Research Proposal

Skill Development Project III - ICT 3206

Bachelor of Information and Communication Technology

(BICT)

Degree Programme

Department of Information and Communication

Technology Faculty of Technology

Rajarata University of Sri Lanka

Mihintale

Details of the Project

Project Title : Automated Potato Disease Detection Android Application

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Submission Date : 2023.10.13

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1 Introduction

Potato farming is a significant agricultural activity in Sri Lanka, contributing to the country's food security and economy. However, the potato crop is vulnerable to various diseases that can adversely affect yields and quality. Disease management is a crucial aspect of potato cultivation, and early detection plays a pivotal role in preventing the spread of these diseases. In recent years, the implementation of modern technologies and innovative solutions for potato disease detection has gained importance in Sri Lanka's agricultural sector.

Potato diseases in Sri Lanka are typically caused by various pathogens, including fungi, bacteria, and viruses. Some of the most common potato diseases in the region include late blight (Phytophthora infestans), early blight (Alternaria solani), bacterial wilt (Ralstonia solanacearum), and potato virus Y (PVY). These diseases can lead to substantial yield losses if left unmanaged, impacting both smallscale and commercial potato farmers across the country.

To combat these issues, researchers, agricultural experts, and farmers in Sri Lanka have been actively exploring technological solutions for early disease detection. These technologies include the use of remote sensing, machine learning, and mobile applications to identify and monitor disease symptoms in potato crops. By integrating these advanced tools with traditional agricultural practices, Sri Lanka is striving to improve its potato disease management and enhance crop resilience.

Efforts to detect and manage potato diseases in Sri Lanka also involve raising awareness among farmers about disease symptoms and preventive measures. This introduction highlights the importance of potato disease detection in Sri Lanka, as well as the ongoing efforts to integrate technology and knowledge transfer to enhance disease management practices and sustain potato cultivation in the country.

2 Problem Statement

The disease known as potato blight, caused by the fungus Phytophthora infectants, poses a significant threat to global potato production due to its destructive and economically disastrous nature. Effective disease management relies on the prompt and accurate identification of this fungus. However, traditional identification methods are often costly, time-consuming, and may lack the necessary accuracy for effective treatment. Moreover, the rapid evolution of more aggressive pathogen strains has exacerbated the problem.

3 Aim

The aim of Automated Potato Disease Detection web-based System is to quickly and accurately identify late blight in potato crops using image processing technology & the system enables early detection of the disease's symptoms & allowing farmers to implement timely control measures and minimize crop damage.

4 Objectives.

- ✓ To Provide a User-Friendly Interface for Easy Access and Navigation, offering information on potato diseases and disorders in an easily accessible format.
- ✓ To identify the existing system and identify its weaknesses-Data collection: use ready-made data from kaggle.
- ✓ To train that data set-Build to CNN (Model building)
- ✓ To connection between both side and access that data-develop a fast api server around that model.
- ✓ To deployment the production -will have develop a working http server
- ✓ To fast access and edit-deploy the Model in Google cloud and GCP
- ✓ To handle all the component of that system by the user-build a web interface where we can drag and drop an image and get result

5 Preliminary Literature Review

The powerful recognition and classification capabilities of CNNs, which work by extracting low-level complex information from images, have attracted significant attention. CNNs are preferred to earlier approaches for automatically recognizing plant diseases due to their higher performance of CNNs. The CNN-based predictive model described by Sharma et al. [2] can be used to classify paddy plants by applying image processing to the associated images. Asritha et al. also used a CNN in their research to identify diseases in rice paddies. The classification of plants often requires between four and six layers of CNNs to be used by scientists. Mohanty et al. [1] accomplished the classification of plant illnesses, and their identification and segmentation, by employing a CNN trained with a transfer learning methodology. CNNs have been applied to a broad range of investigations, and improved outcomes have been reported in some cases; however, the datasets used in these studies were not truly diverse. Narayanan et al. suggested the use of a hybrid CNN to identify the many diseases that can harm banana trees. [3] They coupled a fusion SVM with a CNN and used a median filter to maintain the standard image dimensions without adjusting the default settings of the raw input image. Jadhav et al proposed the use of a CNN that had previously been trained to spot illnesses in soybean plants as a means of detecting and identifying plant diseases. However, despite the better results, the model was inadequate in terms of the variety of illnesses it could categorize. Jadhav et al. improved the performance of DL models by first proposing a novel histogram modification technique for synthesizing synthetic picture samples from low-quality test-set images. [4] Following in the footsteps of Olusola et al., Abbas et al. developed a conditional generative adversarial network to construct a library of synthetic pictures of the leaves of tomato plants. In the past, capturing or collecting data in real-time was not viable owing to the high costs involved, the scarcity of resources, or both. Today, however, real-time data capture and collection are becoming more practical.For example, Anh et al. [5] presented a multi-leaf classification model that was based on a benchmark dataset using a pretrained MobileNet CNN model, which they found to be excellent for classification, with an accuracy of 96.58%. [6] In addition, a multilabel CNN was described for the classification of numerous plant diseases based on transfer learning approaches, such as DenseNet, Inception, Xception, ResNet, VGG, and MobileNet.The authors of this study claimed that they were the first to use a multi-label CNN to categorize 28 distinct illnesses that may affect plants. In the context of the article, an ensemble classifier was proposed as a method for categorizing the diverse illnesses that can affect plants. PlantVillage and Taiwan Tomato Leaves were used in the evaluation process to determine which ensemble classifier performed best.The EfficientNet model, which uses a CNN, was developed by

Pradeep et al. [2] to categorize several labels simultaneously. They determined that CNN's hidden layer network was superior in its ability to detect plant diseases. However, when compared to industry norms, the model did not measure up. The authors of offered a loss-fused, resilient CNN that achieved a classification accuracy of 98.93% based on the freely available PlantVillage benchmark dataset. Later, Enkvetchakul and Surinta introduced a CNN network that used a transfer learning technique to diagnose two plant diseases. Abade et al. evaluated CNN algorithms for the identification of plant diseases. The reviewers considered 121 articles published between 2010 and 2019, concluding that TensorFlow was the most commonly used framework, and PlantVillage was the most widely used dataset. Dhaka et al. provided an overview of the principles underpinning the use of CNN models to identify diseases in leaf samples and examined a selection of CNN models, pre-processing techniques, and foundational frameworks. Another group of researchers, Nagaraju et al., analyzed and discussed the best datasets, pre-processing methodologies, and DL algorithms for a variety of plants. According to Kamilaris et al., DL approaches have the potential to solve multiple issues that arise in the agricultural sector. [7] According to their findings, DL methods performed significantly better than more traditional approaches to image processing. Fernandez Quintanilla et al. conducted research to evaluate weed monitoring systems for agricultural crops. They focused on ground-based and remotesensing weed monitoring in agricultural areas and concluded that monitoring is necessary for the effective management of weeds. They anticipated that the data obtained by many sensors would be kept in the cloud and used effectively. Lu et al. conducted a review and showed for the first time that plant diseases could be classified through the application of a CNN. Golhani et al. [7] wrote a review article about the use of hyperspectral data for identifying plant leaf diseases. They reviewed the status of the field, its potential future applications, and NN techniques for accelerating SDI development, Bangari et al. zeroed in on potato blight as the illness of interest. After reviewing the relevant research, the researchers concluded that CNNs are more effective than other methods of disease detection. In addition, they discovered that CNNs performed a significant role in achieving maximum accuracy in disease identification. Iqbal et al. implemented various ML algorithms using 450 potato leaf images from the PlantVillage dataset. They declared that the random forest (RF) algorithm outperformed the other algorithms. Singh et al. used 300 potato leaf images from the PlantVillage dataset and divided them into three equal classes: early blight, late blight, and healthy. The authors used GLCM to extract the features of dataset images and used these features to classify potato blight using an SVM with an overall accuracy of 96%. Islam et al. [6] segmented potato leaf images extracted from the PlantVillage dataset and used the threshold method to segment the regions of interest (RoI) in the images. They then used the segmented images to train the model using the SVM method and achieved 95% accuracy with 300 samples. Chakraborty et al., using potato leaf images from the PlantVillage dataset, implemented and compared the performance of ResNet 50, VGG 16, MobileNet, and VGG 19 for potato blight classification. The VGG 19 architecture achieved the highest accuracy, at 92.69%. The authors then fine-tuned the VGG 19 architecture and achieved an accuracy of 97.89%. Mahum et al. added extra layers to DenseNet architecture and evaluated the performance of the model by classifying potato blight using potato images from the PlantVillage dataset. [8] The modified DenseNet model achieved a high accuracy of 97.2% compared to the basic DenseNet architecture.

6 Methodology

1. Problem Definition and Objective Setting

- ✓ Define the problem of effectively detecting potato diseases to minimize crop loss.
- ✓ Set specific objectives, including the development of an automated and accurate disease detection system.

2. Literature Review

- ✓ Research existing automated disease detection systems, agricultural image analysis techniques, and machine learning in agriculture.
- ✓ Analyse case studies and best practices in disease detection for insights and potential challenges.

3. Requirement Analysis

- ✓ Engage with stakeholders, including farmers and agricultural experts, to gather system requirements.
- ✓ Document functional and non-functional requirements for the disease detection system.

4. System Design

- ✓ Design the system's architecture, specifying components and their interactions.
- ✓ Define the roles and responsibilities within the system.
- ✓ Plan the integration of machine learning models and image processing techniques.

5. Machine Learning Model Development

- ✓ Train machine learning models on a diverse dataset of potato crop images.
- ✓ Develop models for identifying various potato diseases accurately.
- ✓ Implement real-time disease monitoring features.

6. Frontend Development (Javascript)

- ✓ Design user interfaces for farmers and system administrators.
- ✓ Incorporate image upload and analysis functionalities into the user interface.

7. Backend Development - python(TF serving and Fast API.)

- ✓ Develop API routes for interaction with the machine learning model.
- ✓ Create RESTful APIs to facilitate communication between the frontend and backend components.
- ✓ Implement user management and data handling features.

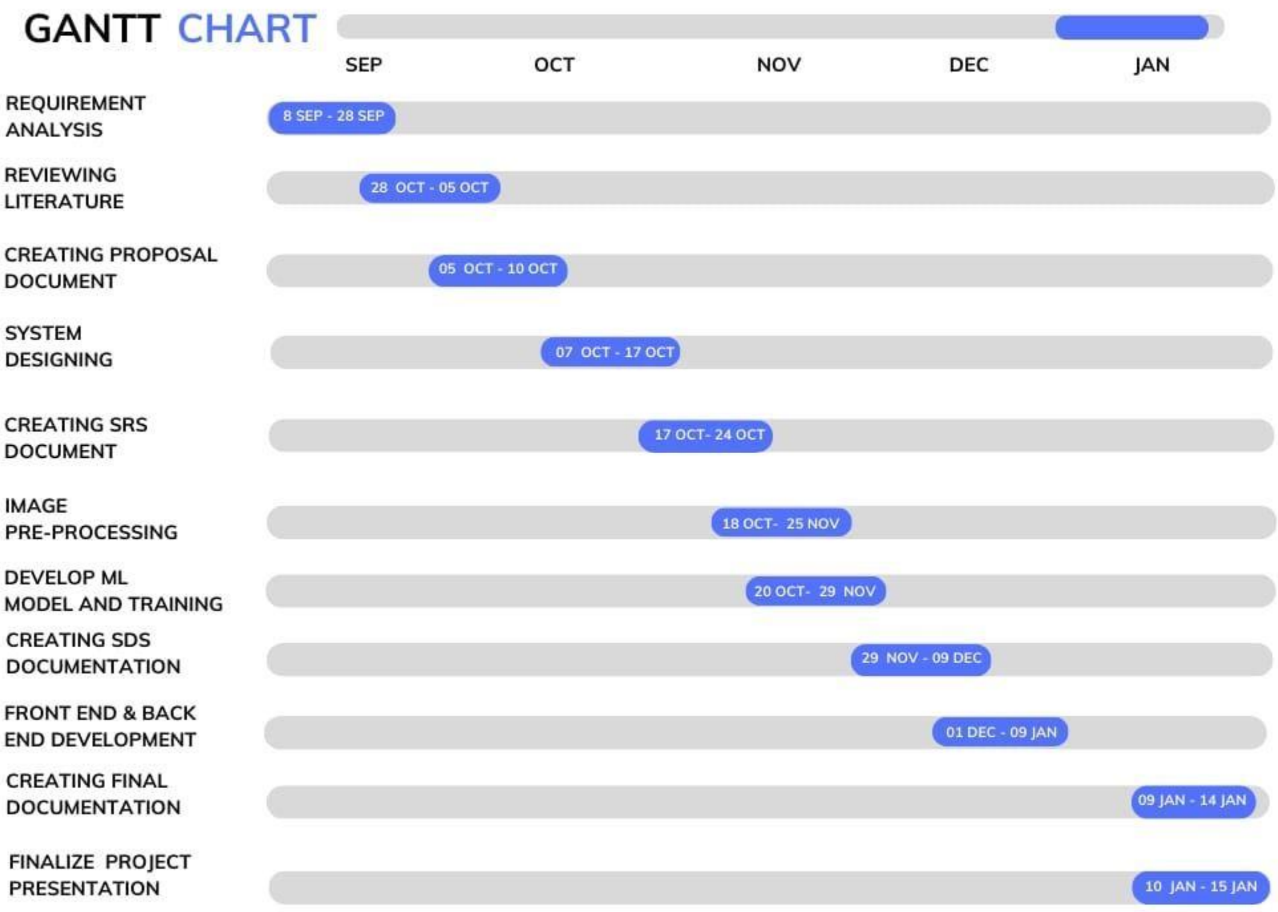
8. Testing and Optimization

- ✓ Conduct comprehensive testing, including model evaluation, user testing, and security assessments.
- ✓ Optimize the system for scalability and performance.

9. Documentation

- ✓ Maintain detailed documentation, including architecture diagrams, code documentation, and user manuals for the disease detection system.
- ✓ This project plan outlines the key stages and activities involved in the development of an Automated Potato Disease Detection System, mirroring the structure of your example project plan

7 Project Gantt chart



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