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MOBILE MACHINE LEARNING APPLICATION FOR EARLY DETECTION OF CASSAVA DISEASES

Soyoye, B. O., Adeduntan, P. A., Adisa, T. O. and Oguntayo, A. B.
Agricultural and Environmental Engineering Department, Federal University of Technology, Akure, Ondo State, Nigeria
**Corresponding author: bosoyoye@futa.edu.ng*

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Abstract
Cassava happens to be a major food crop in Nigeria, yet its production is severely threatened by diseases such as cassava bacterial blight, cassava brown streak disease, cassava green mite and cassava mosaic disease. Timely and accurate detection of these defects and diseases is crucial for minimizing crop losses and improving food security. Hence, this study evaluates the performance of a cassava disease detection mobile application developed using TensorFlow machine learning models. The app classifies cassava diseases based on leaf images and was tested on both young and mature leaf stages to check how well it catches relevant information and its F1 score. A hybrid data collection approach combining on-site farm data from the Federal University of Technology, Akure, and online datasets were employed. Results showed an overall accuracy of 77.44% for mature leaves and 75.60% for young leaves, demonstrating strong reliability in identifying common cassava diseases. The app exhibited high precision and recall values across most disease categories, indicating its potential as an efficient, accessible, and cost-effective diagnostic tool that could be integrated and used by farmers. The study concludes that the integration of machine learning into mobile applications can significantly enhance spotting and tackling cassava diseases early to boost crop yields and food availability.

Keywords: *Cassava, diseases, early detection, food security, machine learning.*

Introduction
Background of the Study
Cassava is a big deal as a staple food globally, especially in tropical areas of Africa, Asia, and Latin America. It is a versatile and resilient crop that can grow in harsh environments, making it an indispensable source of food security for millions of people (Ogbonna *et al.,* 2021). Cassava is a major source of carbohydrates, proteins and vitamins, which makes it an important food crop (Malik *et al.,* 2020). In Nigeria, cassava is cultivated in over 90% of the states, with an annual production capacity of over 54 million metric tons (Malik *et al.,* 2020; Ogbonna *et al.,* 2021). Cassava is a cash crop for farmers as it is used to produce all sorts of products like *garri*, flour, starch and ethanol.

Cassava is a tuber crop that can grow up to 5 meters tall. It has a tuberous root that is the main part of the plant used for food and other applications. The crop is grown from cuttings of stems, which are planted in the soil. Cassava is a drought-tolerant crop that can grow in marginal soils, which makes it an important crop for smallholder farmers in developing countries (Kidasi *et al.,* 2021; Basir *et al.,* 2021; Katono *et al.,* 2021; Parry *et al.,* 2021). In Nigeria, cassava is grown mainly on small farms, and the crop is harvested throughout the year. Cassava cultivation has the potential to improve rural livelihoods and contribute to food security in the country. It is a cornerstone of food security and economic livelihood for millions in Nigeria, prized for its resilience and high yield. However, its cultivation is persistently threatened by devastating diseases such as cassava bacterial blight, cassava brown streak, cassava green mite and cassava mosaic.

The application of Machine Learning (ML), particularly Deep Learning and Convolutional Neural Networks (CNNs), has revolutionized plant phenotyping and disease diagnosis (Mohanty *et al*., 2020; Singh *et al*., 2020). Studies by Ramcharan *et al*. (2017), Yang *et al*. (2018), Tokunaga *et al*. (2020) and Liu *et al*. (2022) have demonstrated the high accuracy of models like Efficient Net in classifying cassava diseases from leaf images. Techniques such as transfer learning and data augmentation have been pivotal in overcoming challenges related to limited dataset sizes and improving model robustness (LeCun *et al*., 2015; Kusumawati *et al*., 2022; Al-Shalout *et al*., 2023). The study achieved state-of-the-art results on the cassava disease dataset and demonstrated the effectiveness of the proposed model. Ye *et al.* (2022) improved the EfficientNetV2 model by incorporating visual attention mechanisms and applied it to cassava disease identification. The results showed that the attention mechanism improved the model's accuracy and robustness to image noise. Abayomi-Alli *et al.* (2021) developed an enhanced data augmentation model and applied it to the recognition of cassava diseases from low-quality images using deep learning. The study showed that the proposed model improved the accuracy of disease recognition from low-quality images.

The timely detection of cassava diseases is essential for effective remediation and limiting the spread of diseases. Traditional diagnosis methods can be unreliable and time-consuming, leading to the loss of crops and substantial economic losses. Therefore, there has been a growing interest in developing innovative and efficient disease detection methods using machine learning techniques. Hence, this research work is based on the development and evaluation of cassava disease detection mobile app on young and mature leaf stages. The mobile app, developed from the intelligent system for cassava disease detection and remediation using machine learning" mother project, uses a model trained on TensorFlow to classify cassava diseases based on leaf images.

Statement of the Problem

The primary challenge is the inadequacy of current disease detection methods, which hinders effective management and control. While a cassava disease detection mobile app, developed using TensorFlow models, offers a promising tool, its practical efficacy remains unvalidated. This study addresses the critical gap of evaluating the app's performance, specifically focusing on its accuracy, reliability, and usability in identifying diseases across different leaf maturity stages; young and mature leaves in a real-world context.

Aim and Objectives

The main aim of this research is to conduct a comprehensive performance evaluation of a cassava disease detection mobile app that utilizes TensorFlow models. The specific objectives are to:

a. develop a user-friendly mobile application that allows farmers to take or upload pictures of cassava leaves;
b. use a trained machine learning model (Crop Net) to identify and classify common cassava diseases based on leaf images; and
c. evaluate the app's performance on both young and mature leaves using standard metrics.

Significance of the Study

This study is significant as it provides empirical evidence on the effectiveness of an ML powered mobile app for cassava disease detection. By evaluating performance at different growth stages, the findings can guide improvements to the app, enhance disease management strategies, and ultimately contribute to increased crop yields, food security, and sustainable agricultural practices for Nigerian farmers.

Methodology

Conceptual Framework

This study was grounded in a conceptual framework that links data collection (hybrid: onsite and Kaggle), preprocessing (image labeling and annotation), model application (the TensorFlow-based mobile app), and performance evaluation (using accuracy, precision, recall, and F1 score) to determine the app's effectiveness on young and mature leaves.

Study Area and Collection of Data

The research was conducted at the Federal University of Technology, Akure (FUTA), Nigeria, a region representative of cassava cultivation zones. High smartphones were used to capture clear and detailed images. Photos were taken under various environmental conditions to capture a diverse range of cassava leaf appearances, including both healthy leaves and ones with damage or infection. The collection process was systematic, capturing leaves from different plants and at various growth stages to ensure thorough data coverage. A hybrid data collection strategy was employed:

i. **Onsite Collection:** Young and mature leaf images were captured directly from cassava plants in the university farm, covering all five disease categories and healthy plants.
ii. **Online Dataset:** Supplementary images were sourced from the Naturalist and ImageNet-21K platforms to enhance dataset diversity and size.

During onsite data collection matured and juvenile leaves were collected from cassava plants infected with common cassava diseases, including Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mottle (CGM), Cassava Mosaic Disease (CMD) and healthy plants. Together with the onsite (local) dataset, additional datasets from sources like Naturalist and ImageNet-21K were used to expand the training data. These online datasets offered a wider variety of plant images, helping the model better generalize across different conditions and species. To ensure consistency, the format and annotations of these external datasets were aligned with the local dataset before training.

The collected leaves were scanned or photographed using a camera. The images were saved in a standardized format and stored in a database for further analysis. The data collected were preprocessed to guarantee that the images are of excellent quality and suitable for testing the machine learning model. This process involves image preparation, labeling, and annotation, as well as removing irrelevant images and those with low quality (Figure 1).

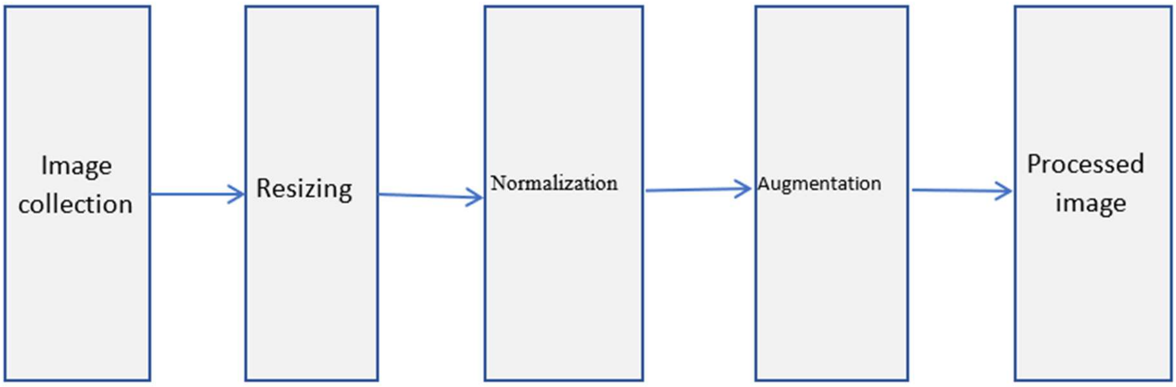

Figure 1: The Sequence of Preprocessing Steps

Figure 2: Labeling and annotation of different cassava diseases

Data Preprocessing

In preparing the cassava leaf images for training, the images were first preprocessed into a uniform size to ensure they were compatible with the neutral network's input requirements. To improve dataset's variety and ensure the model is reliable, it was expanded using augmentation techniques like rotation, flipping and brightness tweaks. This assisted the model become more highly adaptable to different lighting and positions that might be encountered in real-world scenarios. Each image was labeled with the corresponding class either healthy or diseased based on standard annotations. These labels were essential for the supervised learning process. The dataset was then split into training, validation, and test sets using an 80-10-10 ratio. The training set was used to update the model's parameters, the validation set to tune hyper-parameters and prevent over-fitting, and the test set to evaluate the model's performance (Figure 2).

i. **Image Preparation:** Images were resized and normalized to a standard resolution (224x224 pixels) (Figure 1).

Labeling and Annotation: Each image was manually labeled according to its disease category and leaf stage (young or mature) (Figure 2).

Model Training

The cassava disease detection model was built using TensorFlow, leveraging a convolutional Neural Network (CNN) architecture. Given the need for real-time performance on mobile devices, a lightweight model architecture was chosen. The model consisted of multiple convolutional layers, followed by max-pooling layers and fully connected layers, designed to extract features from the images and classify them into the respective disease categories.

The model was trained for 100 epochs with a batch size of 32, using the Adam optimizer with an initial learning rate of 0.001. A categorical cross-entropy loss function was used to measure the difference between the predicted and actual class labels. During training, the model's performance was continuously monitored using metrics such as accuracy, precision, recall, and F1-score. The metrics provided insights into the model's ability to correctly identify diseased and healthy leaves.

Model Deployment and API Integration

The trained cassava disease detection model was deployed on the server to facilitate real-time interaction through a mobile application ensuring efficient processing and accurate inferences. The model was incorporated into a Flask application API, which acted as the intermediary between the mobile application and the server. Flask was chosen due to its lightweight nature and ease of use in handling HTTP requests. The API allowed the mobile app to send preprocessed images of cassava leaves to the server, where the model would further process them and return predictions. This Flask API was hosted on an AWS EC2 instance, providing the necessary infrastructure for handling multiple requests simultaneously. The React Native mobile application was developed as the user interface for farmers, allowing them to interact with the model. Within the app, users could capture images of cassava leaves using the device's camera or upload existing images from their gallery. Once an image was selected, the app sent it to the Flask API via an HTTP request. Upon receiving the image, the API preprocessed it and performed inference using the hosted model. The prediction, indicating whether the cassava leaf was healthy or diseased (healthy, Brown Streak Disease, Mosaic Disease Bacterial Blight, Green Mite,), was then sent back to the app. The app displayed these results to the user, along with recommendations for remediation of disease that was detected.

The system architecture includes a React Native mobile app, a Flask API, and a TensorFlow model hosted on AWS EC2. The mobile app acts as the user interface, letting users capture or upload images of cassava leaves. These images are sent to the Flask API, which handles the request and communicates with the TensorFlow model to detect any diseases (Figure 3).

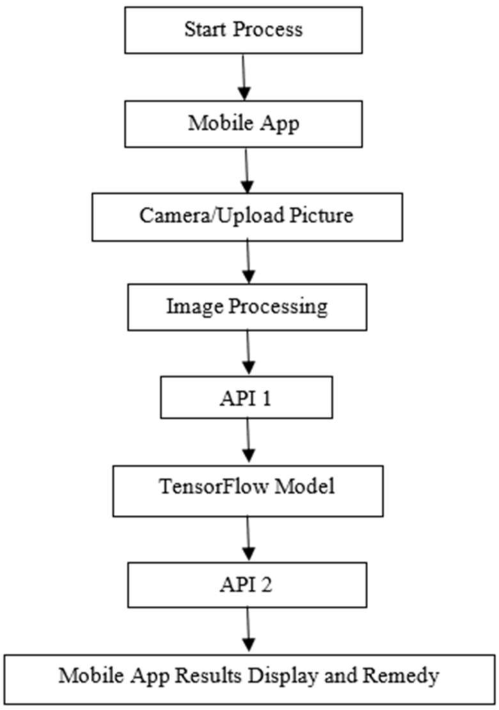

Figure 3: System Architecture Flow Chart

Figure 4: Application interface of cassava disease detection mobile app

Performance Evaluation

The performance evaluation of the app is based on the accuracy, precision and recall, and F1 score.

i. **Accuracy:** In the context of this study, accuracy means the ratio of correctly identified cassava leaves to the total number of cassava leaves. The accuracy of the cassava disease mobile app was evaluated using the confusion matrix, which classifies the predicted and actual values into True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The accuracy of the cassava disease mobile app was computed by using Equation 1;

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

ii. **Precision and Recall:** Precision measures the ratio of correctly identified cassava leaves with the disease to all predicted cassava leaves with the disease. Recall measures the ratio of correctly identified cassava leaves with the disease to all actual cassava leaves with the disease. The precision and recall were computed using Equations 2 and 3 respectively:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

iii. **F1 Score:** The F1 score is the harmonic mean of precision and recall and is a useful metric for evaluating the balance between precision and recall. It ranges from 0 to 1, with 1 being the best score. The F1 score was determined using Equation 4;

$$2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

iv. **Benchmark Comparison:** The app's performance was compared against established benchmarks, such as models trained on the Plant Village dataset, to provide context for its effectiveness.

The evaluation was carried out by testing the app on each disease for both young and mature leaves. As illustrated in Figure 4, the first interface represents the welcome page on the app while it launches to the second interface where images can either be photographed or uploaded. The third interface shows the result of the disease detected and the possible solutions to prevent or maintain the disease. The fourth interface illustrate the confidence scores which helps both traders and researchers to easily navigate through the platform.

Results and Discussion

Performance on Mature Leaves

The app was about 77.44% accurate when testing on mature leaves indicating that the app was able to correctly identify cassava diseases and healthy plants with high accuracy. The precision of the app on mature leaves was found to be 58.54%, indicating that the app did a great job of figuring out which cassava plants were healthy and which ones had diseases. The recall of the app on mature leaves was found to be 82.37%, indicating that the app was able to correctly identify cassava diseases and healthy plants. This result is similar to what was reported by Liu *et al.* (2022) where they introduced a multi-scale fusion model that combines EfficientNet with an attention mechanism, leading to high accuracy in classifying cassava diseases. The F1 score of the app on mature leaves was 0.687, indicating that the app's performance was high.

The app's ability to detect Cassava Bacterial Blight (CBB) on mature leaves was found to be high, with a precision of 98.92%, recall of 77.33%, and F1 score of 0.869. The app's ability to detect Cassava Brown Streak Disease (CBSD) on mature leaves was also high, with a precision of 96.15%, recall of 91.23%, and F1 score of 0.936. The app's ability to detect Cassava Green Mottle (CGM) on mature leaves was found to be high, with a precision of 94.41%, recall of 91.32%, and F1 score of 0.926. The app's ability to detect Cassava Mosaic Disease (CMD) on mature leaves was found to be high, with a precision of 96.15%, recall of 88.40%, and F1 score of 0.922 (Table 1).

Table 1: Performance Evaluation of the App on Mature Leaves

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Overall	77.44	58.54	82.37	0.687
Healthy	98.92	100.00	82.28	0.907
CBB	82.25	98.19	77.33	0.869
CBSD	91.04	96.15	91.23	0.936
CGM	94.50	94.41	91.32	0.926
CMD	94.45	96.15	88.40	0.922

Table 2: Performance Evaluation of the App on Young Leaves

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Overall	75.60	59.23	73.80	0.698
Healthy	97.80	98.90	80.50	0.886
CBB	80.50	98.45	78.20	0.849
CBSD	89.80	95.10	88.70	0.918
CGM	92.30	94.41	91.32	0.926
CMD	93.50	96.10	88.30	0.928

Performance on Young Leaves

The accuracy of the app on young leaves was found to be 75.6%, which is slightly lower than the accuracy obtained for mature leaves. The precision and recall of the app on young leaves were 0.5923 and 0.7380, respectively, which are higher than the precision and recall obtained for mature leaves. Abayomi-Alli *et al.* (2021) reported the same pattern when they developed an enhanced data augmentation model that effectively recognizes cassava diseases even from low-quality images, demonstrating remarkable robustness. The F1 score of the app on young leaves was 0.93, which is also higher than the F1 score obtained for mature leaves (Table 2).

According to the analysis, the app successfully detected cassava diseases on young leaves with high accuracy, precision, and recall. The app was also able to identify healthy plants with high accuracy. The performance of the app on young leaves was slightly lower than on mature leaves, but the difference was not significant.

The model effectiveness was analyzed, and it was found that the app was able to identify the common cassava diseases on young leaves accurately. The machine learning algorithm used in the app was able to learn the features of the cassava diseases from the labeled images and was able to use this knowledge to detect the diseases on new images.

Conclusions

This study successfully evaluated a mobile application for cassava disease detection. The findings confirm that the app is a reliable and accurate tool for identifying major cassava diseases in both young and mature leaves, with performance on mature leaves being particularly strong. This new technology could totally change the way cassava is grown by enabling rapid, on-the-spot diagnosis, leading to timely management practices and improved crop yields.

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