Corn Pests and Diseases Identification Using Deep Learning

Abstract— **In Sri Lanka, plant diseases and pests significantly impact crop production, leading to substantial economic losses. Traditionally, these issues have been identified through manual observations, which have several limitations, such as the inability to detect problems early, misdiagnoses, and delayed treatment. Additionally, the high cost of hiring experts poses a significant challenge. To address these challenges, we developed a mobile application specifically designed to identify diseases and pests in corn, a vital crop in Sri Lankan agriculture. The application not only classifies and identifies issues but also offers tips and recommendations for treatment. A Deep Learning Convolutional Neural Network (CNN) has been utilized for image recognition model, which was trained multiple times across various datasets and fine-tuned the hyperparameters to optimize performance. The model with the highest accuracy was selected as the final solution and integrated into the developed Flutter mobile application. This system is intended to assist a broad spectrum of users, from farmers to agricultural researchers, in effectively managing crop health.**

Keywords—corn disease and pest identification, deep learning, leaf diseases, corn diseases and pests in Sri Lanka, Deep Learning for corn disease and pest identification

I. INTRODUCTION

As a country renowned for its historical prosperity and self-sufficiency, Sri Lanka's economy has long been reliant on agriculture, a tradition that persists to this day.

However, the agricultural sector faces persistent challenges, particularly from diseases and pests that inflict significant losses on crops [1] These adversaries disrupt essential processes such as photosynthesis, water transport, reproduction (including pollination and fertilization), and the early stages of growth (germination) [2]

These agricultural ailments stem from various sources, including pathogens, fungi, bacteria, and viruses. The impact of these diseases underscores the importance of proactive measures and innovative solutions to safeguard crop yields and ensure the continued prosperity of Sri Lanka's agricultural sector.

In practice, the conventional method for identifying and detecting diseases and pests in Sri Lanka has been through visual inspection by experts using the naked eye. Researchers have identified certain drawbacks associated with the traditional approach, which are outlined as follows [2]

- Traditional methods often involve manual observations, which can be time-consuming.
- Furthermore, to identify diseases and pests at an early stage is impossible, as it requires continuous monitoring of the fields by the farmers.
- Farmers may miss crucial signs of disease or pest infestation, leading to misdiagnosis or delayed treatment.
- Most Farmers consult agricultural experts to properly diagnose the issue and to receive proper guidance to cure the plants from the afflicted disease or pest, which in terms is a costly approach.

To address the challenges posed by the traditional approach, we implemented a mobile application for plant disease and pest detection using deep learning, that also recommends and guides the farmer with accurate and efficient methods to cure the plant from the affected disease or the infected pest. The system is a more effective solution to identify pests and diseases early, so that the affected plants can be cured early before they spread to the other plants.

In this research, the primary focus is on corn, an important crop in Sri Lankan agriculture, which experiences a rapid growth in production according to the World Data Atlas. The implemented system only focuses on few diseases and pests that are common in Sri Lankan corn cultivation, such as Northern Corn Leaf Blight, Common Rust, Gray Leaf Spot, Fall Armyworm and Corn Weevil [3]

We hope the deployment of this application will help farmers to gain economic benefits as early identification and curing of diseases and pests can help them prevent economic losses incurred due to diseases and pests.

II. RELATED WORK

A. Similar Projects done at the International Level.

Several Research were done across the globe on computer-based plant disease and pest identification using image-processing techniques, machine learning and deep learning.

One Research done in China built an Internet of Things platform in the complex environment of mountainous areas and carried out research on the CNN (Convolutional Neural Network) model on identification of crop diseases and infested pests [4]

One Research paper published in *IOSR Journal of Computer Engineering (IOSR-JCE) in 2014* [2], provides a comprehensive review of image processing techniques employed in the identification of plant diseases across various plant species. According to the paper, the key classifiers used in disease detection include Backpropagation Neural Network (BPNN), Support Vector Machine (SVM), K-means clustering, and Stochastic Gradient Descent Method (SGDM).

Another research done by [5], conducts a comprehensive review on classification techniques exclusively applied to plant disease identification, emphasizing the criticality of early detection in safeguarding crop quality and yield. The findings underscore that deep learning exhibits superior accuracy compared to conventional techniques, showcasing its potential as a robust tool for plant disease identification.

A study done in India, used SVM classifier to identify diseases in banana plants based on the images of diseased banana plants, which has around 98% accuracy [6]

Another research done in India uses K-Means Clustering Algorithm for disease classification, and they achieved an accuracy of 70% [7]

[8] addresses the longstanding challenge of crop diseases impacting production by introducing a modern approach to disease identification. The proposed method employs Decision Trees and deep learning models, significantly improving accuracy with a 28.5% boost in Decision Trees and achieving a 97.2% accuracy for Convolutional Neural Networks (CNN).

B. *Similar Projects done in Sri Lanka.*

In addition to research efforts in other countries, Sri Lanka has also conducted various research on plant disease identification using computerized methods.

A Research conducted by [9], aims to develop an image recognition system for identifying paddy diseases, focusing on Rice blast, Rice sheath blight, and Brown spot commonly found in Sri Lanka. Here the nearest neighbor algorithm had been used for image classification.

Another research conducted by [10], uses Transfer Learning for disease identification of leafy vegetables (Gotukola and Mukunuwenna). Here the developed model uses CNN for image classification and has a training accuracy of 0.95 and validation accuracy of 0.86.

Another study by [11], focuses on developing an efficient model for the accurate classification of tomato diseases, leveraging computer vision techniques. Various deep learning architectures, including CNNs built from scratch and fine-tuned VGG16, Inceptionv3, and MobileNet models, were trained and tested on tomato leaf images collected from the internet. The proposed CNN model achieved a notable accuracy of 90%, while fine-tuned models demonstrated even higher accuracies, with VGG16, MobileNet, and Inceptionv3 achieving average accuracies of 94%, 97%, and 95% respectively.

III. METHODOLOGY

A. *System Architecture*

The system architecture defines the high-level structure and components of the developed plant disease and pest identification system. The system consists of four major modules.

1. Image Recognition Model - Processes uploaded images to identify plant diseases and pests.
2. Mobile App - Frontend interface for users to capture and upload images as well as to view the classification results.
3. Backend API - Acts as a bridge between the mobile app and the image recognition model.
4. Backend Database - Stores information related to plant diseases, pests, and cure tips. Enables efficient data retrieval for the mobile app.

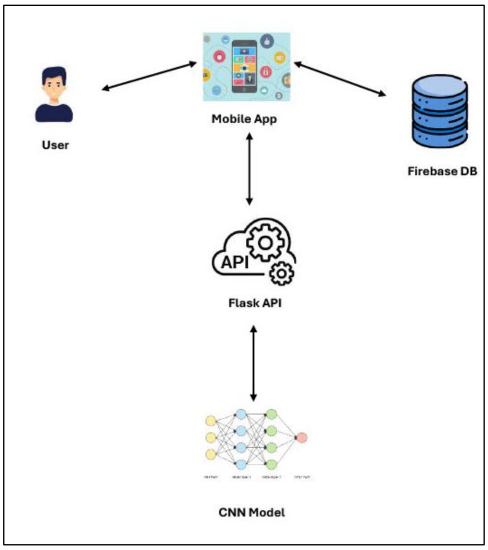

Figure 1 Graphical illustration of the System Architecture

B. *Dataset Collection and Image Preprocessing*

A customized dataset was created based on research requirements, carefully merging several datasets that were publicly available on the internet and images taken from google. The datasets used are: the Kaggle Corn Disease dataset and the Dataset for Crop Pest and Disease Detection from https://data.mendeley.com/datasets/bwh3zbpkpv/1.

The customized dataset was created by selecting only images of diseases and pests affecting corn plantations in Sri Lanka, based on information from the official website of the Agricultural Department of Sri Lanka [3].

Furthermore, image augmentation has been used to multiply the number of images in each category. The final customized dataset contains:

1. 1146 images(non-augmented) of Northern Corn Leaf Blight.
2. 1306 images(non-augmented) of Common Rust.
3. 1121 images (augmented and non-augmented) of Fall Armyworm.
4. 1148 images(non-augmented) of Gray Leaf Spot.
5. 1162 images(non-augmented) of Healthy Leaves.
6. 1182 images (augmented and non-augmented) of Maize Weevil.

Figure 2 Non-augmented image of leaf blight

Figure 3 Augmented image of fall armyworm

C. Model Creation and Training.

Deep Learning CNN (Convolutional Neural Network) has been selected as the model to successfully identify diseases or pests through a leaf image.

This decision was based on their demonstrated superiority in accuracy compared to alternative machine learning models like Support Vector Machines (SVM) or Artificial Neural Networks (ANN), particularly in the context of image classification tasks. One of the key advantages of CNNs lies in their ability to automatically extract relevant features from raw pixel data, alleviating the need for manual feature engineering. Although CNNs typically require a larger dataset for training, their automatic feature extraction capabilities contribute to their effectiveness in image classification tasks, making them a suitable choice for the project [5].

TensorFlow and Keras were used here for model creation, training, and evaluation. The created CNN model contains the following hyperparameter values:

- Number of Convolutional Layers: 3
- Number of Pooling Layers: 3
- Number of Fully connected Layers: 3
- Number of filters: 32, 64, 128
- Kernel Size: 3x3
- Activation Function (In convolutional layers): ReLu
- Pooling Type: Max Pooling
- Pooling Size: 2x2
- Number of neurons in Fully connected layers: 1024, 256, 6
- Activation Function (In fully connected layers): ReLu & Softmax
- Cost Function: Categorical Crossentropy
- Number of Epochs: 8
- Optimizer: Adam

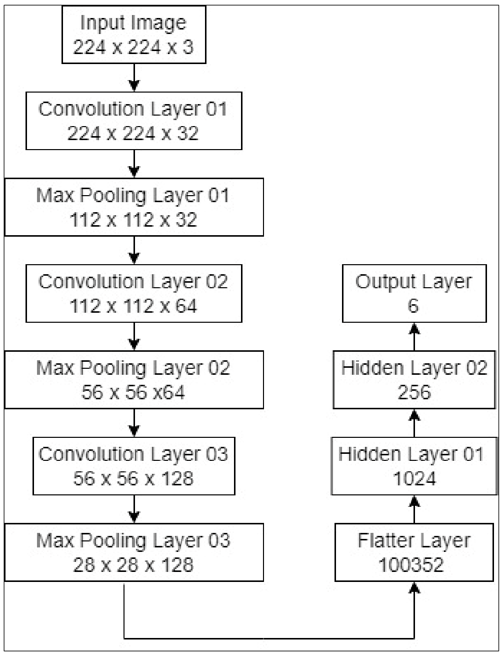

Figure 4 Implemented CNN Model Architecture

D. Mobile Application Development.

The mobile application serves as the intermediate between the system users and the trained CNN model. The app was developed using the Dart programming language, with the Flutter framework for cross-platform compatibility and efficient development. Dart and Flutter were chosen for their unique advantages in mobile app development.

Flutter's cross-platform compatibility ensured that the app could be deployed seamlessly on both Android and iOS platforms, minimizing development efforts.

The Flutter mobile application communicates with the Flask server via the HTTPS protocol. The captured image is sent from the mobile application to the Flask API, which returns the classification result. The application then fetches relevant treatment tips from the Firestore database for the identified disease or pest and displays them on the user interface. This allows the user to view the predicted condition of the corn leaf whether it is healthy or afflicted with a disease or pest and if so the appropriate treatment tips for the plant.

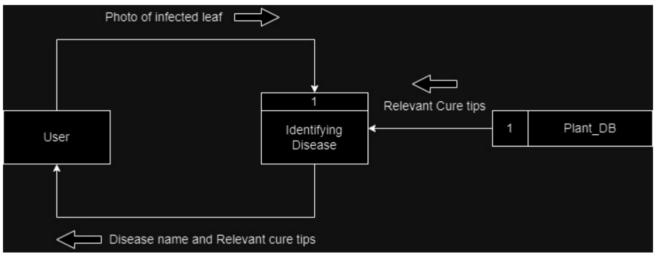

Figure 5 DFD diagram depicting the data flow between the mobile app and the firestore database

Featuring three primary screens: Home Page, Upload Image Page, and Information Page, the application aims to provide a user-friendly experience while connecting with the model through the Flask API for disease and pest identification.

Figure 6 Screenshots of the mobile application's User Interfaces (UIs)

E. Backend API Development.

The Flask framework serves as the foundation for the API designed to manage image submissions originating from the mobile application for disease and pest classification. Upon receiving an image, the API conducts preprocessing operations to optimize the image for classification purposes. Leveraging the capabilities of the loaded CNN model, the API proceeds to identify the specific disease or pest depicted in the image. Subsequently, the classification result is formatted into JSON and seamlessly transmitted back to the mobile application.

F. Backend Database Creation and Integration.

We have developed a Firestore database to store comprehensive information regarding cure topics, sample images, descriptions, and names for each disease and pest. This database serves as a centralized repository, facilitating efficient access and retrieval of relevant information necessary for disease and pest identification and management.

Each document in the Firestore database contains the following fields:

- Name: The name of the disease or pest.
- Description: A detailed description providing information about the characteristics, symptoms, and potential impacts of the disease or pest.
- Sample Image: Representative images showcasing visual cues and manifestations associated with the disease or pest.
- Cure Tips: Information regarding recommended treatments, control measures, and preventive strategies to mitigate the effects of the disease or pest.

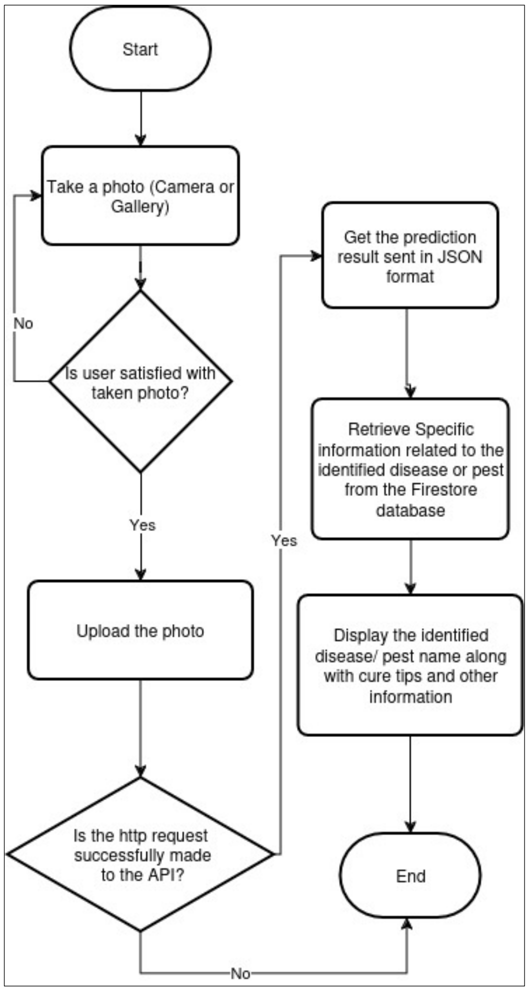

Figure 7 Flowchart diagram of the system

IV. RESULTS AND DISCUSSION

The final trained model was evaluated and achieved the following results:

- Training Accuracy: 0.97
- Validation Accuracy: 0.84
- Total Parameters: 103118662
- Training Loss: 0.07
- Validation Loss: 0.69

The model was trained in total of 8 epochs. And the following graphs depicts how the training accuracy, training loss, validation accuracy and validation loss change with the number of epochs.

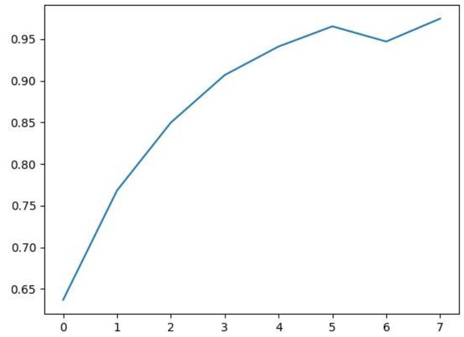

Figure 8 Matplotlib graph depicting how Training Accuracy changes with the number of epochs.

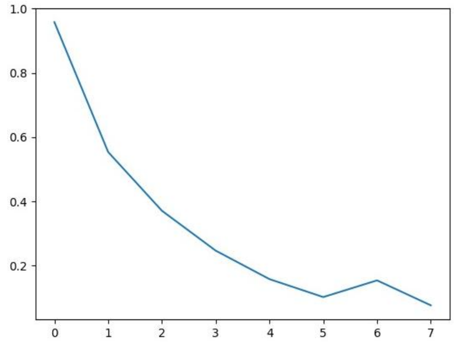

Figure 9 Matplotlib graph depicting how Training Loss changes with the number of epochs.

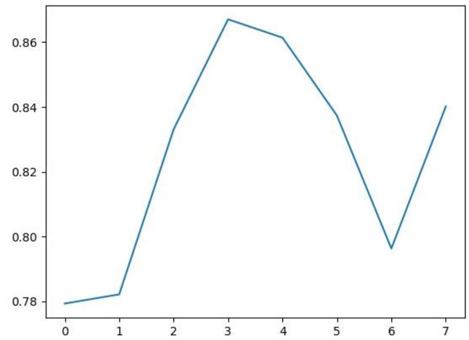

Figure 10 Matplotlib graph depicting how Validation Accuracy changes with the number of epochs

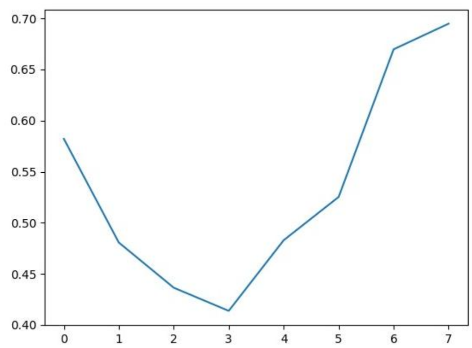

Figure 11 Matplotlib graph depicting how Validation Loss changes with the number of epochs.

The system underwent extensive testing, including unit and integration. Carefully designed test cases were used to ensure thorough coverage, and any bugs discovered along the way were promptly addressed and resolved.

After fixing the bugs, a full system testing was conducted to test the system's overall functionality. During this overall system testing, it was noted that the Flutter mobile application successfully enabled users to select an image from either the camera or gallery and transmitted the image to the Flask server. The Flask server, running a pre-trained CNN model, accurately processed the received image. The classification result was then sent back to the mobile application in JSON format. The mobile application successfully retrieved relevant treatment tips and additional information from the Firestore database for the identified disease or pest and displayed them on the user interface.

This outcome confirms that the developed system not only functions as intended but also provides accurate and reliable results, validating its effectiveness.

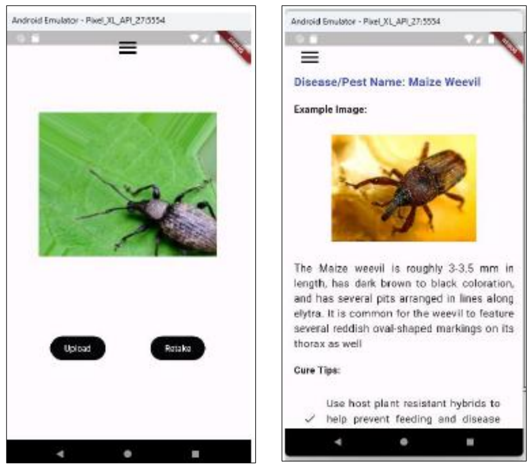

Figure 12 Two screenshots of the mobile application depicting how the system successfully identifies the disease or pest from the selected image and displays the identified disease or pest details along with cure tips.

Compared to previous research [4] [5] [8] [10] [11], the developed model achieved lower validation accuracy, even though it was trained using CNN. This may be due to the small dataset size.

Additionally, most prior research has primarily focused on diseases, while the model implemented in this study is capable of detecting both diseases and pests.

Unlike previous studies in Sri Lanka [9] [10] [11], which have concentrated on crops like rice and tea, this research focuses on corn, making it unique.

Furthermore, the trained model is fully integrated with the developed Flutter mobile application—a feature not covered in previous research. After identifying the disease or pest, the mobile app retrieves relevant treatment tips from the Firestore database, another unique feature that has not been discussed in earlier work.

V. FUTURE WORK

The developed system has delivered a promising solution, albeit with a few limitations that pave the way for future enhancements. Firstly, the validation accuracy of 84% may be insufficient for practical plant disease and pest detection applications. To address this, we aim to bolster accuracy and data integrity by curating a larger, more comprehensive dataset. At present, the model is specialized in identifying only a limited number of diseases and pests in corn. However, we envision expanding the project's scope to encompass various diseases and pests across multiple crops. Improving user-friendliness and experience within the mobile application is paramount. While the current system is user-friendly, additional features such as Sinhala language support and a feedback mechanism can enhance user engagement and satisfaction. The limitation of hosting the Flask server locally necessitates transitioning to a cloud platform for improved scalability and accessibility. Finally, integrating the system with IoT devices holds immense potential for real-time monitoring of plants for diseases and pests.

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