Smart Agricultural Technology 7 (2024) 100423

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Mobile-Based convolutional neural network model for the early identification of banana diseases

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A R T I C L E I N F O

Keywords:
Black sigatoka
Classification
Convolutional neural network
Deep learning
Fusarium wilt
Mobile application

A B S T R A C T

This study aimed to deploy a deep learning model in a mobile application for the early identification of Fusarium Wilt and Black Sigatoka in bananas. In this paper, a Convolutional Neural Network (CNN) model for the classification of Black Sigatoka banana disease and Fusarium Wilt disease is assessed. A dataset of 27,360 images of diseased and healthy banana leaves and stalks that were collected from the farms using a mobile phone camera served as the training data for this model. An extra class of 407 images that are not of the banana plant downloaded from the internet was used to help the model detect other images not of the banana plant. The CNN model achieved an accuracy of 91.17 % and was deployed in a mobile application for the classification of the diseases. This study shows that deep learning can be implemented and assist in the early identification of banana diseases. The application could detect images of healthy and diseased banana leaves and stalks and images not of the banana plant with a confidence score of more than 90 % in less than five seconds per image and provide research-based mitigation recommendations.

1. Introduction

Tanzania is mainly an agricultural economy, with 60 % of the people relying on agriculture for a living [1]. The agricultural sector contributed 26.9 % of Tanzania's Gross Domestic Product (GDP) [2]. Banana and plantain here referred to as bananas, are major staple food and cash crops depended upon for food security by many Africans [3]. The crop serves more than 50 million people in East Africa due to its year-round fruit production and offers a sustainable source of food [4]. Most of the bananas produced by smallholder farmers in Africa are consumed locally [5]. Despite being an important crop, banana production is highly affected by Fusarium Wilt and Black Sigatoka fungal diseases [6, 7]. It is reported that yield losses due to these diseases range from 30 % to 100 % [8–10].

Fusarium Wilt is a highly destructive disease caused by the soil-borne fungus *Fusarium oxysporum* f.sp. *cubense* race one (Foc). The disease symptoms are first seen on the oldest leaves, which become yellow from the leaf margin. These leaves later collapse at the petiole, causing a skirt appearance on the banana plant [11]. In young plants, this disease causes stunted growth and failure in flowering. In plants that succeed to flower the disease causes fruit filling failure. It also causes colour discoloration from pale to dark red on the corm and stalk or pseudostem when cut. Sometimes, the disease causes vertical pseudostem splitting at the base [12].

Black Sigatoka, sometimes called Black Leaf Streak Disease (BLSD) is a disease that results in leaf spots on banana trees and is caused by a heterothallic and airborne fungus called *Pseudocercospora fijiensis*. On young banana leaves small pale-yellow spots appear 10 to 14 days after infection [13]. The symptoms run through the veins parallel. Within a few days, the spots expand in centimetres and turn brown and their centre colour changes to grey. The patches spread and the lesions surrounding the tissue deteriorate and turn yellow [13]. The leaf turns brown interfering with photosynthesis and eventually dies when the lesions merge [14]. Farmers can control the disease by applying fungicides weekly [10].

Even though extension officers and farmers battle with various strategies for mitigating the effects of the two banana diseases, there is a need for a more effective method of identifying these diseases at early stages to avoid high yield losses. Smallholder banana growers in East Africa have limited background knowledge of banana agronomy [4]. There is also a limited uptake of recommendations on banana agronomy from research [4].

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https://doi.org/10.1016/j.atech.2024.100423
Received 28 November 2023; Received in revised form 28 February 2024; Accepted 28 February 2024
Available online 29 February 2024
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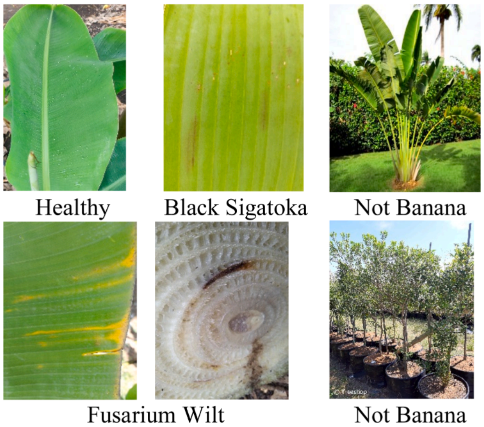

Fig. 1. Samples of banana leaves and stalk and other images from the dataset.

Table 1
Data distribution for the CNN model.

Class of Images	Number of images
Healthy Leaves	9120
Black Sigatoka infected leaves	9120
Fusarium Wilt infected leaves and stalks	9120
Not banana leaves or stalk	407
Total	**27 767**

Artificial Intelligence has played a crucial role in enabling precision agriculture by providing automation, efficiency, flexibility, accuracy, and cost-effective solutions [15–18]. The identification of plant diseases has been used repeatedly with deep learning approaches. To create deep learning models for plant disease detection in bananas, tomatoes, strawberries, maize, potatoes, grapes, and beans [19–28] several studies have employed image datasets. Some studies have gone further to deploy deep learning models for plant disease detection into mobile applications to improve farmers' use of them [29–33].

Early identification of Black Sigatoka banana disease and Fusarium Wilt can help farmers recover their yields and minimize financial loss by helping them become aware of the conditions quickly and take the necessary action. This study presents a mobile application called "Plant Diseases Finder" that deploys a deep learning model to identify Fusarium Wilt banana disease and Black Sigatoka banana disease. The application also provides research-based recommendations that the farmers can follow to rescue their yields in case any of the two diseases are identified.

2. Material and methods

The TensorFlow framework was used in training the CNN model for identifying Fusarium Wilt banana disease and Black Sigatoka banana disease. A dataset comprising 27,360 images divided into three classes which are healthy banana leaves, Black Sigatoka infected banana leaves, and banana leaves and stalks affected by Fusarium Wilt was used. This dataset was collected from farms in the Arusha, Kagera, Kilimanjaro, Mbeya, and Dar es Salaam regions of Tanzania. These regions were selected based on banana production and disease presence. The image dataset was collected on the farms using mobile phone cameras under

Table 2
CNN model training hyperparameters.

Parameters	Value (s)
Batch size	32
Epoch	100
Optimizer	Adam with a Learning rate of 0.001
Loss	Categorical Crossentropy
Evaluation metric	Accuracy, Precision, Recall, and F-measure

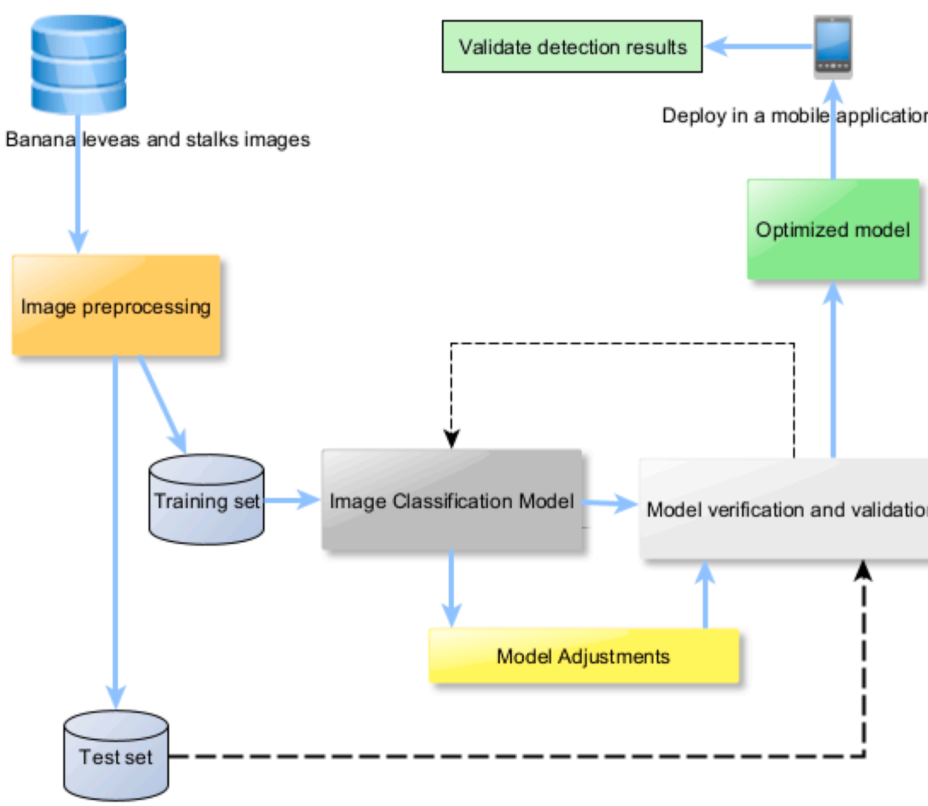

Fig. 2. The conceptual framework.

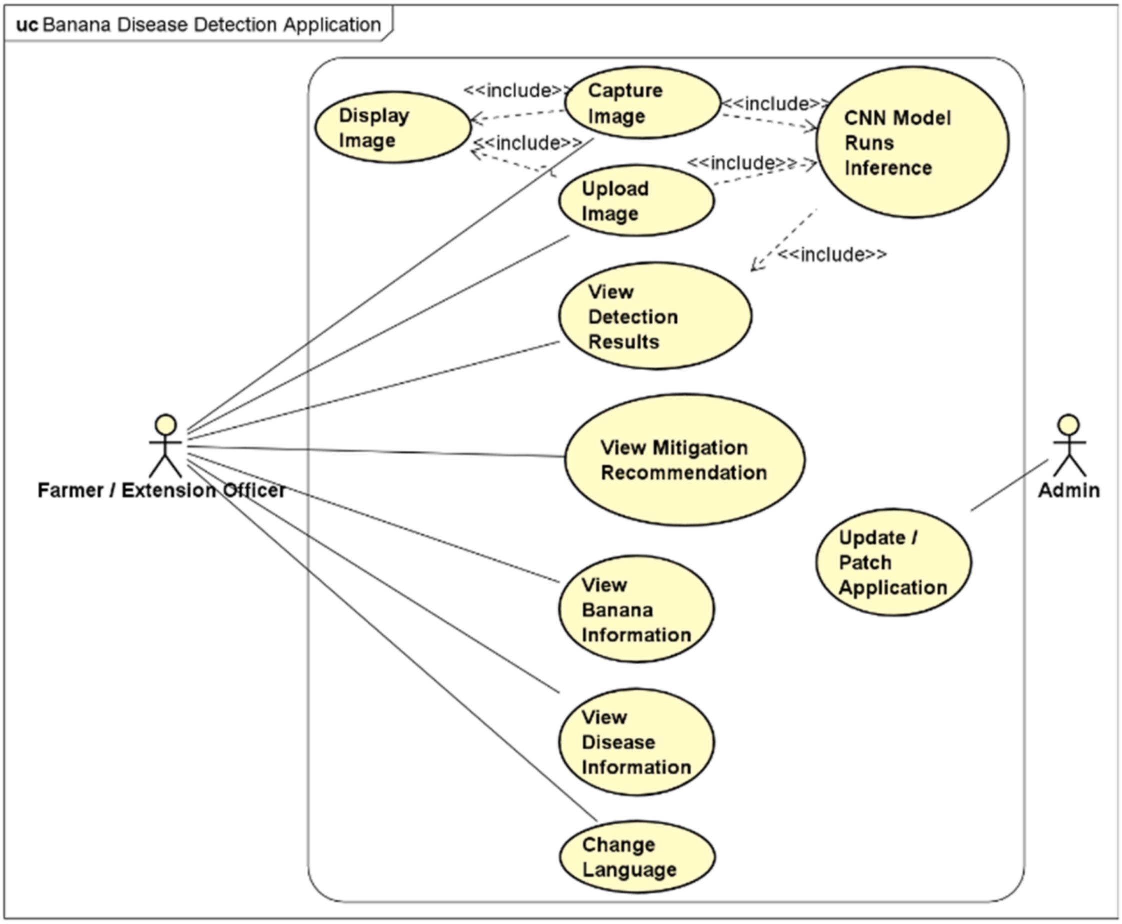

Fig. 3. Use case diagram for the mobile application for banana disease identification.

the supervision of agricultural experts. An extra fourth class of 407 images was introduced in the dataset that comprises other plants and things that are not banana plants. The data for this extra class was obtained from the Internet. Fig. 1 illustrates some examples of images from the dataset. Table 1 shows the data distribution for the CNN model.

The tests were done on a PC running Windows 11 Pro with one Intel® Core ™ i5–8250 U CPU @ 1.60 GHz 1.80 GHz and 8GB of RAM. The notebook was run on Google Colab Pro Plus with a Tesla T4 GPU and 54.8GB of RAM. The network was implemented using Python 3, the Keras library, and a TensorFlow [34] backend. Several experiments were done with hyperparameter tuning, and the model's performance was given by the evaluation metrics. The best-optimized model was deployed in a mobile application. Fig. 2 illustrates the study's conceptual framework.

2.1. Data preprocessing

The collected data was cropped to focus on the banana leaf or stalk and reduce the background. VisiPics and Duplicate Photo Finder applications were used to check for and remove duplicates in the images. The clean images were renamed to have class names with consecutive numbers for easy handling using the Bulk Rename Utility application.

2.2. The CNN classification model

A sequential model was used for the implementation. The model contained four convolutional layers. A max-pooling layer followed each convolutional layer and was then followed by a dropout layer with a rate of 0.2. The first and second convolutional layers had 16 and 32 filters while the third and fourth each had 64 filters. Three by three convolutional filters were used and the ReLu activation function. The results were flattened by a flattened layer and entered into a dense layer with 512 neurons and the ReLu activation function. Four neurons comprised the output dense layer as the number of classes and had a softmax activation function. Images were rescaled to normalize them to a range of zero to one and resized to 512×512 pixels. Table 2 summarizes the CNN model training hyperparameters. As the number of parameters of the model increases, the complexity of the CNN algorithm also increases [35]. The CNN model had a total of 6485,604 parameters which describes the model's complexity. This number of parameters is contributed by the mentioned number of filters and the number of neurons in the hidden layers. A study done by [35] had three parameter designs for their CNN model which are Simple, Medium, and Complex designs whereby their total number of parameters were 6.1 thousand, 48 thousand, and 276 thousand respectively. Their study found that their medium and complex CNN classifiers performed slightly better than

Table 3
Use Case Descriptions.

Use case	Description	Actor (s)
Capture an image	The application user (s) can take a picture of a banana plant through the mobile phone camera.	Extension officer or farmer
Upload an image	The application user (s) can upload an image of a banana plant from the phone's gallery.	Extension officer or farmer
Display Image	The application user (s) can display the captured or uploaded image.	Extension officer or farmer
CNN Model Runs Inference	The CNN deep learning model will be used by the application to automatically execute inference on the captured or uploaded image.	Extension officer or farmer
View detection results	The application user (s) can view detection results from the application.	Extension officer or farmer
View mitigation recommendations	The application user (s) can view the mitigation recommendations against the banana diseases detected in the mobile application.	Extension officer or farmer
View banana information	The application user (s) can view broad details on banana farming such as: a) different types of bananas, b) the banana types that provide the most yields, c) the banana types that have high demand in the market, and d) the best practices in banana farming.	Extension officer or farmer
View disease information	The application user (s) can view details on Fusarium Wilt and Black Sigatoka banana diseases. This includes: a) their causes, b) symptoms, c) transmission mechanism, and d) mitigation strategy. Including how to eradicate sick banana plants without spreading the disease further.	Extension officer or farmer
Change language	The application user (s) can choose which language they prefer for the application either English or Swahili.	Extension officer or farmer
Update/Patch the application	The admin can update or patch the mobile application from a web-based backend system.	Admin

their simple CNN classifier.

2.3. Model deployment

The process of putting a deep learning model into use so that it can be utilized to make predictions or find patterns in data is known as model deployment. The model was deployed in a mobile application so that it could be accessed and used by farmers and agricultural extension officers to detect banana diseases at an early stage. After the discovery of either Fusarium Wilt or Black Sigatoka disease, the mobile application additionally offers users research-based recommendations so they are aware of the steps they may take to ameliorate the situation on their farm. Deep learning models are resource-intensive. To function, they require a lot of storage and memory space. To meet the resource limitations in a mobile phone environment and increase inferencing speed, TensorFlow Lite in Python was used to transform the model into a lighter format. The CNN deep learning model was implemented in a mobile application after being translated to TFlite format. However, the use of a compressed TensorFlow Lite format model proved to be less efficient because the ability of the model to detect diseased and healthy banana leaves and stalks was reduced tremendously. The original TensorFlow model could detect or predict more accurately than when it was converted to TensorFlow Lite. As a result of this, the study opted to deploy the original TensorFlow model on a web server and create an API to access this model from the mobile application. The requirements for the development of the mobile application were obtained by consulting the stakeholders, including the prospective users, which are farmers, agricultural extension officers, and other agricultural experts. This study used agile development methodology using extreme programming (XP) for developing the mobile application. The Flutter framework that uses the Dart language was used in the Android Studio IDE to develop the mobile application for the Android platform, which was tested using a Samsung A71 mobile phone device.

2.4. Software design

The mobile application designs were illustrated by using Unified Modelling Language (UML) diagrams. Use case diagram, activity diagram, and sequence diagram were used. A use case diagram illustrates the activities that are done by the users of the system. The use case diagram for the mobile application for banana disease identification is shown in Fig. 3. Table 3 describes the use cases in Fig. 3.

Furthermore, the interaction between the actors and the objects in a system is modelled using a sequence diagram. It depicts the interactions happening in a particular use case or use case instance. Fig. 4 shows a sequence diagram that was used to illustrate the capture/upload image use case. Moreover, activity diagrams are used in business process modelling. It depicts the processes that a user of the mobile application can go through from the beginning when the user launches the application to when the user achieves their goal and closes their application. The activity diagram for the mobile application for banana disease identification is shown in Fig. 5.

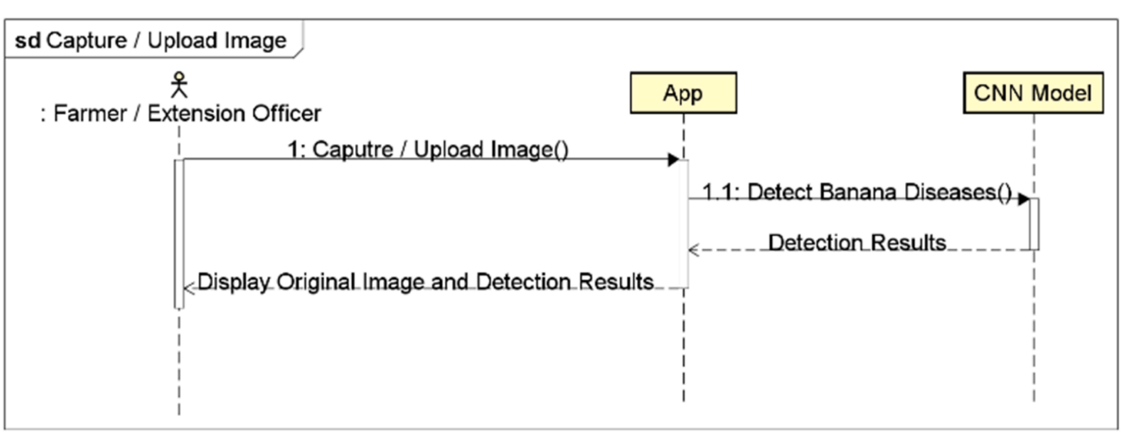

Fig. 4. Sequence diagram for the capture / upload image use case.

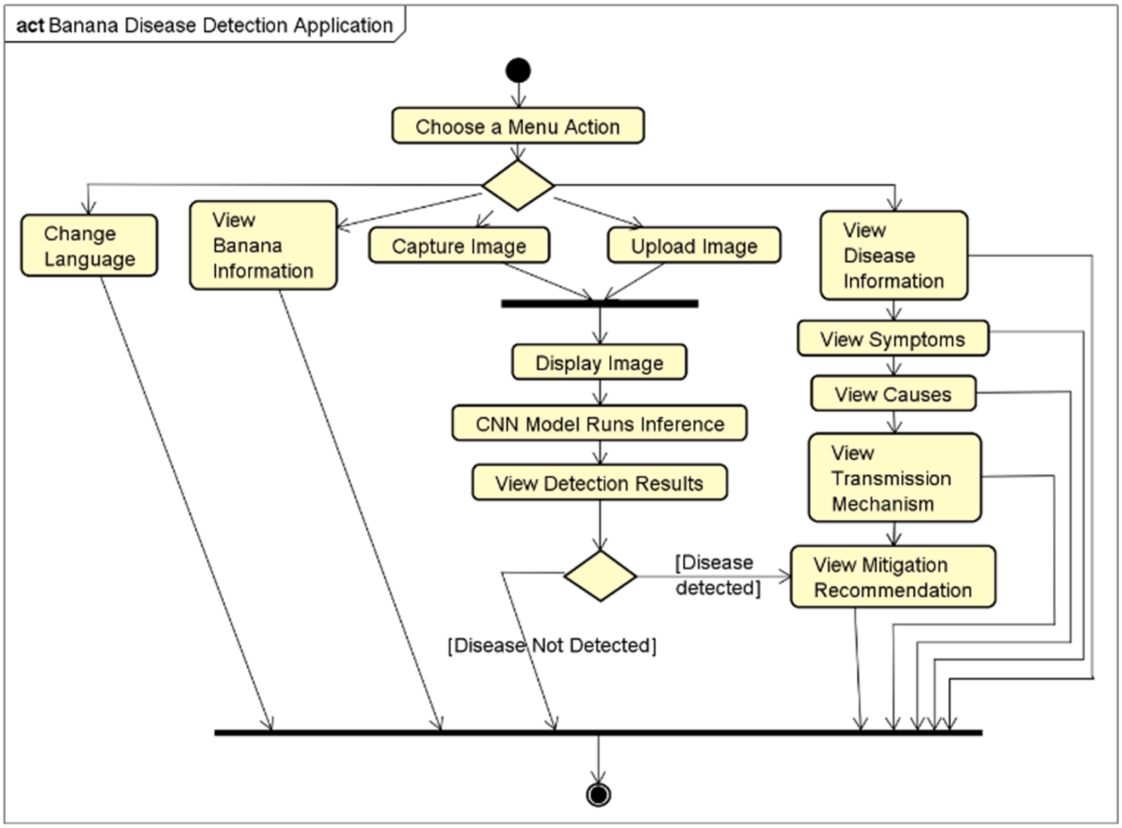

Fig. 5. Activity diagram for the mobile application for banana disease identification.

Table 4
CNN model performance for detecting banana diseases.

CNN Group	Epoch	Validation loss	Precision (%)	Recall (%)	F-measure (%)	Validation Accuracy (%)
CNN Group 1	100	0.7621	65.75	65.81	65.70	65.86
CNN Group 2	100	0.2683	91.08	91.62	90.55	91.17
CNN Group 3	100	0.7367	78.52	78.12	78.12	78.59
CNN Group 4	100	0.6775	84.74	84.05	84.45	84.77
CNN Group 5	100	0.5418	83.28	84.00	82.57	83.49

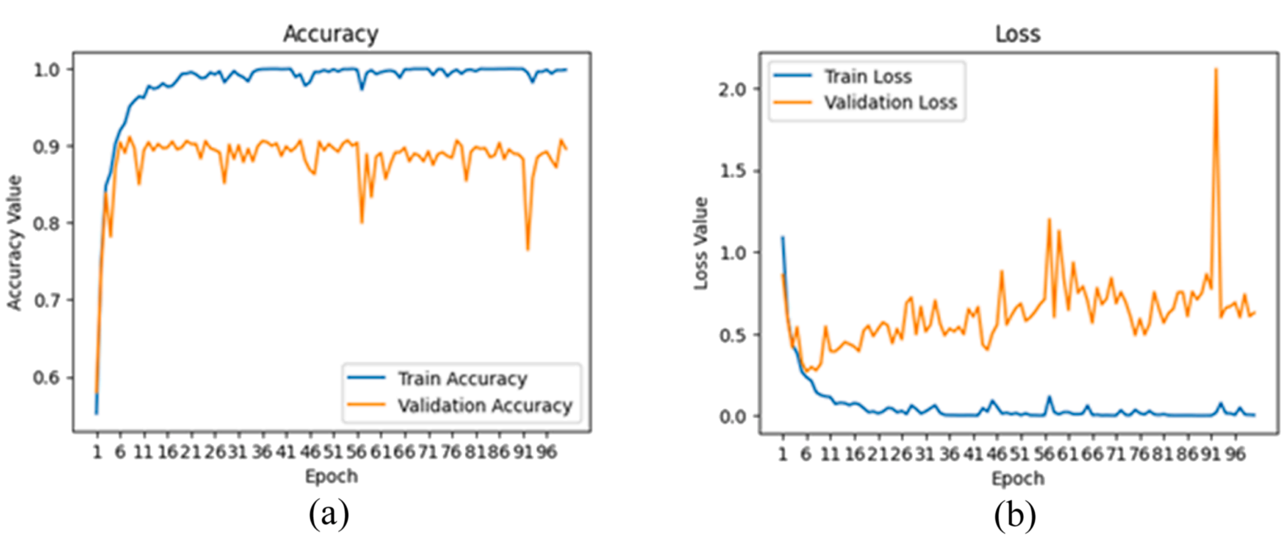

Fig. 6. Performance for the best CNN model.

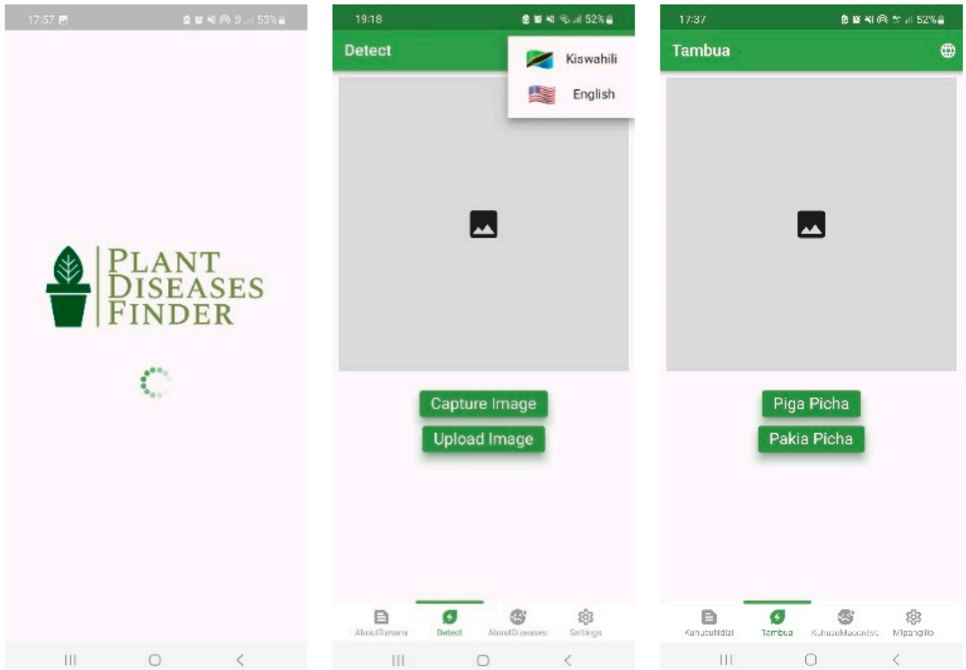

Fig. 7. Banana disease identification mobile application splash screen and detect page in English and Kiswahili language.

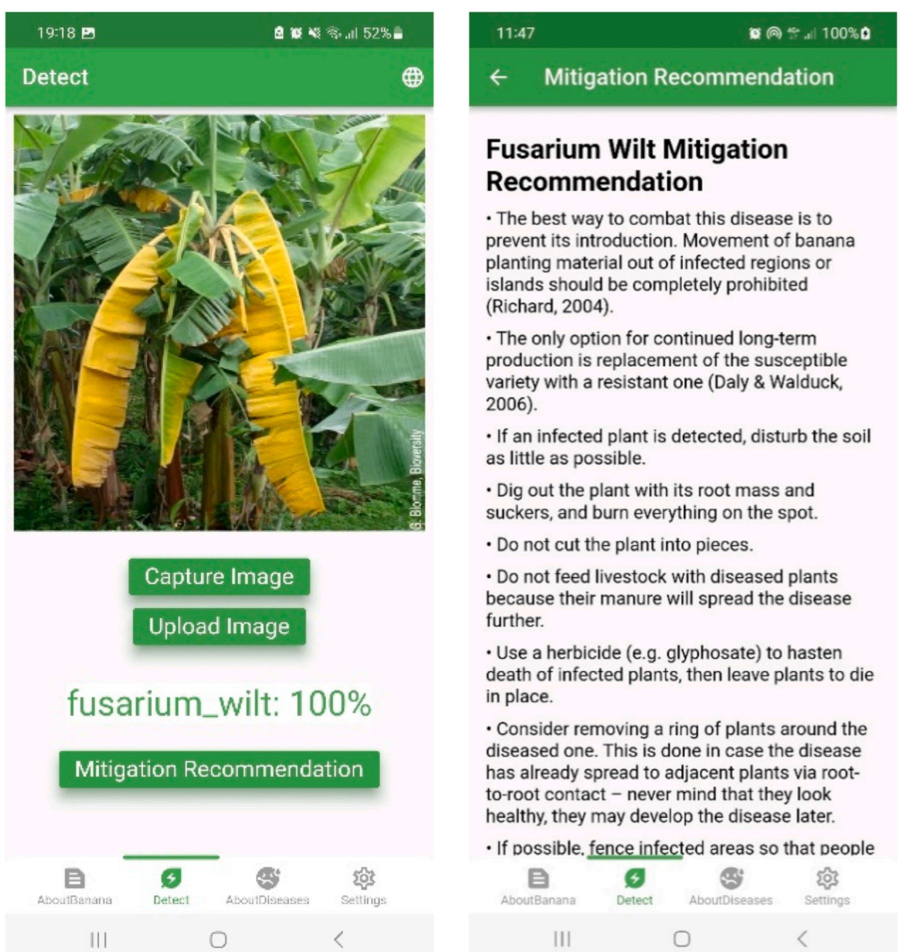

Fig. 8. Banana disease identification mobile application detect page with detection results for Fusarium Wilt and mitigation recommendation page for the detected disease.

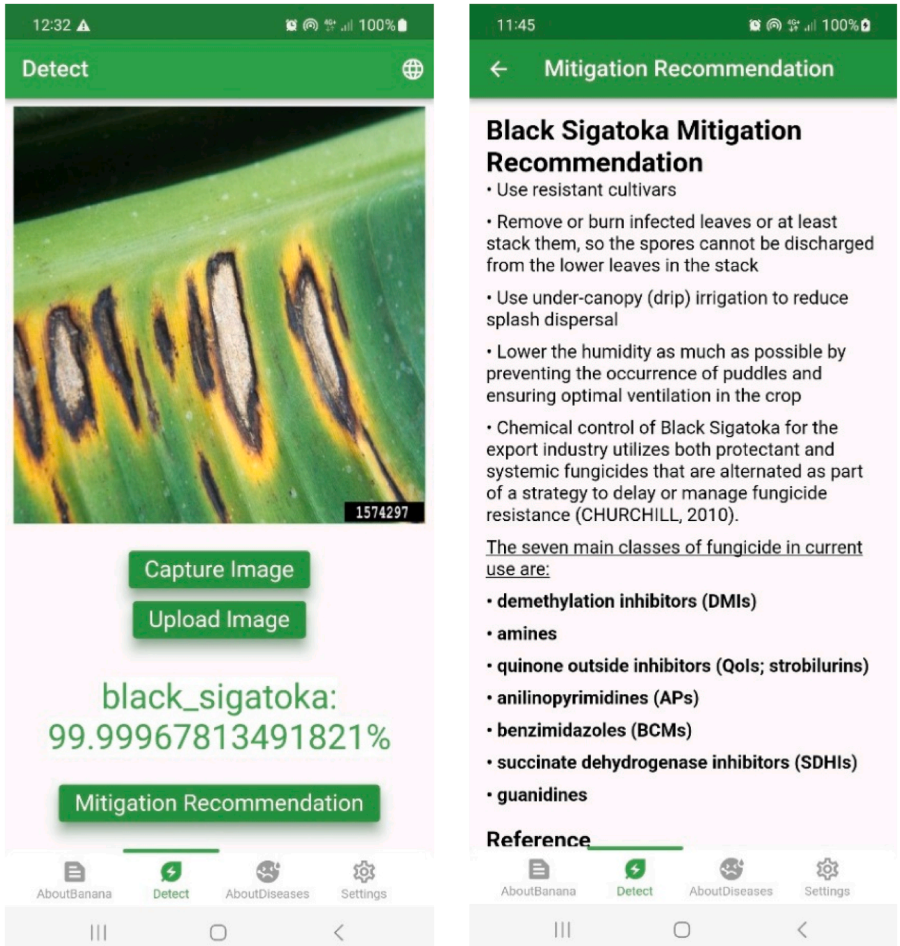

Fig. 9. Banana disease identification mobile application detect page with detection results for Black Sigatoka and mitigation recommendation page for the detected disease.

3. Results and discussion

The CNN deep learning model's effectiveness was assessed using the following metrics: validation accuracy, validation loss, f-measure, recall, and precision. The model was trained in groups, where the output weights used to train the first group were used as input for training the second group, and so on. The model was trained in groups because of the large number of datasets. Table 4 summarizes the results that were achieved by the CNN model in all the groups.

The average performance for all the CNN groups was 80.776 %. Fig. 6 shows the CNN's model performance for the best performing group. On the accuracy over epoch graph on part (a) of Fig. 6, results show that the validation accuracy rose rapidly to the sixth epoch, then remained steady around 90 % with some fluctuations, hitting a maximum of 91.17 %, while the training accuracy followed the same pattern without fluctuations, rising higher than the validation accuracy. This shows that the model could generalize well. On the loss over epoch graph in part (b) of Fig. 6, results showed that the training loss decreases rapidly in the early epochs, and at epoch 21, it starts to decrease steadily until the end, while the validation loss decreases rapidly from the beginning, and from epoch six, it started increasing steadily with fluctuations.

Since a competent CNN model should attain an accuracy of at least 70 % [36], the achieved accuracy of 91.17 % was regarded as good. Related results of a 95.41 % accuracy rate were reported by [37] when using an Inceptionv3 model. The evaluated model is therefore precise and appropriate for application in the early identification of banana diseases.

An interactive and intuitive mobile application was developed to deploy the CNN deep learning model.

An intuitive and easy-to-use mobile application was developed to help farmers and extension officers identify Fusarium Wilt and Black Sigatoka banana diseases early. When the application is opened, a splash screen is displayed for a few seconds, then the detect page is opened (see Fig. 7). On the "Detect" screen, users can upload an image from their gallery or take a picture using their phone's camera. When a banana leaf or stalk image is captured or uploaded, the application automatically runs inference on the image in the background and displays the detection results. If either Fusarium Wilt or Black Sigatoka diseases are identified, the disease name and confidence score will be displayed together with a mitigation recommendation button, as seen in Fig. 8 and Fig. 9. When this mitigation recommendation button is tapped, it takes the user to a page that contains research-based mitigation recommendations for the specific identified disease. This button will not appear

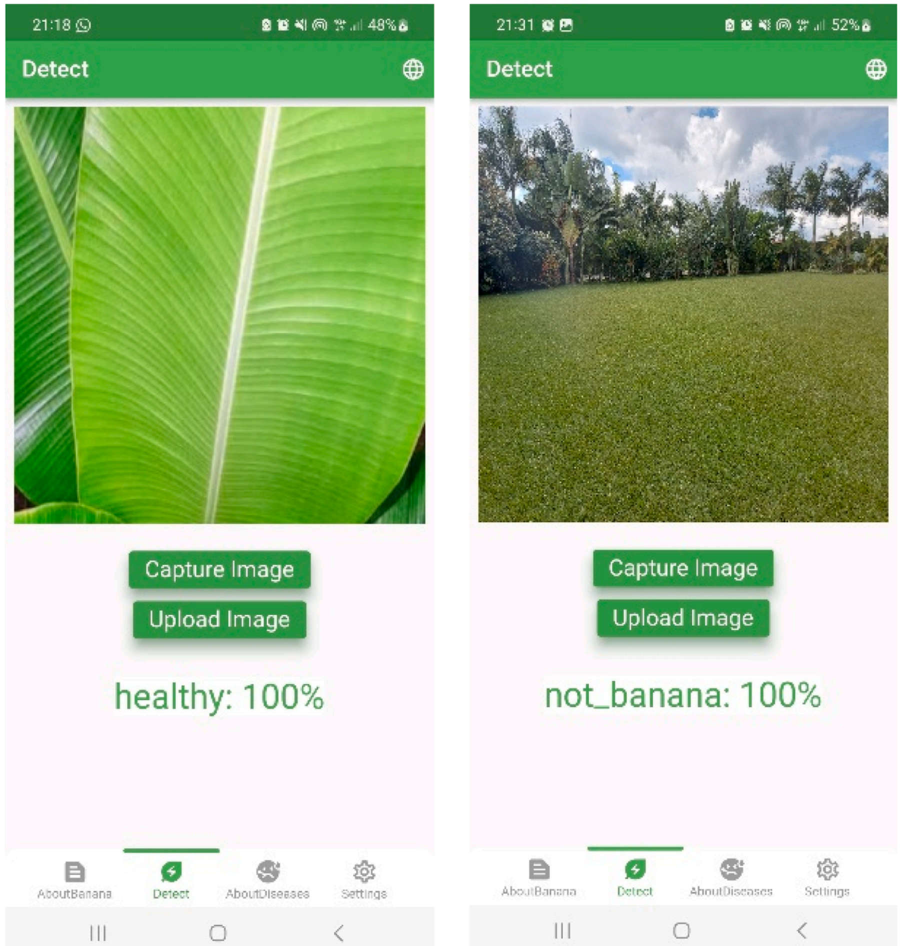

Fig. 10. Banana disease identification mobile application detect page with results for a healthy banana leaf and an image that is not of a banana leaf or stalk.

when a healthy banana leaf or stalk is identified as seen in Fig. 10. If an image is captured or uploaded that is not of a banana leaf or stalk, the model will identify it, as not banana. The detect page, about banana page, and about diseases page also have a change language feature on the top right where the user can select either of the two languages supported by this application, which are English and Kiswahili (see Fig. 7). This feature is also included in the settings page, and it converts the entire application into either English or Kiswahili language, as selected. This feature will help the local farmers who do not understand English to access the application in Kiswahili.

The mobile application also provides research-based information about bananas, including different types of bananas, the banana types that provide the highest yields, the banana types that have high demand in the market, and the best practices in banana farming in Tanzania as seen in Fig. 11. This banana information was gathered as a requirement from farmers. Furthermore, the mobile application provides research-based information about Fusarium Wilt and Black Sigatoka banana diseases. Information about the symptoms, causes, transmission mechanism, and mitigation recommendations are provided for each disease. The users can prevent the occurrence of these two banana diseases by knowing their transmission mechanisms and avoiding them.

4. Conclusion and future work

This paper proposes a simple mobile application for the early identification of Black Sigatoka and Fusarium Wilt banana diseases. The mobile application deploys a CNN model that classifies these two diseases, healthy banana leaves, and images that are not of a banana leaf or stalk. The mobile application was able to correctly classify images with diseases, healthy images, and images that are not of the banana plant with a confidence of 90 % and above in less than five seconds per image. The application could identify banana diseases at an early stage and provide research-based mitigation recommendations that extension officers and farmers can use to avoid yield losses and financial losses. The application also provides research-based information on banana farming and the two diseases. The feature of supporting English and Kiswahili languages plays a huge role in helping local farmers in rural areas who do not understand English. This study demonstrates how deep learning may be used to accurately identify plant diseases early enough for farmers to take the necessary precautions to reduce the damaging

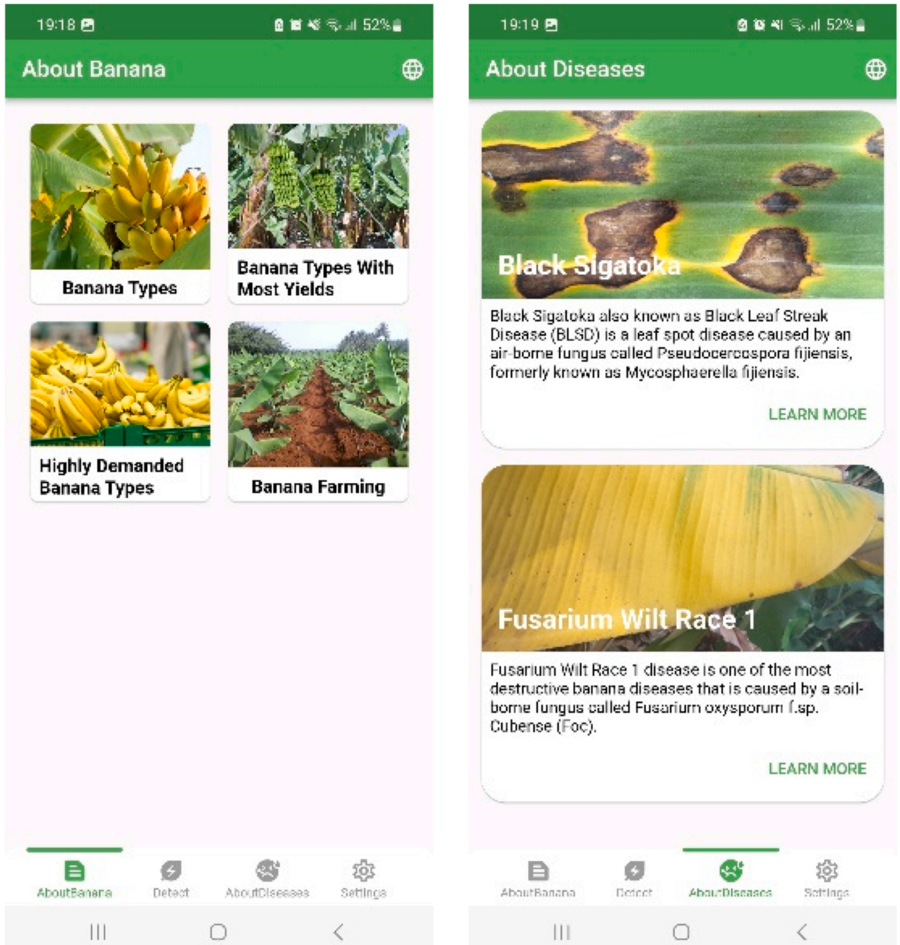

Fig. 11. Banana disease identification mobile application about banana page and about diseases page.

impacts of these diseases and save their yields.

In the future, we expect to add the detection of other plant diseases and continuously improve these detection models to provide farmers and extension officers with robust prediction models.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

CRediT authorship contribution statement

Christian A. Elinisa: Writing – original draft, Validation, Software, Methodology, Investigation, Conceptualization. **Neema Mduma:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

Acknowledgement

This research is entirely funded by the International Development Research Centre (IDRC) and Swedish International Development Cooperation Agency (SIDA) through Artificial Intelligence for Development (AI4D) Africa program under the Africa Centre for Technology Studies (ACTS).

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