Maize Plant Disease Detection Using Convolutional Neural Network

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ABSTRACT

Convolutional Neural Networks (CNNs) have become a cornerstone of computer vision, particularly in image classification tasks. In agriculture, early identification of crop diseases like those affecting maize such as northern leaf blight, common rust, and gray leaf spot is important in order to reduce yield losses and ensure food security. However, accurate diagnosis remains a challenge for farmers without specialised expertise. This research leverages the power of CNNs and mobile technology to develop a mobile application capable of classifying maize diseases from leaf images. The system uses a CNN algorithm to classify the maize leaf diseases. The CNN model was trained on a dataset using a Google Collaboration framework, and it was integrated into an application built with React Native framework. To enhance accessibility for diverse farming communities, the application provides multilingual support, displaying disease symptoms and treatment recommendations in the user's preferred language. By combining deep learning with mobile accessibility, this system aims to empower farmers with instant, actionable insights to safeguard their crops. The CNN model was trained and integrated into a React Native mobile application, achieving 88% validation accuracy whilst the model achieved an accuracy of 92.4%.

Keywords: Convolutional neural networks, disease detection, image classification, deep learning, mobile technology

INTRODUCTION

With 15 per cent contributing to Gross Domestic Product (GDP), Zimbabwe's agricultural sector is a vital component of the nation's economy (Kazunga, 2024). Maize offers a staple grain for millions of Zimbabweans and is a base of securing food in the country, hence diseases can adversely affect the production and quality of the grain. Early disease detection is vital for managing and controlling these diseases, in order to assist farmers in decreasing losses and maintaining a sustainable production (Mwaza, et al., 2023, p. 3).

Traditional methods of maize disease detection rely on the expert visual judgment of an agronomist. Such decisions can take a long time, or worse still, if it is done hurriedly, it might cause a bad visual or on the spot assessment. Sometimes, there is no readily available specialised knowledge that can affordably offer a decision making process and each day that it takes increases the chances of a disease spreading and can result in drastically lowered agricultural first grade output. The system detects the maize diseases using image processing and machine learning techniques. Image classification is an important task in computer vision that involves assigning a label to an input image based on its visual content. Deep learning using a convolutional neural network (CNN), a type of artificial intelligence that has been successful in computer vision was applied. CNNs are especially good at identifying patterns and features in images (Dube & Bhuru, 2022 p.3). This system utilises the capabilities of CNNs to deliver accurate, fast, scalable disease detection to farmers using tools they can use to safeguard their crops

Related Work

Maize is a staple crop used mainly for human consumption and animal feed. There are negative effects when it runs out or becomes scarce, these include increase on food prices, food insecurity and malnourishment (Chari, et al., 2023, p. 99). Maize output is at risk from a number of diseases, including Fusarium Ear Rot, Grey Leaf Spot, and Maize Leaf Blight. In 2022, the maize crop was short by 1.7 million tonnes mainly due to diseases and the prolonged dry weather. With an estimated annual corn requirement of 2.2 million metric tons, Zimbabwe had to import approximately 450,000 metric tons of corn in marketing year 2023/24 (Chari, et al., 2023. p. 100). This excludes the requirement that a minimum strategic grain reserve of 500,000 metric tons must be kept in physical grain stocks.

The application of technology in agricultural operations has experienced rapid growth during the last few years specifically for disease recognition and control purposes. Today farmers worldwide benefit from different multinational systems which help them detect plant diseases at their earliest stage thus protecting yields while ensuring food security. This literature review examines existing systems that leverage image processing and machine learning techniques, specifically focusing on their methodologies, effectiveness, and applicability to maize disease detection.

Current Systems in use

Visual assessment stands as the primary and conventional technique for disease diagnosis in Zimbabwean maize fields because farmers physically observe plant symptoms including spots and discolorations and wilting or deformities. Manganese Streak Virus and Gray Leaf Spot can be identified through physical symptoms alongside northern corn leaf blight (Nagababu, et al., 2024. p. 180). Visual examination of maize plants serves farmers well because it needs no laboratory equipment but its results depend heavily on the observer's expertise. Smallholder farming operations in developing areas usually demonstrate deficiencies in disease identification skills because most farmers lack professional training regarding disease diagnosis (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2023).

Traditional diagnosis of crop diseases is often performed through farm inspections carried out by agricultural extension officers (AGRITEX). Trained extension officers serve as professionals who assist farmers by diagnosing diseases and suggesting relevant solutions for problematic crops (Somanje, et al., 2021, p. 15). The experts detect diseases by using their training as well as field experience together with visual inspection methods (Masere & Steven, 2021, p.30). The service provided by extension professionals results in better disease recognition compared to independent farmer evaluations yet their operational capabilities remain restricted by delivery challenges. The COVID-19 pandemic outbreak in 2020 restricted normal agricultural extension service operations along with agricultural produce transportation to markets because direct extension services became unavailable due to travel restrictions and gathering bans (Muvhuringi, et al., 2021. P. 15). The developing world faces a major challenge with extension officers providing services to thousands of farmers (Somanje et al., 2021, p. 19). Minimal frequencies together with reduced contact areas lead to late disease screenings and treatments. The knowledge held by extension officers shows limited updating capacity when it comes to emerging diseases as well as pest outbreaks.

Agricultural institutions supply farmers along with extension officers with manuals and guides which include printed materials to aid their practices. The agricultural materials provide both pictures and written information about usual maize diseases to help farmers detect disease symptoms. The Food and Agriculture Organisation (FAO) along with regional agricultural research centers supply their members with disease handbooks as one example of printed materials. These reference materials provide useful information but demonstrate restrictions in applied use in the field (Mekouar, 2022. P. 301). Disease symptom patterns show similarities which makes farmers struggle to distinguish between diseases through static pictures combined with written diagnostic information only. The printed material fails to address every disease as well as regional differences thus rendering farmers helpless against uncommon and location-specific diseases (Khakimov, et al., 2022. P. 10).

Related Systems

Techniques such as image segmentation, feature extraction, and pattern recognition play pivotal roles in identifying symptoms of diseases in plants. For instance, a study by (Chetan, 2024) implemented a hybrid image processing approach that combines color, texture, and shape features to classify various plant diseases. The authors highlighted how pre-processing steps, including noise reduction and image enhancement, significantly improved the accuracy of disease classification. Their system demonstrated an overall accuracy of 97% in detecting diseases in sunflower plants, suggesting that similar methodologies could be adapted for maize disease detection.

Machine learning together with deep learning has transformed the recognition and classification of images in modern technology. CNNs established themselves as the leading approach for image data processing through their automatic capability to learn hierarchical features. Research conducted by (Verma, 2023. p. 32) created a multimedia CNN system to diagnose diseases across multiple crops types. By applying their model to more than 50,000 images they obtained 99.35% detection accuracy between healthy and diseased plant leaves. Research findings demonstrate that CNNs demonstrate outstanding potential to detect plant diseases efficiently with accuracy so farmers can intervene in time for agricultural practice operations. (Goel & Nagpal 2022. P.426) conducted a comparative research to assess the performance of Support Vector Machines (SVM), Random Forest and CNNs for plant disease classification. The assessment showed traditional machine learning models performed with satisfactory results but CNNs surpassed them because they can handle complex imaging data inputs.

A classifier was developed in real time to predict tomato leaf diseases using a CNN and an accuracy of 93% was achieved by the system in the prediction of the diseases. (Dube, S.S, et al., 2023 p.3), also proving the capability of CNNs in handling complex imagery.

The rise of smartphones triggered development for mobile applications which help farmers identify diseases in their crops (Ahmed & Gopireddy, 2021, P.471). Farmers make use of Plantix, a mobile application which uses image recognition technology to detect plant diseases. The application lets users submit pictures of their harvests which deep learning technology examines to deliver evaluation and control information to users. The diagnostic effectiveness of Plantix app was evaluated at 85% by (Akinyemi, et al., 2023, p.70) which confirms mobile technologies can equip farmers with fast insights about their crops. Plantix together with PlantVillage Nuru have become popular choices among farmers because they provide users with accurate and straightforward diagnosis capabilities.

Transfer learning features extensively in maize disease detection to decrease deep learning model costs for training time while maintaining efficiency. The pre-trained models VGG16 and ResNet as well as Inception have demonstrated their effectiveness in maize disease classification through fine-tuning processes (Dash & Sethy, 2023, p. 228). The four pretrained models VGG16, ResNet50, InceptionV3 and Xception classified three common diseases of maize leaves from 18,888 images of both healthy and diseased leaves. Research teams benefit from transfer learning because they can utilise models trained with ImageNet to adapt their use for maize-specific datasets which produces better outcomes from minimal input data. A fine-tuned ResNet-50 model successfully detected maize diseases while it performed with high precision and decreased the time needed for training as opposed to reconstructing a model from the beginning (Singh, , 2023. p. 2421).

The research conducted by (Wosula, et al., 2024) tested the PlantVillage Nuru application to identify cassava diseases in Tanzania. The app delivered 83% accuracy while offering affordable disease monitoring services for smallholder farmers who reside in underprivileged regions.

Research gap

Numerous researches rely on datasets that are frequently restricted to particular geographic areas. The researcher made use of both publicly available datasets and AGRITEX (Agricultural Extension Service) data sets containing diseases specific to the Southern Africa region. The majority of disease detection systems are available in English, while others, like Plantix, are multilingual. However, quite a number of small holder farmers do not understand these languages. Therefore, it was necessary to develop a system that translates the treatment recommendations into the native languages (such as Zimbabwean Shona and Ndebele languages).

METHODOLOGY

Several critical factors influenced the methodological choice when developing the maize plant disease detection system. These factors included the need to address user requirements, alongside complete knowledge acquisition

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about the examined issue as well as providing flexibility in system design along with emphasis on team coordination efforts to achieve continuous improvements. The research methodology used is the Design Science Research (DSR). This method was selected because of the agricultural complexity that affects smallholder farmers' particular requirements. Design Science Research also offers a deep understanding of farmer difficulties related to maize disease identification and control.

The artefact assessment approach in DSR differs from qualitative and quantitative methods because it concentrates on creating and validating specific operational designs that handle actual-world issues. The purpose of DSR aims to produce artefacts through an evaluation process to solve actual problems by developing models and implementing frameworks and algorithms.

Personal Extreme Programming (PXP) was used for software development as it provides a development framework which follows Extreme Programming (XP) principles but it centres development activities on individual programmers. The research had specific goals which included accurate disease detection ability and an easy-to-use mobile application features.

The React Native framework for mobile app development was used to cater for the Android and IOS operating systems using a single codebase. Openweather API and Google Translate API were also used in the development phase. Async storage was used to temporarily store the diagnosis results.

System Architecture

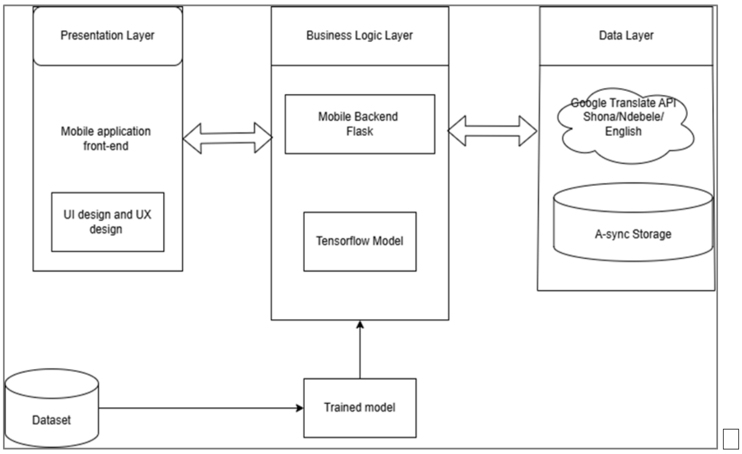

Figure 1 System Architecture

The maize plant disease detection system follows a simple client-server architecture designed for accessibility and multilingual support. In the presentation layer, farmers interact with a mobile application to capture images of maize leaves or selecting images from the gallery (see Figure 1). The application sends the image to the Flask backend server via an HTTP POST request which is in the business logic layer. The backend pre-processes the image by resizing it to 128x128 pixels, converting to RGB and feeds it into a CNN model which is part of the backend for disease classification. The model predicts one of five possible outcomes and returns a numerical index. The Flask server then maps this index to the localised disease information, including symptoms and treatment recommendations stored in the disease information dictionary. The user then selects their preferred language between English, Shona or Ndebele and, the backend sends the structured, language-specific response back to the mobile application, where results are displayed to the farmer.

Model Training

The dataset used for training the model was a combination of images obtained from the internet and images from Agritex. It contained 10933 images which belonged to five classes, namely the Gray Leaf Spot, Healthy, Northern Leaf Blight, Common corn rust and the not maize class which contained images of plants which are not maize. Figure 2 are some images which were used to train the model.

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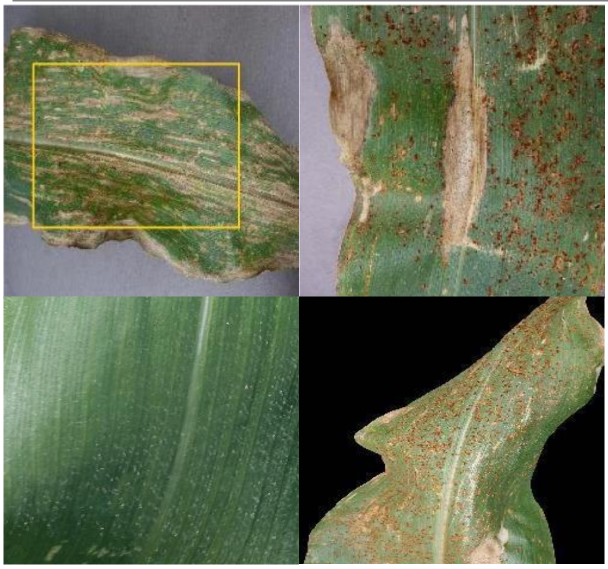


Figure 2 Dataset images

The model follows a custom Convolutional Neural Network (CNN) architecture built with TensorFlow/Keras. The model takes 128x128 RGB images as input and processes them through five convolutional blocks, each consisting of two Conv2D layers with ReLU activation followed by MaxPooling. The number of filters increases from 32 to 512 across these blocks, allowing the model to hierarchically learn features from simple edges to complex disease patterns. After feature extraction, a 25% Dropout layer helps prevent overfitting before flattening the output. The classification head includes a large Dense layer of 1,500 neurons with ReLU and a final softmax output layer for five classes, with an additional 40% Dropout layer for regularisation. The model is compiled with the Adam optimiser with learning rate=0.0001 and uses categorical cross entropy loss, making it suitable for classification of multiple classes.

RESULTS

Testing is interleaved with the development process such that every block of code is tested, every iteration is tested and every new functionality is tested. The model was tested in VS code after training to determine that it was classifying images correctly and accurately. Figure 3 is a confusion matrix showing the results obtained after training the model.

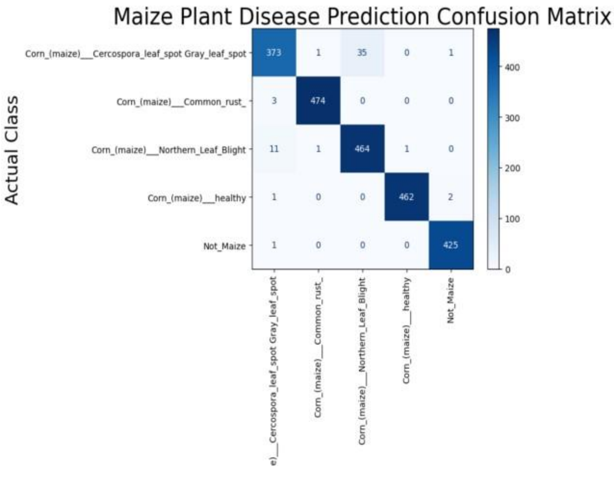


Figure 3 Confusion matrix

The performance of the model was captured using a confusion matrix. The confusion matrix represents how well the model is able to distinguish between the different maize plant diseases. The confusion matrix was also used to evaluate the performance of the classification model. It shows the counts of true positive, true negative, false positive, and false negative predictions for each class. Rows represent the true classes of the maize plant images while the columns represent the predicted classes by the model.

Each cell in the matrix contains the number of instances that belong to a particular actual class and were predicted to belong to a different predicted class. The confusion matrix below shows the highest value of false prediction between Cercospora leaf spot Gray leaf spot and Northern Leaf Blight 35 instances of Gray Leaf Spot were predicted as Northern Leaf Blight this is due to the visual similarities between the two diseases.

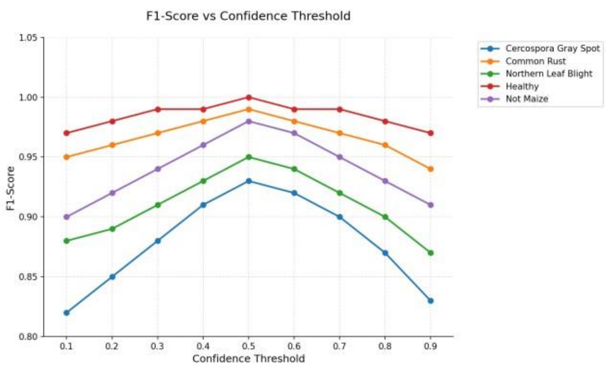


Figure 4 F1 scores

Figure 4 shows how the F1-score changes for each class as the confidence threshold for predictions is adjusted. Confidence Threshold is the probability above which a prediction is considered positive for a particular class. For example, a threshold of 0.7 means that the model needs to be at least 70% confident to assign an instance to that class. F1-Score is a metric which balances precision and recall, giving a good overall measure of a model's performance for a class. Higher F1-scores indicate better performance.

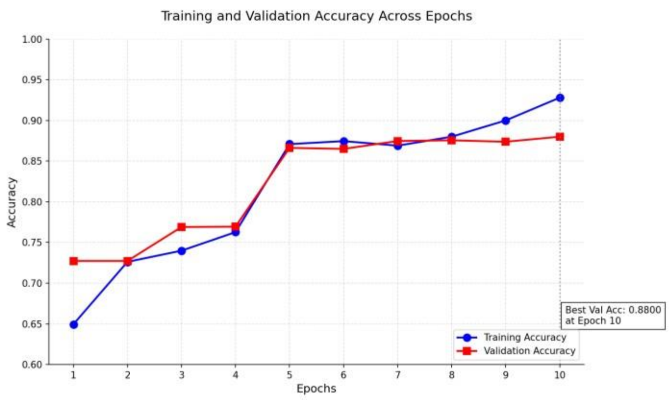


Figure 5 Model accuracy

Figure 5 shows the training and validation accuracy of the machine learning model across 10 epochs of training. The blue line shows the training accuracy, which increases from 64.9% to 92.4%, indicating that the model is effectively learning from the training data. The red line shows validation accuracy, which improves from 72.7% to 88.0%, demonstrating that the model is generalising well to unseen data. The vertical dashed line highlights epoch 10 as achieving the best validation accuracy of 88.0%. The close tracking between training and validation accuracy suggests that the model is not overfitting, while the consistent upward trend in both metrics indicates successful training. The significant performance jump between epochs 4-5 suggests the model learned particularly useful features during that phase of training.

Integration testing

Integration testing was conducted to ensure that different modules and components of the application worked together. This phase focused on testing the interaction between the user interface, backend services, and third-party APIs. Key integration points that were tested included the communication between the image capture component and the TensorFlow model used for disease classification, the connection between the weather API and the weather display section on the dashboard, as well as the interaction between the Google Translate API and the language selection feature. Integration testing also verified that diagnosis results could be saved and retrieved from a sync storage correctly.

User Interface

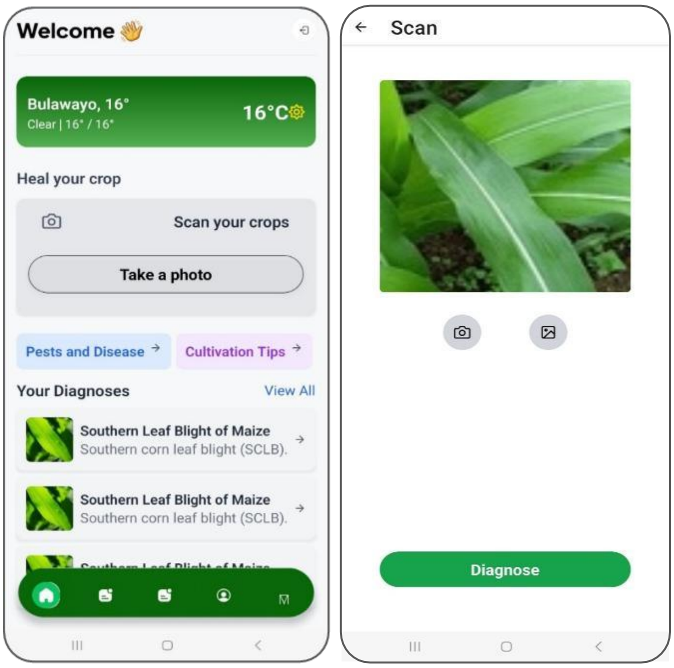
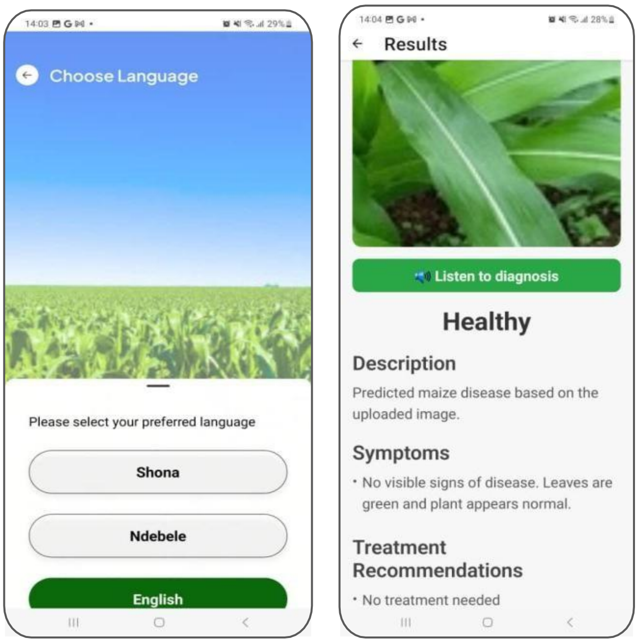


Figure 6 User Interface

Figure 6 shows the main screen of the mobile application. The mobile application features an intuitive interface designed for farmers with different levels of technical expertise. The main screen serves as the hub with clearly labeled buttons, the “Take a photo” button which initiates the diagnosis process, leading users to a capture screen where they can either take a new picture of their maize plant using their device's camera or select an existing image from their gallery. Once the image is ready, a "Diagnose" button triggers the analysis.



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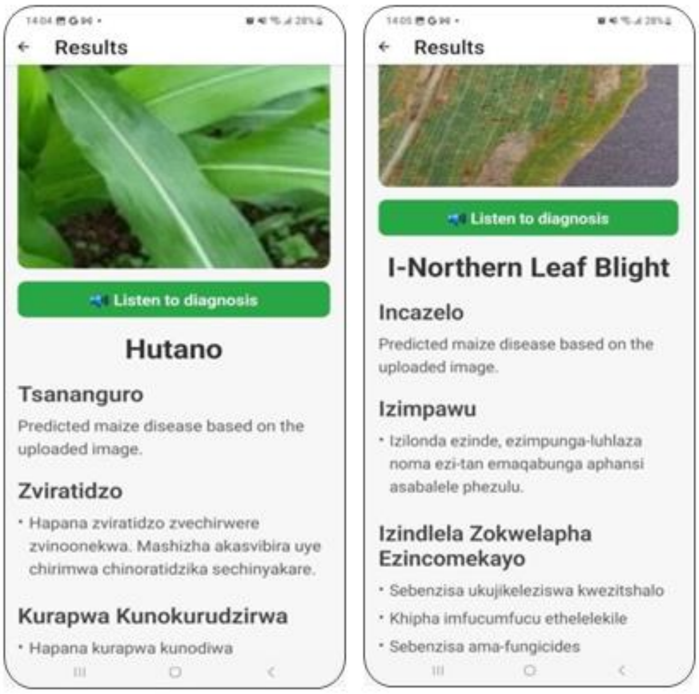

Figure 7 Syst eme Functionality

System testing was performed after integration testing to validate the entire application's functionality as shown in Figure 7. Tests were conducted on all major user journeys, such as registering a new user, logging in, diagnosing a crop disease using the camera, and viewing past diagnosis history. System testing also examined the end-to-end flow of translating diagnosis results into different languages and checking weather conditions. Performance was also monitored during this phase to ensure the application remained responsive under normal usage. The objective was to confirm that all features worked together smoothly and the application maintained data integrity, usability, and responsiveness.

DISCUSSIONS

The Implementation and Testing phase successfully transformed the project's theoretical framework into a functional system, ensuring alignment with the defined objectives. Through iterative coding, testing, and refactoring, the CNN model was trained and integrated into a React Native mobile application, achieving 88% validation accuracy.

Achievements of the system

1. Upload images of plants.
2. Classify the disease based on the image.
3. Provide information about the identified disease
4. Display solutions for the identified disease in English as well as Shona language.

The application has the ability to launch the phone camera and also load images from the gallery. Once the image is uploaded it is sent to the trained CNN model for classification. The CNN model is capable of classifying common diseases such as maize rust, leaf blight, and gray leaf spot using image processing and deep learning techniques. After the classification the model returns the name of the disease affecting the maize plant, and also the signs and symptoms. The system also returns the treatment recommendations of the disease and displays the symptoms and treatment recommendations in English, Shona and Ndebele languages. This is enabled through the use of Google translate API. The user, after loading the image clicks on the diagnose button.

CNN-based app with maize disease detection has a lot of advantages with regard to usability by small holder farmers who have limited technical skill. It has a user friendly interface where a farmer can simply capture an image of a maize leaf using their smartphone and the application immediately processes the images to detect any disease. This reduces the use of complex menus and typing or reading long texts and this makes using it easier even by a first time smart phone user. The app includes the use of local languages like Shona and Ndebele and this aids in increasing accessibility and ensures that the lack of understanding the local language is not a hindrance to accessing the results or the treatment plan instructions. The main screen serves as the central hub with three clearly labeled buttons, the “Take a photo” button (see Figure 6) which initiates the diagnosis process, leading users to a capture screen where they can either snap a new image of their maize plant using their devices’ camera or to select an existing image from their gallery. Once the image is ready, a "Diagnose" button triggers the analysis. The main screen also includes a "Pests and Disease" button that opens an educational section with detailed information about common maize pests and diseases, complete with visual examples and management strategies. Additionally, a "Cultivation Tips" button provides valuable agricultural guidance, offering best practices for planting, growing, and maintaining healthy maize crops.

Comparative analysis

The CNN model used for this mobile application achieved an accuracy rate of 92.4% whilst the diagnostic effectiveness of Plantix application was evaluated at 85% by (Akinyemi, et al., 2023), and, finally four pretrained models VGG16, ResNet50, InceptionV3 and Xception classified three common diseases of maize leaves from 18,888 images of both healthy and diseased leaves, achieving an accuracy rate of 72% (Dash & Sethy, 2023).

CONCLUSION

The maize plant disease detection system is a very useful tool to small holder farmers and various improvements can be made to it. Firstly the researcher recommends further training of the CNN model, to increase the accuracy of the model by additionally adding more diverse data reflecting varied environmental conditions, including different lighting angles, partial obstructions etc. Data can also be augmented to improve the model robustness and accuracy. Training the model on different plants such as millet, groundnuts and cotton, and other indigenous languages is another suggestion.

Furthermore, combining soil and meteorological data may result in a more complete disease prediction system. Future enhancements could include offline inference by embedding the CNN directly into the mobile app or cloud deployment for broader accessibility.

By facilitating early and precise disease identification, the maize plant disease detection system demonstrates how machine learning can revolutionise agricultural practices.

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