Artificial Intelligence Assisted Early Blight and Late Blight Potato Disease Detection Using Convolutional Neural Networks

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Abstract

Developing countries like Ethiopia have resources suitable for the production of different varieties of crops. Potato is the fourth as a major crop in the world, after rice, wheat, and maize. In Ethiopia, one of the crops produced and consumed in mass is potatoes. Nonetheless, the yield per unit area of potatoes is very low compared to other countries. There are a plethora of reasons and one of them is potato disease. The major disease, which affects the major potato production area is late blight, according to researchers on the field estimated losses range from 6.5 to 67.7% depending on the accessibility of varieties. As plant pathologists mentioned not to take early late blight disease management would destroy the whole farm within a few days. For decades many researchers have experimented on plant disease detection and classification using computer vision via different approaches and algorithms. Most researchers used traditional machine learning algorithms that require a handcrafted feature extraction to classify and detect a given image as per its classes. The contribution of this work is twofold, using deep learning for potato disease detection and developing an AI-based android application prototype. An Image dataset that is labeled with three classes as 'Healthy', 'Early blight', and 'Late blight' is used as a benchmark. The pre-trained models of deep learning, MobileNet, and EfficentNet have shown 98% prediction performance. Finally, the model was built integrated with the android application and tested with unseen data.

Keywords: Convolutional Neural Network, Deep Learning, Potato Disease Detection, EfficentNet, MobileNet, Potato Leaf Disease

Introduction

Ethiopia's economic growth is stronger over the past decades. The major source of economic growth is the agriculture sector. It participates in 37 percent of GDP which is the highest percentage in the sub-Saharan countries and also contributes about 83.9 percent of exports. Additionally, the sector employs around 72 percent of the total population (FAO, 2018). Despite a large number of agricultural products, the country remains dependent on imports of substantial amounts of semi-processed and processed food.

One of the highly consumed food items in Ethiopia is the potato, it serves as both cash and food security crops. In the ruler area, about 68 percent of the total production was used for household consumption, and only 20 percent sold in the market. Furthermore, due to its nutrition, Ethiopia is considered a strategic commodity for ensuring food security (Zimmerman & J., 2015).

Potato is one of the crops, which is a faster-growing crop not only in Ethiopia but also in other sub-Saharan countries. The total area of land covered with potatoes has increased dramatically from 500,000 Mg to about 3,700,000 Mg in 10 years. The growth of potato production allows the country to achieve the food security program. Nonetheless, the productivity of the crop is low with an average yield of around 12.3 Mg/ha, the amount is very low compared to the attainable yields of 50 Mg/ha using improved farm management with improved varieties. The research identified Bacteria Wilt and Late Blight as the major potato production constraints and the number one disease that the farmers manage (Tafesse, et al., 2018).

Yitagesu Tadesse Demissie researched Ethiopian farmers' know-how about potato Late Blight disease that only a few farmers have information about potato's Late Blight disease (Demissie & Tadesse, 2019). This implies the need for technological solutions to support farmers and individuals who are investing in the agriculture sector. Furthermore, the problem has a great impact on developing countries because agriculture is the backbone of the economy and basic needs, especially in Ethiopia where the mainstream of the population is a farmer.

Plant disease can cause social, economic, and ecological losses (Oberoi, Khan, & Ashish, 2019). Appropriate plant disease detection at an early stage prevents the devastation of the farm and the risk of food security of human beings. Some diseases are challenging to detect crop disease through naked eye observation. One of the challenges is the similarity of the diseases of the crop, in this case, to be sure of the exact disease of the crops requires a laboratory test by a plant pathologist. The problem challenged farmers and added effort on experts. Therefore, to overcome this problem researchers studied computer vision with machine learning and it achieved promising results. Currently, the state of the art technology uses deep learning which is a subset of machine learning, and achieved excellent results in plant disease detection using different parts of the plant.

Ethiopia has a good climate and soil cultivation for many different types of crops including potato, and it grows in different regions with various agro-economic conditions. Moreover, potato is one of the important cash crops, which gives ready cash to farmers. It is also known as 'complete food' as it contains carbohydrates, proteins, vitamin B, vitamin C, and minerals like phosphorus, calcium, and iron required for body growth. It is the richest source of starch, unlike other crops, it produces more food per unit area with a short time (Demissie & Tadesse, 2019).

The production of potato crops is affected by *biotic* and *abiotic* factors. Among those, the major factor is the *biotic factor*, that caused by microorganisms like bacteria, fungus, and viruses. Many potato diseases affect the growth and production of the crop, to mention some of the diseases are *Early Blight, Late Blight, Septoria Leaf Spot,* and *Virus*. Besides, several factors affect potato yield, and that's called *abiotic factors*. To mention some, lack of well-performing cultivars, poor fruit setting due to heavy rains, and excessive-high temperature, and pets.

Late Blight disease is the major disease that affects potato farms of Ethiopian farmers compared to other potato diseases. Consequently, the yield per unit of potato is low relative to countries like Rwanda, Egypt, and Kenya. The disease is highly studied and it is the most destructive one. It was responsible for a loss of $5 billion annually and became a threat to food security (Demissie & Tadesse, 2019). Unless necessary management of the disease is taken, it could destroy 100% of the farm. Therefore, developing countries like Ethiopia need early detection of Late Blight disease, to save people's life and economy.

Artificial Intelligence (AI): refers to the simulation of human intelligence in computers designed to think and imitate humans' behavior. The term can also be applied to any system that shows characteristics linked to a human mind, such as learning and problem-solving. The concept of AI is based on the idea that human intelligence should be described in such a way that a computer can easily imitate it and perform tasks, from the easiest to the most complicated ones. Machine learning, deep learning, and CNN is a subset of AI. Figure 1 presents the AI and its subclasses.

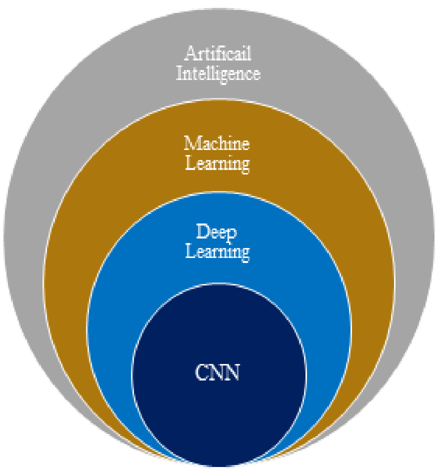

Figure 1: AI and its subclasses

Machine Learning: In classical programming, programmers feed data to the system with a rule, which applies to it, and finally based on this rule, the machine produces an output, which is an answer for a specific problem. However, some scholars began to ask a question like "could a computer go beyond what was ordered to perform?" and learn on its own how to perform a specified task? Could a computer surprise us? (Tyagi & Vipin, 2018). Those questions brought an opportunity to discover another programming paradigm called *Machine Learning*. In this paradigm, programmers input data and answer, expecting *rules* as for output. These rules can be applied to the new data to provide the answer. Unlike classical programming, in machine learning the machine is trained rather than explicitly programmed. For example, to build an automating photo tagging system for vacation photos, a machine learning algorithm can be used. The machine learns a statistical rule by associating previous vacation photographs. Therefore, the vacation photograph is easily tagged.

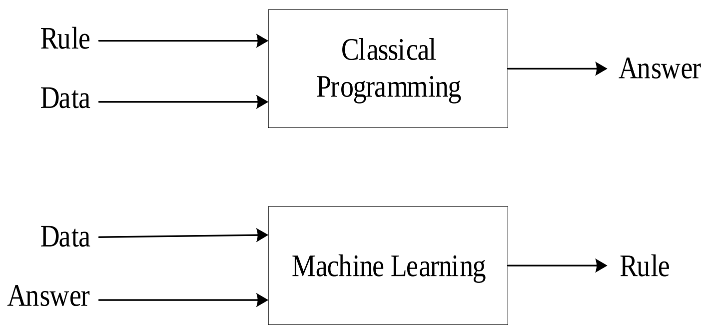

Figure 2: Classical programming vs Machine Learning

Deep learning: Deep Learning is a subfield of Artificial Intelligence (AI) that imitates the work of the human brain in the processing of data and the development of patterns for decision-making use. Deep learning is a subset of machine learning in AI that uses unlabeled or unstructured data as input to learning from it (Ashqar, Abu-nasser, & Abu-naser, 2019).

Plant disease shows visual symptoms, which helps to classify and identify the disease affecting the crop that is used as an input for computer vision using a deep CNN algorithm. D. Oppenheim et al. (Oppenheim, Shani, & Erlich, 2019) used CNN to classify potato tuber disease with five classes, the first class as healthy, and the other four were infected. The datasets collected have potato tubers with a variety of cultivars, size, and disease and also the image datasets labeled by plant pathologists. The dataset contains 400 images of disease-infected potato tubers having smooth skin with different color, shape, and captured using a standard camera under uncontrolled illumination. Captured images labeled with Matlab 2014b software, and images transformed to grayscale with a dimension of 224x224 pixels. Before training the dataset a data augmentation was applied to increase the number of images, finally, a different experiment was conducted on the data partitioning of the dataset, the best result scored was 80-20 training and testing set data partitioning. The proposed CNN architecture is VGG and it has 8 learnable layers, the first five are convolutional layers followed by three fully connected layers, and finally, the end activation function used was Softmax, which helps to classify images into their classes and the model accuracy achieved was 95.8%.

M. Sardogan, A. Tuncer, and Y. Ozen used CNN and learning vector quantization (LVQ) for tomato leaf detection and classification, the dataset contains 500 images of the plant leaves under five classes, the first class is health tomato leaf and the other four class contain the plant's disease i.e. bacterial spot, Late Blight, Septoria Leaf spot, and yellow curved leaf disease (Sardogan, Tunc, & Ozen, 2018). Among the total dataset 400 images were used for training the model and 100 for testing the model. The source of the dataset is the PlantVillage repository (spMohanty, PlantVillage-Dataset, 2020) using this public benchmark dataset has limitations (Singh, et al., 2020) like the efficiency of the model when tested in a real-world image because of the real cultivation area heterogeneous and complex background. To train the model CNN was used and for the data classification, LVQ has been used. LVQ is a powerful and heretic algorithm proposed by Kohonen and widely used for classification problems. It has three layers i.e. input layer, the Kohenen layer, and the output layer. The input layer and Kohenen layer are fully connected, while the Kohenen and output layer are partially connected. One of the challenges in (Sardogan, Tunc, & Ozen, 2018) was the uncanny similarity of some tomato leaf diseases, finally, the classification accuracy achieved was 86%.

H Durmu et al., experimented on plant disease detection using two deep learning architecture that is AlexNet and then SqueezNet. Using Nvidia Jetson TX1 both models, the training and validation were done. The dataset has ten different classes including the healthy category. The trained models were tested with images from the internet. The authors compared the models using multiple metrics i.e. testing accuracy, model size, and inference time. Based on the comparison metrics of the two models finally, the SqueezNet model was chosen for mobile deep learning classification because it is light and computationally efficient compared to AlexNet (Durmus, Gunes, & Kirci, 2017).

K. P. Ferentinos has developed a deep learning model called CNN to detect and classify potato disease by using their leaves. The potato plant's leaves were sorted out as healthy and disease infected and a deep learning methodology was applied to it. To train a deep learning model the author used an open image database that contained 25 different plants in a set of 58 classes (Ferentinos, 2018). By experimenting with several deep learning model architectures one of the best achieved selected, which has 99.53% success.

Materials and Methods

Dataset

To detect Late Blight and Early Blight potato disease the required dataset is an image dataset that is a potato leaf image dataset, images of potato leaf collected from benchmark dataset (spMohanty, PlantVillage-Dataset, 2020), each picture of potato leaf captured by a high-resolution camera and the disease infected area is visible. The data collected sorted into three categories i.e. 'Healthy Potato Leaf', which has 152 images, 'Late Blight Infected Leaf', which has 1000 images, and 'Early Blight Infected leaf', which has 1000 amount of images. All the images' dimension is resized to 256*256 and the type of image is RGB. Furthermore, the benchmark dataset was preprocessed by experts to remove unnecessary features.

Data partitioning

The dataset is partitioned into training, and testing set. The training set is used to train the model to learn image features like curve, line, texture, and other features. Finally, the test set is used after the model and hyperparameters are selected to measure the proposed model performance with unseen data. The total amount of data without partitioning is 2152 images, at first 85% of data used for the training set, which equals 1829 images per each class, 15% of the data is used for testing the model, which equals 323 images.

Model Training Tool

Many types of deep learning frameworks are available to implement deep learning to mention some of them *Theano*, *Keras*, *PyTorch*, *Teachable Machine*, and *TensorFlow*. There is no strict rule, which deep learning frameworks to use for implementing and solving problems of machine learning, however, the parameters that are efficient for the task are considered. Some of the parameters are the size of the dataset, availability of hardware components like GPU because AI research requires the high performance of the computer. During experimentation to train a neural network, Teachable Machine was used. The tool is an AI experimented by Google, which a web tool that makes it quick and simple, no coding is necessary, to build machine learning models for your projects. The tool can be used to recognize pictures, sounds, & poses after it is trained. Finally, the model export for your websites, android applications, and more. There are many advantages to using a

Teachable Machine. Some of the advantages are:

- It requires no top-performing hardware components like GPU.
- To train the neural network requires less effort compared to other API of deep learning
- The trained model easily exported and integrated with the website or android application
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Model Evaluation

To evaluate how much a model is effective and performs well model evaluation is critical. A computational problem like detection that predicts, which class instance belongs uses evaluation metrics accuracy, precision, recall, and F1-score. Those metrics calculated using the classification metrics. The classification metrics give an insight into the performance of a model for each class. All metrics mentioned above calculated based on the confusion matrix value i.e. TP(True Positive), TN(True Negative), FP(False Positive), FN(False Negative). The confusion matrix of the trained model is presented in Figure 5.

TN: Observation is positive and predicted to be positive.

TP: Observation is negative, and predicted to be negative.

FP: Observation negative, but predicted positive.

FN: Observation is positive, but predicted negative.

i. Accuracy: Answers the question about how often the model predicts the classes correctly i.e. healthy leaf and disease infected leaf.
ii. Precision: It gives insight into how often a positive value prediction is correct. Example: Predicting image as a disease infected, how often the prediction precisely predicts.
iii. Recall: Also known as sensitivity it describes how sensitive the classifier is while detecting positive instances.
iv. F1-Score: Is the harmonic mean of the precision and recall, and the lowest value of F1-score is 0, which means one of the metrics has a value of 0. It indicates perfect precision or recall.

- $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$ Equation 1: Accuracy Metric
- $Precision = \frac{TP}{TP+FP}$ Equation 2: Precision Metric
- $Recall = \frac{TP}{TP+FN}$ Equation 3: Recall Metric

- $F1 - Score = \frac{2}{\frac{1}{Recall} + \frac{1}{Precison}}$ Equation 4: Recall Metric

Software tools

After the model was trained and exported in Tensorflow lite format, to integrate with an android application using Android Studio. The Android Studio was built based on JetBrains' IntelliJ Concept software and specifically developed for Android creation; Android Studio is the official integrated development environment for Google's Android operating system.

Algorithm

The deep learning algorithm (Convolutional neural network (ConvNets)), which has a wide application in computer vision was used. The algorithm is a widely used neural network to solve problems related to image classification, object detection, face recognition, image recognition, and others. The convolutional neural network is widely used in many applications to list some of them: image processing, image restoration, speech recognition, natural language processing, and bioinformatics. CNN is capable of detecting and classifying objects with minimal pre-processing, therefore it can achieve a high result to analyze objects, and also a separation of a feature with multilayered is easily done (Medium, 2020). The algorithm performs well on large amounts of data because as the data size increases during the training phase the neural network learns features that finally help to classify or recognize objects. Since the amount of data used in the experiment is relatively less. To overcome this problem transfer learning was used. The next section explains transfer learning.

Transfer Learning

One of the most powerful ideas in deep learning is transfer learning, which a neural network is transfer learning, which is taught for a given task with data, and the knowledge generated would be transferred to another task (Ng, 2020). Formally transfer function is defined as Given a learning task T_t based on D_t and we can get help from D_s for the learning task T_s. Transfer learning aims to improve the performance of predictive function $f_T(.)$ for learning task T_t by discovery and transfer latent knowledge from D_s and T_s, where $D_s \neq D_t$ and /or $T_s \neq T_s$. Furthermore, in most cases, the size of D_s is much larger than the size of D_t, $N_s >> N_t$ (Tan, et al., 2018). The trained model was exported to EfficientNet and MobileNet pretrained model formats, which are designed for running on mobile platforms because compared to other pretrained models it has the good processing power and memory with good speed after it converted to Tensorflow lite.

Results and Discussion

Using benchmark data as an input image with an RGB image format, which shows the Late Blight symptom in detail experiment was conducted. Before integrating a model with the android application different parameters were tested to achieve the best result. Among several experiments, the trained model scored 98% accuracy in detecting Early Blight disease, 99% in detecting Late Blight Disease, and 96% in detecting the Healthy leaf. The best parameters, which scored the best score are epoch of 50, batch size of 16, and learning rate of 0.00002.

Figure 4 presents the accuracy trained model, at the beginning of the training, the model's accuracy i.e. training accuracy and the testing accuracy is low and gradually it increases the performance. Furthermore, in the figure, the training and testing accuracy of the model has no gap between them, this shows the model is not overfitted. Since the overfitted model has a problem during the testing phase. Figure 3 also has the same interpretation, because the loss of the training and testing is dropping and the graph has no gap between them.

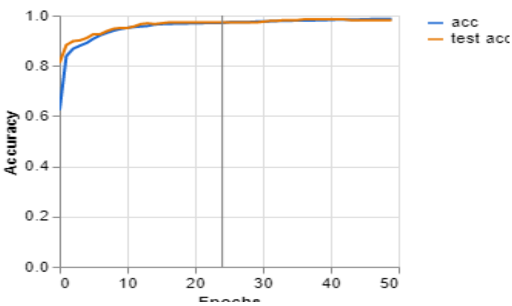

Figure 4: Training and testing accuracy

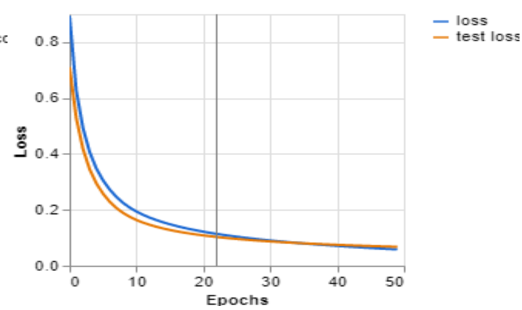

Figure 3: Training and testing loss

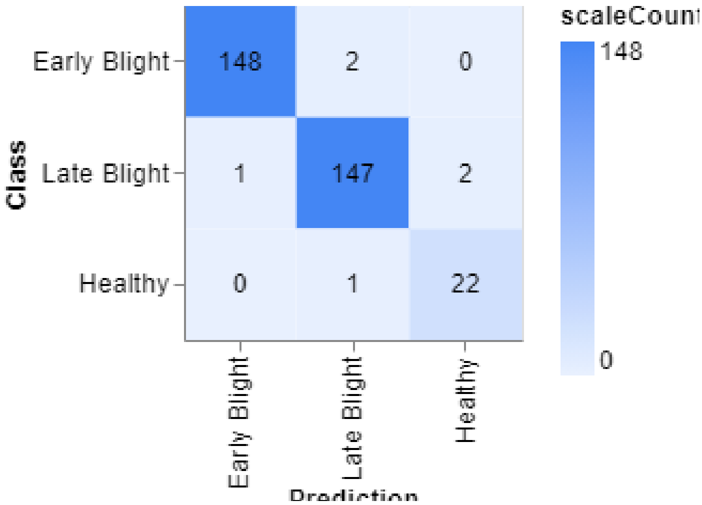

Figure 5: Confusion matrix of the model

Figure 5 presents the accuracy of the model per each class. It was interpreted as, in Early Blight class out of 150 images used for testing 148 images were detected correctly, and in Late Blight class out of 150 images used for testing 148 were detected correctly, and finally in the Healthy class out of 23 images 22 images detected accurately by the model. The accuracy of the model for each class is summarized in Table 1.

Table 1: Accuracy per epoch

Accuracy per class		
Class	Accuracy	#samples
Early Blight	0.99	150
Late Blight	0.98	150
Healthy	0.96	23

Figure 6 presents the use case diagram of the potato's leaf disease detector application. The diagram depicts the actors and interactions with the system. The actor is named 'users' because it is representative of the potential actors, the term includes actors like farmers, plant pathologists, and other individuals. There are three use cases in the figure, the major one is 'ViewDiseaseType'. The use case has a high relationship with 'SelectModel', and 'SelectDevice'. In the 'SelectModel' use case, the users select the pretrained model from the Combo box, and the 'SelectDevice' use case gives the option to select hardware like CPU, GPU (Graphical Processing Unit), and NNAPI (Neural Network Application Program Interface).

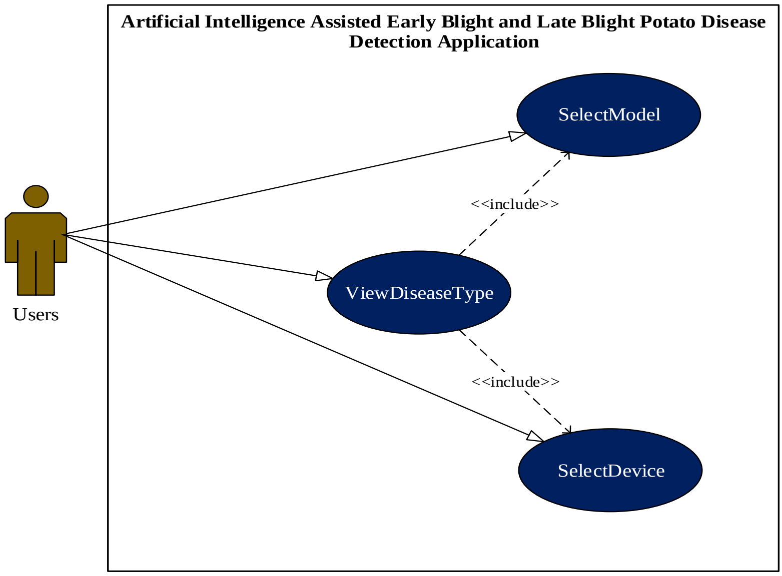

Figure 6: Use case diagram of potato disease detector application

Table 2 presents the detailed use case description of the application. The table description describes the end objective of the use case, actors, pre/post conditions, and flow between the actors' actions and systems action. The use case description helps to understand the major use case and the activities performed in the use case.

Table 2: Use case description

	Use Case ID: PROJ.AI.1.1	
Use Case Name:	View Disease Type	
End Objective:	To view the potato's disease (Late Blight, Early Blight)	
User/Actor:	Any user	
Pre-condition:	Users should open the application accordingly	
Post-condition:	Detecting the type of disease affected the crop	
Main flow:	Actors actions	System actions
	1. Users open the application. 3. User slide up the arrow displayed in #2 5. User click the labels combo box and select the model and /or devices	2. The application displays the home interface 4. The application displays the label 'Model' and 'Device' with a combo box. 6. The application's camera detects the type of disease in real-time 7. The confidence of disease with the label displayed 8. Use case ends.

The model was integrated with an android application using the Tensorflow Lite for android application. The steps help to detect the potato's disease is presented in Figure 7. As depicted in the figure the model predicts the Late Blight and Early Blight potato's leaf disease with high confidence.

Steps to use the potato plant disease detector application

The user interface of the application is simple and easy to use. Here steps to use the application are listed as follows.

Step 1: Open the disease detector application

Step 2: Slide the up arrow to view model and device Combobox

Step 3: Select the model to detect the potato's disease. Selecting the device type is optional.

Finally: The application camera becomes active and detects the disease in real-time showing the percent confidence, in which category the disease is found. Figure 7 shows the steps to use the application.

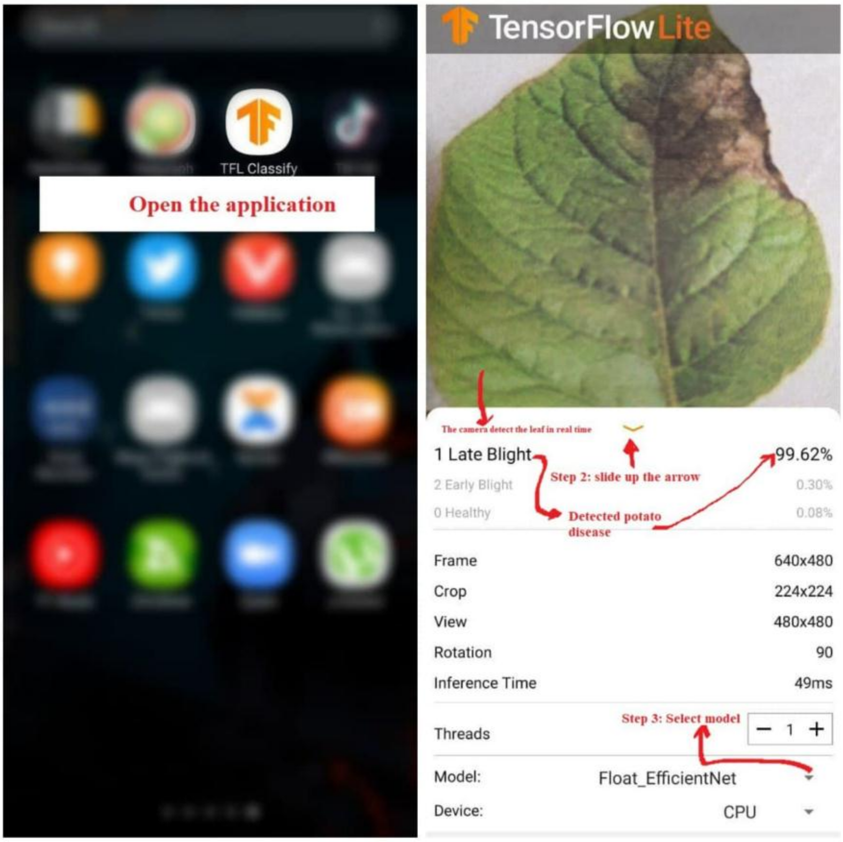

Figure 7: Steps to use the application

Conclusion and Recommendation

In this study, a potato disease detection android application was built which is capable of detecting the disease accurately. The diseases have the potential to destroy the whole potato field within a few days if there is ineffective management of the disease. The proposed model and application is capable of accurately detecting the Late Blight and Early Blight disease, which benefits not only the farmer but also maintains the country's food safety program. Having a sufficient amount of data the android application can be used for other several crop disease detection.

The crop potato was affected by several major diseases, and in this study, an AI-based android application was developed to detect the diseases ‘Late Blight’, and ‘Early Blight’. To do so, computer vision with deep learning was used. Comparatively, a small dataset prepared and used, but it’s better to collect and prepare a large local dataset based on the problem domain because the deep learning model becomes better at detecting the disease as the number of images increased, and also beside the leaf part of the potato crop including the fruit and steam parts help to completely detect and classify the crop’s disease.

For farmers and others working in the agricultural sector, estimating the severity of the disease may be beneficial because it offers information about how much the plant is affected by a disease and what course of action must be taken. This allows the sector to have accurate information about the stage of the disease, which simplifies the steps needed to be taken to handle the disease. Finally, in Ethiopia and other developing countries, the agricultural sector is the source of life and promises to ensure people's food security. Nevertheless, as per our observation, there are only a few studies conducted by scholars that combine artificial intelligence with the agricultural sector. Researchers should work together to change conventional farming practices by applying various technological solutions for a better outcome in the field.

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