model's ability to learn and make predictions based on the training data. The number of Trainable parameters in the table were the same as the total parameter i.e 187,747

Non-trainable Params: Non-trainable parameters are the parameters that are not updated during the training process. In this case the number of non-trainable parameters were zero.

The overall interpretation of the table is that all the parameters were trained.

EVALUATION OF THE MODEL'S PERFORMANCE

Given below is a snippet of code to evaluate its performance.

TRAINING AND VALIDATION ACCURACY

```
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(range(EPOCHS), acc, label='Training Accuracy')
plt.plot(range(EPOCHS), val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(range(EPOCHS), loss, label='Training Loss')
plt.plot(range(EPOCHS), val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Evaluation of the trained model was then done on the test dataset which in this case was the plant village dataset to measure its accuracy, precision, recall, and F1-score for each disease class. After which the results were analyzed and interpreted to assess the effectiveness of the CNN model for tomato. The evaluation graphs are shown in figure 7 below

During

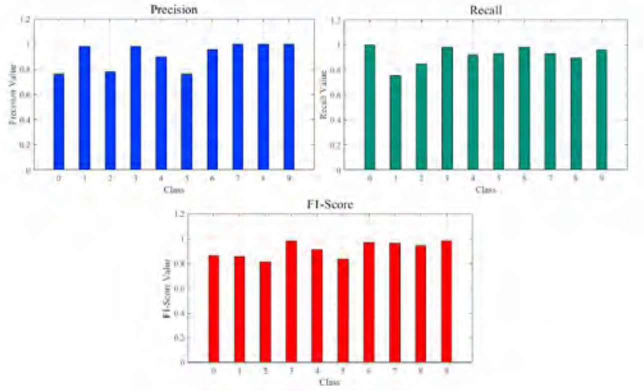

Figure 7: Performance evaluation metrics

TRAINING AND VALIDATION LOSS

The training and validation loss was monitored to evaluate the model's performance and determine if it is learning effectively. The loss is a measure of how well the model is able to make predictions compared to the ground truth labels. Whereas the training loss The training loss represents how well the model is fitting the training data.

During the training process, the model was trained on the training dataset, and the loss was determined after each iteration or batch of data. Figure 5 shows that at the validation loss had an upward trend, meaning that it was higher. As the epochs (iterations) increased, the training and validation loss reduced as the epochs increased.

Figure 6: training loss and validation loss

The graph shows that the validation and training accuracy of the model which depicts the levels of precision, increased as the number of Epochs (iterations) increased.

b. CONCLUSION

The CNN based model to detect the disease in tomato crop was built. The CNN based architecture was used, which comprised of 3 convolution and max pooling layers with varying number of filters in each layer. For the experiment purposes, the tomato leaf data from the Plant Village dataset was used. The dataset consists of 9 disease classes of diseased and healthy leaves.

Training a deep learning CNN model is crucial because it enables the model to learn from data, adapt to specific tasks, generalize to new examples, and continuously improve its predictions. It is through training that the model acquires the knowledge and ability to accurately detect and classify plant diseases, ultimately supporting agricultural practices and crop management. Experimentally, it was observed the testing accuracy of the model is ranging from 75% to 100%. Moreover, the average testing accuracy the model is 95.8%.

RECOMMENDATIONS

It is recommended to continuously iterate and refine the developed model and training process based on the insights gained from analyzing the training results. Moreover, As a future work, the model can be modified with a greater number of images with additional crops, other than tomato.

It is also important to note that training a deep learning CNN model requires experimentation and fine-tuning to achieve optimal results. It is therefore recommended to exercise patience and willingness to iterate and refine the approach used, based on the insights gained from each training.

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