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Detection of Rust Disease in Maize Crop Using Image Processing Techniques

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Abstract— *The Maize Common Rust Disease Detection System using Image Processing Techniques is an innovative Android-based application designed to automatically detect the presence of maize rust disease in plants. This system utilizes image processing and machine learning techniques to identify the disease, providing farmers and agricultural experts with an accurate diagnosis in real-time. The application, built using Android Studio with Java, Kotlin, and TensorFlow Lite, leverages the camera to capture images of maize plants, processes these images, and predicts the disease with a specified accuracy rate. The system's model, trained using a dataset of rust infected and healthy maize plants, outputs the disease type and the confidence level of the prediction. The use of TensorFlow Lite allows for efficient on-device inference, making the system fast and accessible for rural farmers with limited internet connectivity. This project aims to improve the management of maize rust disease, offering an affordable and user-friendly solution for early detection and timely intervention. The implementation of this system holds significant promise for enhancing agricultural productivity by enabling farmers to take swift action against crop diseases, thereby reducing crop loss and improving overall yields.*

Keywords— *Maize Rust Disease, Image Processing, Disease Detection, TensorFlow Lite, Android Application, Machine Learning, Agricultural Productivity, Crop Management, Real-time Diagnosis.*

I. INTRODUCTION

With the advancement of computer vision and artificial intelligence (AI), new approaches to disease detection have emerged. Image processing techniques, in particular, have shown promise in identifying visual symptoms of plant diseases with high accuracy. By training machine learning models on images of diseased and healthy plants, systems can learn to classify and detect diseases automatically, often in real time (Zhao et al., 2021). This work presents the design and implementation of a mobile-based maize rust detection system using image processing and machine learning. The system leverages a pre-trained TensorFlow Lite model integrated into an Android application built with Java, Kotlin, and XML. The app enables users— especially farmers and agricultural extension workers—to take photos of maize leaves and instantly determine whether the plant is infected with common rust. By making disease detection mobile and automated, the system aims to empower users with a practical tool for improving crop health monitoring and boosting maize yield. Therefore, there is an urgent need for a lightweight, accurate, and user-friendly mobile solution capable of detecting maize rust at an early stage. Such a tool should empower farmers with real-time, on-the-go disease detection without requiring deep technical knowledge or internet connectivity. Bridging this gap between research and field application is the core problem this project seeks to address.

II. LITERATURE REVIEW

TensorFlow Lite (TFLite) is a framework designed for running machine learning models on mobile devices, including smartphones and embedded systems. Unlike the standard TensorFlow framework, TensorFlow Lite is optimized for low-latency inference and low-resource environments. This makes it ideal for mobile applications that need to deliver real-time performance without draining device resources. In agricultural applications, TensorFlow Lite can be used to deploy models for plant disease detection directly on smartphones. For example, once a maize common rust detection model is trained using a powerful desktop or cloudbased server, it can be converted into a TensorFlow Lite model and deployed on a mobile device. This allows farmers to capture images of plants using their smartphones and receive real-time disease diagnoses without needing an internet connection. The lightweight nature of TensorFlow Lite also ensures that the model can be used on a wide range of devices, including low-cost smartphones, which are more common in rural areas. This makes it easier to provide disease detection tools to farmers in remote locations, who may have limited access to the internet or high-performance computing resources. Machine learning and deep learning have transformed various industries, including agriculture. These technologies allow computers to identify complex patterns in large datasets, making them invaluable for detecting diseases in crops. In agriculture, ML and DL techniques are typically used to classify images, detect anomalies, and predict the health of crops. The primary types of machine learning models used in agricultural disease detection include decision trees, support vector machines, and convolutional neural networks (CNNs). CNNs, a type of deep learning algorithm, are particularly well-suited for image-based tasks due to their ability to automatically detect relevant features in images. In plant disease detection, CNNs can be trained to recognize patterns associated with specific diseases, such as rust spots, lesions, or discoloration on plant leaves. By using large datasets of annotated plant images, CNNs learn to distinguish between healthy and infected plants with high accuracy.

For instance, in their study on plant disease detection, He et al. (2019) demonstrated that CNNs outperformed traditional machine learning models in terms of accuracy and efficiency in classifying plant diseases from images. They showed that DL models could be trained on diverse datasets to handle variations in lighting, angles, and disease progression, making them robust for real-world applications. The use of TensorFlow Lite for

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deploying machine learning models on mobile devices has been explored in several studies. In a research project by Kumar et al. (2021), the authors successfully deployed a plant disease detection model on a mobile device using TensorFlow Lite. This research demonstrated the potential of TensorFlow Lite to run complex models on smartphones, providing real-time disease detection to farmers in rural areas with limited internet access.

III. Materials and Method

The materials and method used in designing the application, such as:

User Interface Design: The app is designed with a simple and intuitive interface that allows easy capture of plant images. This includes:

- Splash screen (briefly showing your logo or project title)
- Camera layout for image capture
- Display of disease name and accuracy percentage after image processing

Accuracy and Speed: The system needs to detect diseases in real-time with high accuracy. Therefore, an efficient model, such as TensorFlow Lite, is used to ensure the system can work seamlessly on mobile devices with limited resources.

Model Optimization: The model is trained in Python and converted to TensorFlow Lite (.tflite) format to run efficiently on Android using Java or Kotlin. This allows the app to run faster on mobile devices with less power consumption.

Integration with Camera: The app interacts with the Android device's camera to capture images in real-time. The captured image is processed locally, and the result is displayed instantly.

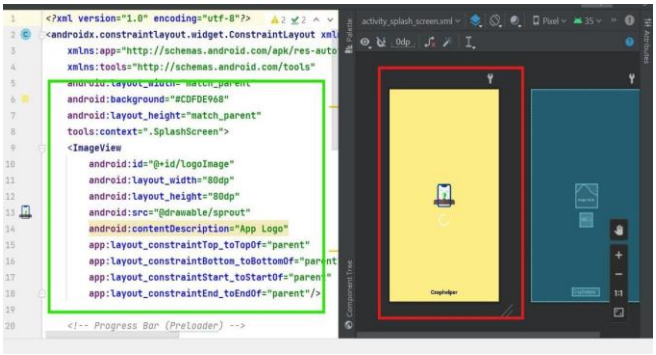

Fig.1: Splash screen Coding Interface

- Image Capture: Using Android's Camera API, the app captures an image of the plant/flower. The layout includes a button for capturing the image and a preview area for the camera feed.
- Model Inference: After the image is captured, it is sent to the TensorFlow Lite model (trained on a dataset of maize diseases) for inference. The model predicts the disease and provides a confidence score (accuracy percentage).
- Result Display: The detected disease name and accuracy are displayed on the screen for the user to see.
- Optimization: TensorFlow Lite is used to optimize the model for mobile devices, allowing efficient inference without overloading the device.

Data Preprocessing: Images are resized and normalized to meet the input requirements of the model (e.g., 224x224 pixels). Augmentation techniques may also be applied to enhance the dataset, such as rotation, flipping, and color adjustments.

TABLE 1: Dataset Summary

S/N	Category	Number of Images	Description
1	Healthy Maize	500	Images of healthy maize leaves for baseline comparison.
2	Common Rust	450	Images of maize leaves affected by the common rust disease.
3	Other Diseases	300	Images of maize leaves affected by other diseases (e.g., maize blight).
	Total Dataset	1300	Total number of images in the dataset.

To ensure smooth operation, here are the hardware requirements for running the app:

Device Specifications:

- Minimum RAM: 2GB
- Minimum Android Version: Android 5.0 (Lollipop)
- Processor: ARMv7 or ARMv8 (64-bit) or Qualcomm Snapdragon processor for optimized performance.
- Camera: Minimum 8 MP camera for better image quality (though lowerquality cameras can still be used).

Hardware Specifications

S/N	Specification	Minimum Requirement	Recommended Requirement
1	RAM	2 GB	4 GB
2	Android Version	Android 5.0 (Lollipop)	Android 8.0 (Oreo) or higher
3	Camera	5 MP or higher	8 MP or higher

IV. Results

- Coding Environment:
  - Android Studio: The app was developed using Android Studio, which provided the IDE and tools for building and testing the app on Android devices.
- Programming Languages: Java and Kotlin were used for the app's logic and interaction. XML was used for designing the user interface.
- TensorFlow Lite: The trained machine learning model was saved in *.tflite* format and integrated into the Android app for disease detection.

```kotlin
// Code snippet to trigger camera for image capture
val cameraIntent = Intent(MediaStore.ACTION_IMAGE_CAPTURE)
startActivityForResult(cameraIntent, CAMERA_REQUEST)

// OnActivityResult to handle captured image
override fun onActivityResult(requestCode: Int, resultCode: Int, data: Intent?)
    super.onActivityResult(requestCode, resultCode, data)
    if (requestCode == CAMERA_REQUEST && resultCode == Activity.RESULT_OK) {
        val imageBitmap = data?.extras?.get("data") as Bitmap
        // Process image for disease detection
    }
}
```

Fig: 2 Camera API Snippet

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- Android SDK/Camera API: Android's Camera2 API (or CameraX API) was utilized to capture real-time images for processing.

Codes Used and Simulation for Each Sub-System

- Camera Capture Sub-System: The camera sub-system captures real-time images of the plant. After capturing, the image is passed on to the disease detection sub-system for processing.

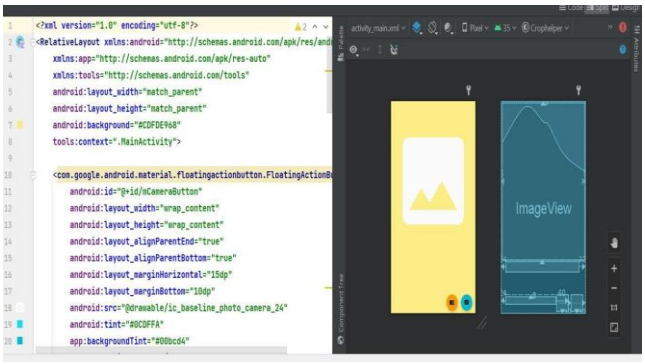

Fig: 3 Code Snippet (for Mainactivity)

- Model Inference Sub-System: The model inference sub-system uses TensorFlow Lite to load the pre-trained model and predict the disease in the captured image.

```
// Loading the model from assets
val tfliteModel = Interpreter(loadModelFile("model.tlite"))
// Preparing input image
val inputImage = preprocessImage(capturedImage)
// Running inference
val output = Array(1) { FloatArray(3) } // Assuming 3 classes for diseases
tfliteModel.run(inputImage, output)
```

Fig: 4. Code Snippet (for TensorFlow Lite Inference)

- Result Display Sub-System: The result display sub-system handles how the output of the inference is presented to the user. It shows the predicted disease and the accuracy score.

```
// Update the UI with the disease result and accuracy
resultTextView.text = "Detected Disease: $diseaseName\nAccuracy: $accuracy%"
```

Fig: 5 Code Snippet Example (Displaying result)

This section should present the actual results of your implementation. This includes:

- App's performance in terms of speed and reliability.
- Accuracy of the model in detecting diseases, including accuracy metrics like precision, recall, F1-score, etc.
- User Interface (UI): Showcase how the app looks and works by including screenshots of the app after it detects maize disease.

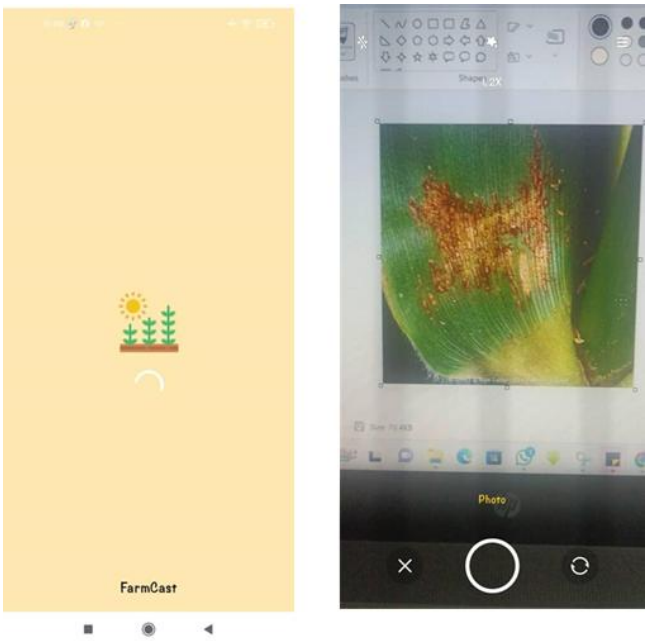

Fig: 4. Result Display I

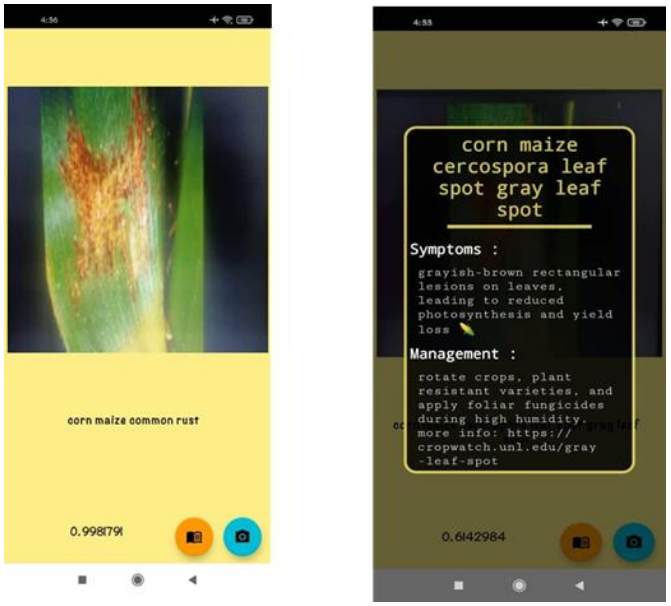

Fig: 5 Result Display II

V. Conclusion and Recommendation

The Maize Common Rust Detection System Using Image Processing Techniques" project has been successfully completed, demonstrating the potential of mobile technology in agricultural disease management. This project focused on developing an Android application capable of detecting maize common rust disease through image processing techniques. By leveraging machine learning models (TensorFlow Lite), the system analyzes images captured by the user via their smartphone camera to diagnose the disease and provide an accuracy measurement.

The system's implementation was based on a user-friendly interface, where after the splash screen, users were prompted to capture an image of the plant or flower suspected of carrying

the disease. The system then processed the image, identified the disease, and displayed the results, along with an accuracy value. This approach ensures that farmers can easily access a tool for early disease detection, contributing to more effective crop management.

The project successfully achieved its objectives of developing a disease detection system that is both accessible and reliable for maize farmers. The use of Android Studio, Java, Kotlin, and TensorFlow Lite has made the application lightweight and fast, which is crucial for its practical application in rural areas with limited access to powerful computing devices.

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