A TensorFlow-Based CNN Model for Widespread Detection of Rice and Potato Leaf Diseases

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Abstract

Rice and potatoes are major crops in Bangladesh, frequently affected by major disease outbreaks that challenge food security. Inaccurate disease identification often contributes to yield losses. Recently, machine learning garnered much attention in identifying crop diseases. The present study was conducted to develop a deep learning model-based image-analysis system that automatically identifies key diseases of Bangladeshi rice and potato, and integrates it into a web app to provide farmers with rapid, accurate diagnoses. The system employs a convolutional neural network (CNN) implemented with TensorFlow's Sequential API, featuring ReLU-activated hidden layers and a Softmax output layer. A dataset of 4,809 images, comprising both healthy and diseased, was collected and processed through pre-processing, feature extraction, and classification. A web-based application was deployed utilizing the Python Streamlit framework. This application integrates the proposed model to predict 2 rice diseases viz. blast (*Magnaporthe oryzae*), bacterial leaf blight (*Xanthomonas campestris*), and 2 potato diseases viz. Early blight *(Alternaria solani) and* Late blight (*Phytophthora infestans*) from uploaded images, providing a confidence score for the predictions with approximately 92.84% for all detected diseases. The proposed model achieved a training accuracy of 0.9357, a validation accuracy of 0.8983, and a test accuracy of 0.9333. The developed web application indicates strong diagnostic performance for four major diseases, offering Bangladeshi farmers an accessible tool to make timely management decisions.

Keywords: deep learning; TensorFlow; CNN; crop disease; disease detection

Introduction

Bangladesh's economy and food system rely heavily on agriculture, nearly two-fifths of the national workforce is employed in agriculture, and the sector still contributes close to 20 % of gross domestic product (World Bank, 2020; Bangladesh Finance Bureau, 2014). Rice and potato are major staple crops in Bangladesh, cultivated year-round across most agro-ecological zones. Bangladesh is the world's third-largest producer of rice, seventh in global potato production (Rahim *et al*., 2023). However, frequent extreme-weather events, soil degradation, and a shortage in water supplies are shaking the resilience of food systems and pushing millions into food insecurity. These pressures are compounded by the growing prevalence of insect pests, plant diseases, and weed infestations (Nasif *et al.,* 2024).

Among the biotic stresses that threaten staple-crop production, plant diseases are particularly damaging. In rice, blast (*Magnaporthe oryzae*) and bacterial leaf blight/spot (*Xanthomonas oryzae* pathovars) can reduce yields by up to 70 % in favorable environments, attacking foliage, collars, panicles, and grains at every growth stage (Simkhada & Thapa, 2022; Naqvi, 2019; Chakrabarti, 2001). In potatoes, early blight (*Alternaria solani*) deteriorates foliage integrity and tuber quality, while late blight (*Phytophthora infestans*) can destroy entire fields within a few days under humid conditions (van der Waals, 2001; Tiwari, 2021). Considering the rapid spreading nature of these pathogens, early and accurate identification is essential.

Rural agricultural diagnostics in developing countries, including Bangladesh, traditionally involve visual inspection by extension officers or farmers. This process is slow, labor-intensive, costly for large farms, and can result in mis-identification (Al-Hiary *et al*., 2011, Bai *et al.,* 2018). Recent advances in convolutional neural networks (CNNs), combined with prevalent smartphone cameras and cloud connectivity, create an opportunity to replace subjective field scouting with rapid, image-based diagnosis (Panpatte, 2018; Yang & Guo, 2017). When deep learning models are pre-trained on huge image datasets can be fine-tuned to detect even faint lesion patterns, allowing for quick on-site predictions that allow for immediate intervention (Kussul *et al*., 2017; Yalcin, 2017; Kamilaris and Prenafeta-Boldú, 2018). For example, Mohanty *et al.* (Mohanty *et al.,* 2016) trained a deep learning model for recognizing 14 crop species and 26 crop diseases. To detect four cucumber diseases, downy mildew, anthracnose, powdery mildew, and target leaf spots, Ma et al. (Ma *et al*., 2018) used a deep CNN, based on their symptoms. (Kawasaki *et al*., 2015) developed a CNN-driven system for recognizing cucumber leaf disease, reporting an accuracy of 94.9%, etc. Despite promising findings in the literature, existing investigations are often limited by the diversity of their image databases. The majority of photographic materials include images exclusively taken in experimental (laboratory) settings, rather than depicting genuine field scenarios. Importantly, images collected in actual cultivation fields inherently include diverse backgrounds and a wide array of symptom characteristics (Barbedo, 2018). Most of the previous studies collected datasets online, mostly from Plant Village datasets (Mohameth *et al.,* 2020; Falaschetti *et al*., 2022; Aldakheel *et al.,* 2024). In current study, the photographs included were taken in both actual field condition and laboratory setups.

In this paper, a Streamlit UI web-based application is developed using an ML-based model to detect these plant diseases. The application has a straightforward, user-friendly interface. Based on the TensorFlow model, which is integrated into the application, the application makes predictions about the diseases. For the model preparation, CNN-based image classification APIs are used. Using this application, farmers can identify the disease early, allowing assistance in taking preventive measures.

In order to validate methodology, the majority of the studies mentioned in Table 1 used either their own datasets or publicly accessible datasets. Proposed method is validated using both of them. In addition, this current study has more observations overall than the other studies listed in the table. Despite these facts, proposed model's effectiveness in detecting rice and potato diseases is comparable to that of some other models. The minor differences in detection accuracy, with the researchers in this table performing slightly better, is understandable because their dataset was limited to just one disease. Given the strength of its datasets, real-time detection capability, and precise accuracy, proposed model is therefore slightly superior compared to existing methods for identifying potato and rice leaf diseases found in the literature.

Table 1 Cross-study performance benchmarking of Rice and Potato disease detection models

Researchers	Methods	Dataset source	Image acquisition device	Sample size	Accuracy (%)

Zhou *et al.* (2019)	FCM-KM and Faster R-CNN fusion	Rice field of the Hunan Rice Research Institute, China	Canon EOS R (pixel: 2,400 * 1,600)	3,010	Rice blast: 96.71% Bacterial blight: 97.53% Blight: 98.26%
Ramesh & Vydeki (2020)	DNN-JOA (Optimized)	Farm field	High-resolution digital camera	650	Rice blast: 98.9% Bacterial blight: 95.78% Brown spot: 94% Sheath rot: 92% Normal leaf: 90.57%
Prajapati, Shah & Dabhi (2017)	SVM	Farm field	12.3MP Nikon D90 DSLR	120	Training Accuracy: 93.33% Testing Accuracy: 73.33% Cross-validation: 5-fold: 83.80% 10-fold: 88.57%
Rathore & Prasad (2020)	CNN	Kaggle dataset	–	1,000	leaf blast: 99.61%
Rahman *et al.* (2020)	Simple CNN	Rice fields of Bangladesh Rice Research Institute (BRRI)	Four different types of cameras	1,426	Mean validation accuracy: 94.33%
Bari *et al.* (2021)	Faster-RCNN	Both on-field data and PlantVillage dataset	Smartphone camera (Xiaomi Redmi 8)	16,800	Rice blast: 98.09% Brown spot: 98.85% Hispa: 99.17% Healthy rice leaf: 99.25%
Tiwari *et al.* (2020)	VGG19 and CNN	PlantVillage dataset	-	2152	Early Blight and Late Blight of potato with 97.8% accuracy

Rashid *et al.* (2021)	*YOLOv5 and PDDCNN*	Plant Village dataset and field data from Central Punjab region of Pakistan	Mobile phone cameras and digital cameras	4062	Early blight: 93.87% Healthy: 84.47% Late blight: 92.25%
Nazir *et al.* (2023)	improved EfficientNetV2	PlantVillage repository	-	3000	Early blight of potato: 98.11%, Late blight of potato: 98.01% accuracy
Proposed Model	Tensorflow deep learning model (CNN)	Both on-field data and PlantVillage dataset	Smartphone camera (Samsung A-32)	4,809	Potato Early Blight: 99.96% Potato Late Blight: 99.14% Rice Bacterial Leaf Spot: 86.98% Rice Brown Spot: 93.63% Rice Leaf Blast: 89.59% Rice Leaf Smut: 87.76% accuracy

In the current study, it was hypothesized that a single, CNN-based image-analysis model, trained on a diverse set of rice and potato-leaf photographs, can accurately distinguish multiple high-priority diseases. When embedded in an ultra-light web interface, it can also serve as an on-farm diagnostic assistant. Specifically, it was argued that (i) transfer-learning with an AlexNet-style architecture will extract robust lesion features even from modest training datasets, and (ii) integrating this model into a Streamlit application will allow farmers and extension workers to obtain near-real-time, confidence-weighted predictions that inform rapid, disease-specific management decisions.

Materials and methods

TensorFlow for deep learning

TensorFlow is one of the most popular libraries in the field of deep learning, created by researchers at Google. Neural network is a collection of interconnected layers of neurons that work together to learn from data, which has gained popularity in areas like computer vision, natural language processing, and bioinformatics (Krizhevsky *et al*., 2012; Collobert and Weston, 2008; Min *et al*., 2017). The TensorFlow framework enables training and inference on deep neural networks in heterogeneous environments, with compelling performance in various real-world applications (Abadi *et al*., 2016). Among different types of neural networks, the CNN is specifically designed to learn spatial hierarchies of features from images (Pang *et al*., 2020). CNNs excel in machine learning tasks, particularly image classification with multiple layers and parameters affecting their efficiency (Albawi *et al*., 2017).

Stages of the experiment

The stages of model building and deployment are presented in Fig. 1. The process begins with importing the essential libraries needed for machine learning. Next, the necessary parameters are defined with the partitioning of the datasets into training, validation, and testing sets. Several preprocessing techniques are then applied to enhance accuracy and ensure a smooth training process. Once the model is successfully trained and tested, it is deployed through a web-based application using the Python Streamlit framework.

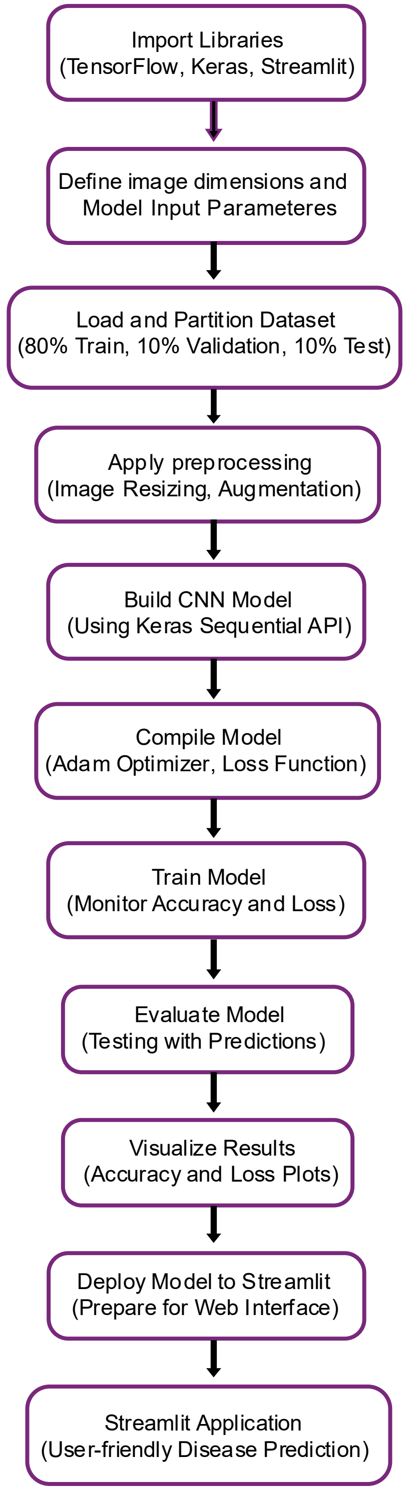

Fig. 1 Flowchart of methodology in disease detection system.

Key Stages in a CNN Processing Pipeline

Feature extraction

A feature is a distinct, measurable characteristic of an image, such as edges, textures, colors, shapes, or patterns, that helps differentiate one object from another. In certain image recognition tasks, features are specific groups of pixels, such as edges and key points, that the network analyzes to identify patterns and recognize objects (Kumar *et al*., 2022). CNN works as a feed-forward neural network, which is designed to extract features from data using different convolutional layers.

Feature recognition

It is the process involved in identifying and analyzing key features from an image. The process of extracting visual features from an image, carried out by the use of a convolutional layer, generating a feature map that represents the image's visual elements. Many procedures are typically used to preserve the image's intricate details.

Activation function

In a neural network, each neuron receives input from the previous layer and transforms it using an activation function that determines which information is important, and then transmits the resulting output to the neurons in the next layer, allowing the network to learn and make decisions in a layered, step-by-step manner (Li *et al*., 2020). An effective activation function helps speed up the learning process and reduces the loss function, leading to better model performance (Kashim *et al*., 2024). Among frequently used activation functions like sigmoid, tanh, ReLU, PReLU, Swish, ELU etc., the nonlinear ReLU (Rectified Linear Unit) activation function was used in this current study.

Flattening

In TensorFlow convolutional neural networks (CNNs), the flattening process converts multi-dimensional input into a 1D format. In order to connect convolutional layers to fully connected layers, this step is essential, enabling the model to process and classify data more effectively. Flattened CNNs can greatly reduce the number of parameters, resulting in faster feedforward execution while maintaining accuracy (Jin *et al.,* 2014).

Description of dataset

An extensive and well-curated dataset is crucial for accurately identifying each stage of an object throughout both the training and testing phases (Nagaraju and Chawla, 2020). Primarily, sample data on rice and potato diseases was collected from BRRI (Bangladesh Rice Research Institute) and BARI (Bangladesh Agriculture Research Institute), and high-resolution image was captured for machine learning dataset. In order to mitigate overfitting by reducing noise and improving the validation accuracy (Chen *et al*., 2020), images were added that are available in Kaggle dataset (www.kaggle.com). Four types of rice plant diseases, namely Rice leaf blast, Rice leaf smut, Rice bacterial leaf blight and Rice brown spot and one type of Rice healthy plant dataset were used. In addition, two types of potato plant diseases, namely Potato early blight and Potato late blight, and one type of Potato healthy plant dataset were used in current study. In total, the dataset comprised 4809 images, which were used in this study. Here is a brief description of the six diseases of rice and potato as well as healthy plants.

Rice Brown Spot

Brown spot disease (Fig. 2a), primarily caused by the fungus *Bipolaris oryzae*, is a serious threat to rice production worldwide. It appears as small, dark brown to purple-brown spots on rice leaves and can cause severe crop losses. Historically, this disease has led to devastating consequences, including contributing to major famines like the 1943 Bengal Famine (Padnamadhan, 1973).

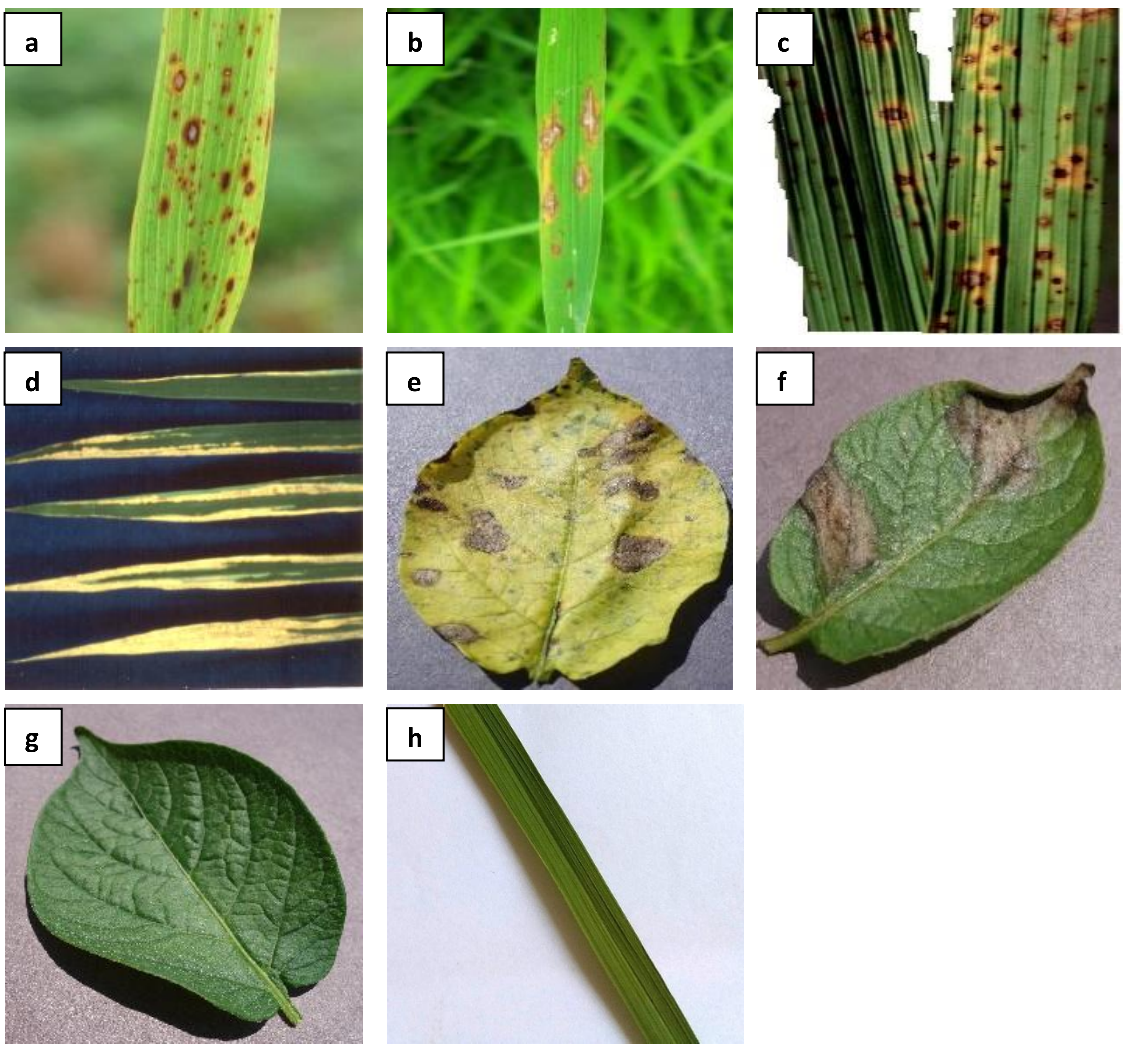

Fig. 2 **a** Rice Brown Spot Disease; **b** Rice Leaf Blast Disease; **c** Rice Leaf Smut Diseases; **d** Rice Bacterial Leaf Blight Disease; **e** Potato Early Blight Disease; **f** Potato Late Blight Disease; **g** Potato Healthy Leaf; **h** Rice Healthy Leaf

Rice leaf blast

Rice blast generates diamond-shaped white to gray or reddish-brown lesions with reddish-brown margins on the leaves (Fig. 2b). The lesions have the potential to grow, clump together, and destroy entire leaves. Simple, gray conidiophores bearing terminal, pear-shaped, primarily two-septate conidia are produced by the responsible pathogen *Pyricularia oryzae.*

Rice leaf smut

Leaf smut of rice (Fig. 2c) is a fungal disease caused by *Entyloma oryzae*, which affects rice crops by producing small black or brown angular smut-like and slightly raised lesions on both sides of the leaves. Carried by airborne spores, the fungus overwinters on contaminated leaf fragments left in the ground.

Rice Bacterial Leaf Blight

Xanthomonas campestrix pv. Oryzae is the causative agent of this common rice plant disease. Symptoms typically begin as small, water-soaked, linear areas on the leaf blades and sheaths. These areas quickly lengthen and merge, forming narrow, irregular stripes that are yellowish or brownish, eventually turning whitish with wavy edges (as seen in Fig. 2d). Drops of bacterial ooze may be observed on young lesions.

Potato Early Blight

Early blight, a significant foliar disease affecting potatoes (*S. tuberosum*), is caused by the fungus *Alternaria solani* Sorauer. (Fig. 2e) This disease is recognized by its distinctive dark brown to black lesions with concentric rings, creating a 'target spot' appearance. Symptoms first appear on older, aging leaves (Van der Waals, 2001).

Potato Late Blight

Potato late blight, a destructive global disease, is caused by the oomycete pathogen *Phytophthora infestans* (illustrated in Fig. 2f). Infection usually begins with dark grey to brown, water-soaked spots on the leaves. These spots are often surrounded by a white, moldy growth along the edges (Gevens *et al.,* 2013).

Potato Healthy Plant

Healthy potato leaves (Fig. 2g) typically have a well-developed epidermis and mesophyll, which are essential for photosynthesis and gas exchange (Bisognin *et al*., 2006) and also, they have robust linear leaf dimensions and a higher number of stems, which correlate positively with yield (Rozentsvet *et al.,* 2024).

Rice Healthy Plant

Healthy rice varieties (Fig. 2h), particularly those with heavy panicles, exhibit larger leaf dimensions and a higher leaf area index (LAI), which enhances light capture and photosynthetic efficiency (Ma *et al.,* 2006). Rice healthy plant leaves exhibit characteristics such as vibrant green color, absence of lesions or spots, and overall uniformity in appearance, indicating a lack of diseases or abnormalities (Gayathri and Neelamegam, 2019).

Preprocessing of dataset

Load the dataset

The collected images were labeled with their respective disease features and placed in the appropriate folder corresponding to that disease. The operations and data were done manually. Finally, there were 8 labeled classes viz. i. Potato__Early_blight, ii. Potato__Late_blight, iii. Potato__Healthy, iv. Rice_Bacterial_Leaf_blight, v. Rice_Leaf_Blast, vi. Rice_Leaf_Smut, vii. Rice_Brown_spot, and viii. Rice_Healthy. The classification using these datasets was done in the Jupyter Notebook program.

Creating dataset by partitioning dataset validation and training

Initially, all the required libraries, including TensorFlow, numpy, matplotlib etc. were called to perform the classification job. Then, to keep consistency of the image size its height and width were mentioned specifically. Using the "image_dataset_from_directory" function of Tensorflow keras API module, the dataset from a specific folder was fetched. Among 4809 total images, 3848 (around 80%) were used for training the dataset, and 961 (around 20%) were used for validating the dataset.

Configuring dataset for performance

To improve the process of data training "Autotune" function is applied to the training and validation dataset. Autotune function optimizes the data pipeline by automatically adjusting the number of batches to be prefetched based on the current runtime condition, such as CPU/GPU load, I/O speed, and memory use. In addition, it improves the pipeline efficiency by keeping the images in memory (Dataset. cache) after they're loaded off disk during the first epoch and overlaps data pre-processing and model execution while training (Dataset.prefetch).

Standardization of data

The input dataset first goes through a preprocessing layer where the images are resized to a specific target height and width to keep a consistent shape. Next, to ensure the RGB channel values are compatible with the model, the pixel values are rescaled to reduce their range, making the input values smaller and easier for the model to process.

Augmentation of data

Data augmentation involves a set of methods designed to expand and improve the quality of training datasets, making it easier to develop more effective deep learning models (Shorten and Khoshgoftaar, 2019). Dataset augmentation was performed to enhance the diversity of the training set by applying random transformations to the images. This process makes the images appear more realistic and exposes the model to a broader range of data variations, helping it to generalize better. Augmentation also helps reduce the risk of over-fitting, which can occur when the training set is small or limited for a specific class.

Machine learning process

Model creation

To create image classification system, the "Sequential API" is used which is one of the simplest and efficient ways to create a neural network model. It built models layer-by-layer in a linear stack where each layer had exactly one input tensor and one output tensor. It consists of three convolution blocks (Conv2D) with a max pooling layer (MaxPooling3D) in each of them. In the first layer, the input shape needs to be defined and then other layers, such as Conv2D, MaxPooling3D, Flatten, and Dense are added as per model processing. The "ReLU" activation function is used at each layer to improve the model performance by enhancing the learning process and decreasing the model loss function. The lossless flow property (LFP) of ReLU plays a crucial role in reducing training loss while maintaining a low generalization error (Javid *et al*., 2021). Finally, "Softmax" activation function is used in the output layer of a classification model to convert raw model outputs (logits) into a probability distribution over multiple classes.

Model compiling and training

In order to prepare the model for training, compilation is a crucial step that defines several components that will be required during the training process. An optimizer is added to minimize the loss function by adjusting model weights, including Adam, SGD (Stochastic Gradient Descent), RMSProp (Chollet, 2021). The loss function quantifies the amount of the model's predictions matching the actual target value. Metrics are used to evaluate the performance of the model during training and testing. For example, accuracy is a commonly used metric for classification problems (Chollet, 2021). After the model was compiled, it was ready for training. The `fit()` function was then used to train the model, specifying parameters such as the datasets, batch size, number of epochs, validation data, and others. The epoch is a hyperparameter that defines how many times the CNN model goes through the entire dataset during training, while batch size refers to the number of data samples processed by the CNN model at one time (Muslim *et al*., 2023).

Model evaluation

After the completion of model training, it was further examined with test data, and its accuracy and loss were evaluated. Graphical analysis (ROC curve) was performed in order to understand the accuracy of training and validation as well as the loss of training and validation. An ROC curve illustrates how well a test distinguishes between diseased and non-diseased groups, with perfect separation indicating ideal accuracy and complete overlap showing no discrimination (Hajian-Tilaki, 2013).

TFLite model conversion

TFLite Model Conversion is the process of converting a trained TensorFlow model into the TensorFlow Lite (TFLite) format, which is optimized for deployment on devices like smartphones, microcontrollers, and IoT devices by reducing model size and enhancing performance. This conversion is done using the `convert` function, where the necessary parameters are provided to transform the model into a TFLite format suitable for edge device deployment.

Streamlit web-application

Streamlit is an open-source Python framework that facilitates the development of interactive and dynamic data applications. (Fig. 3) depicts the proposed design of application system for detecting rice and potato disease using a web-based approach.

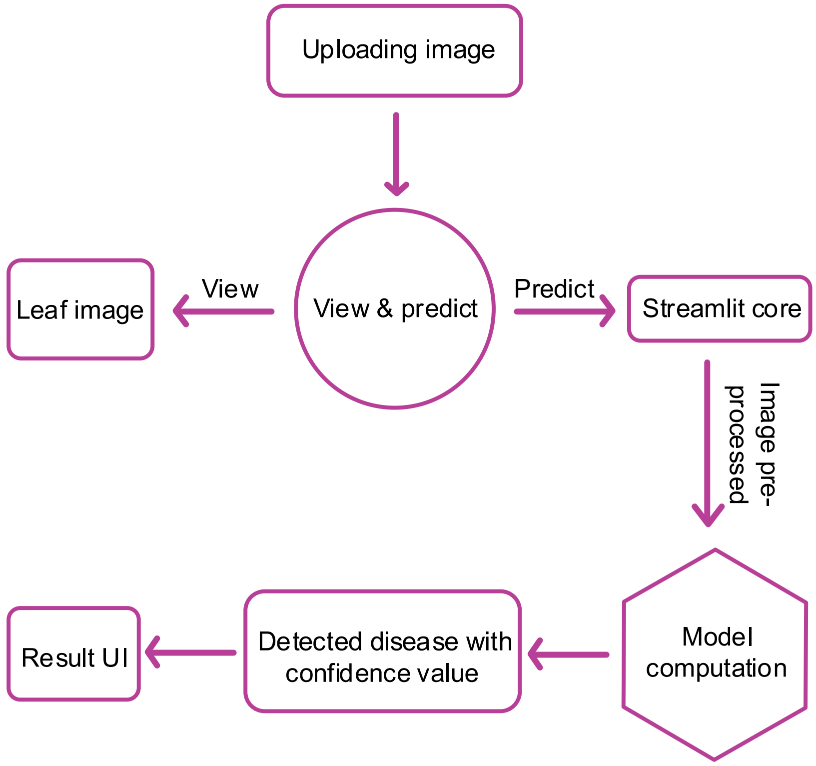

Fig. 3 Streamlit workflow structure

Results

Data training and validation

This research demonstrates how TensorFlow and Convolutional Neural Networks (CNNs) can be effectively used to detect and classify diseases in rice and potato plants through image recognition. TensorFlow was chosen for its scalability and high performance in deep learning tasks. While CNNs were selected for their strength in recognizing spatial hierarchies in images (e.g., disease patterns on leaves).

The study utilized eight major datasets of potato and rice diseases, including Potato Early Blight, Potato Late Blight, Potato Healthy, Rice Bacterial Leaf Blight, Rice Leaf Blast, Rice Leaf Smut, Rice Brown Spot, and Rice Healthy. 4809 disease-affected leaf images, of which 3,848 (approximately 80%) were leveraged for validating the datasets was collected, utilizing TensorFlow deep learning model to train the complex datasets.

Based on the outcome of the data training and validation for rice and potato, the number of epochs was 50 and the batch size was 32. The number of training data was 3848, divided by the batch size of 32, which gives approximately a batch of 121 (Fig. 4)

```
Epoch 36/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 92s 758ms/step - accuracy: 0.9167 - loss: 0.2240 - val_accuracy: 0.8439 - val_loss: 0.4461
Epoch 37/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 92s 761ms/step - accuracy: 0.9053 - loss: 0.2479 - val_accuracy: 0.8835 - val_loss: 0.3219
Epoch 38/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 95s 783ms/step - accuracy: 0.9116 - loss: 0.2398 - val_accuracy: 0.9022 - val_loss: 0.2873
Epoch 39/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 95s 789ms/step - accuracy: 0.9300 - loss: 0.1926 - val_accuracy: 0.8845 - val_loss: 0.3347
Epoch 40/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 95s 786ms/step - accuracy: 0.9257 - loss: 0.2125 - val_accuracy: 0.8751 - val_loss: 0.3928
Epoch 41/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 93s 769ms/step - accuracy: 0.9319 - loss: 0.1871 - val_accuracy: 0.8949 - val_loss: 0.3022
Epoch 42/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 91s 749ms/step - accuracy: 0.9386 - loss: 0.1848 - val_accuracy: 0.8855 - val_loss: 0.3414
Epoch 43/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 94s 778ms/step - accuracy: 0.9368 - loss: 0.1843 - val_accuracy: 0.9084 - val_loss: 0.2774
Epoch 44/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 91s 749ms/step - accuracy: 0.9418 - loss: 0.1659 - val_accuracy: 0.8897 - val_loss: 0.3113
Epoch 45/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 91s 753ms/step - accuracy: 0.9430 - loss: 0.1707 - val_accuracy: 0.8939 - val_loss: 0.3045
Epoch 46/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 94s 779ms/step - accuracy: 0.9346 - loss: 0.1736 - val_accuracy: 0.9126 - val_loss: 0.3063
Epoch 47/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 91s 755ms/step - accuracy: 0.9188 - loss: 0.2197 - val_accuracy: 0.9001 - val_loss: 0.2876
Epoch 48/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 95s 784ms/step - accuracy: 0.9291 - loss: 0.1938 - val_accuracy: 0.8939 - val_loss: 0.3251
Epoch 49/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 96s 788ms/step - accuracy: 0.9422 - loss: 0.1569 - val_accuracy: 0.9032 - val_loss: 0.2822
Epoch 50/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 94s 778ms/step - accuracy: 0.9316 - loss: 0.1906 - val_accuracy: 0.9220 - val_loss: 0.2100
```

Fig. 4 Result of data training and validation of rice and potato diseases

Training and validation accuracy and loss

A gradual increase in the training and validation accuracy was observed while training the CNN model. It is crucial to monitor the validation loss and accuracy curve to observe the model over-fitting. Training accuracies recorded were 0.9251, 0.9248, and 0.9215, while validation accuracies reported were 0.909, 0.8813, and 0.8668, indicating progressively sound learning without severe overfitting (Fig. 5a). It definitely indicates the steady growth of the accuracy of the training and validation of the CNN model.

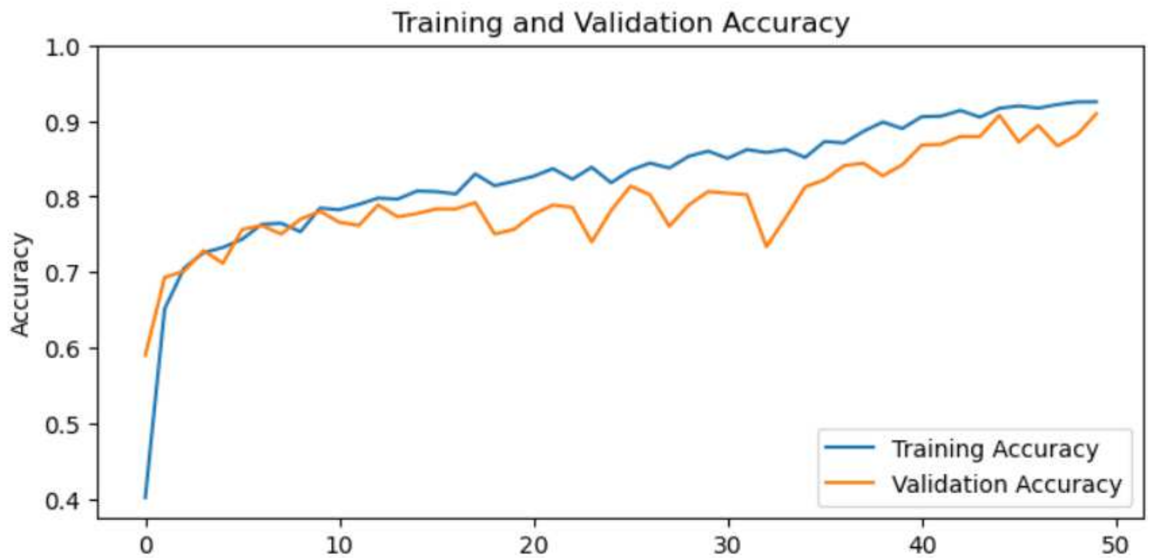

Fig 5a Training and validation accuracy

On the other hand, there was a gradual decrease in the training and validation loss while training the CNN model. The result shows that the final level of training loss was 0.2015, followed by 0.2185 and 0.2097, while it was 0.2631 for validation loss, followed by 0.3554 and 0.3892 for the current CNN model (Fig. 5b). This clearly indicates that the loss was decreasing steadily for training and validation of the CNN model.

Fig. 5b Training and validation loss

Evaluation and testing result of the CNN model

using the 'evaluate()' function of the TensorFlow library an overall accuracy and loss prediction was evaluated, where the accuracy and loss of the training dataset was around 94% and 0.1662 respectively (Fig. 6a), while it was 89% (0.8983) and 0.2984 for validation dataset (Fig. 6b) and finally it was 93% (0.9333) and 0.2069 for test dataset (Fig. 6c) of the CNN model. Disease predictions on randomly selected test images showed high confidence, affirming the CNN's capability in real-world disease classification.

```
loss,accuracy = model.evaluate(train_ds)
121/121 ━━━━━━━━━━━━━━━━━━━━ 28s 234ms/step - accuracy: 0.9357 - loss: 0.1662
```

Fig. 6a Accuracy and loss of the CNN model of the training dataset

```
loss, accuracy = model.evaluate(val_ds)
31/31 ━━━━━━━━━━━━━━━━━━━━ 9s 210ms/step - accuracy: 0.8983 - loss: 0.2984
```

Fig. 6b Accuracy and loss of the CNN model of the validation dataset

```
loss,accuracy = model.evaluate(test_ds)
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 194ms/step - accuracy: 0.9333 - loss: 0.2069
```

Fig. 6c Accuracy and loss of the CNN model of the test dataset

Randomly selected image was passed through a test of the CNN model prediction of disease of rice and potato. The result of randomly selected images is provided in Fig. 7, which is clearly labelled with the actual class of the disease, predicted disease of the CNN model, and finally confidence percentage.

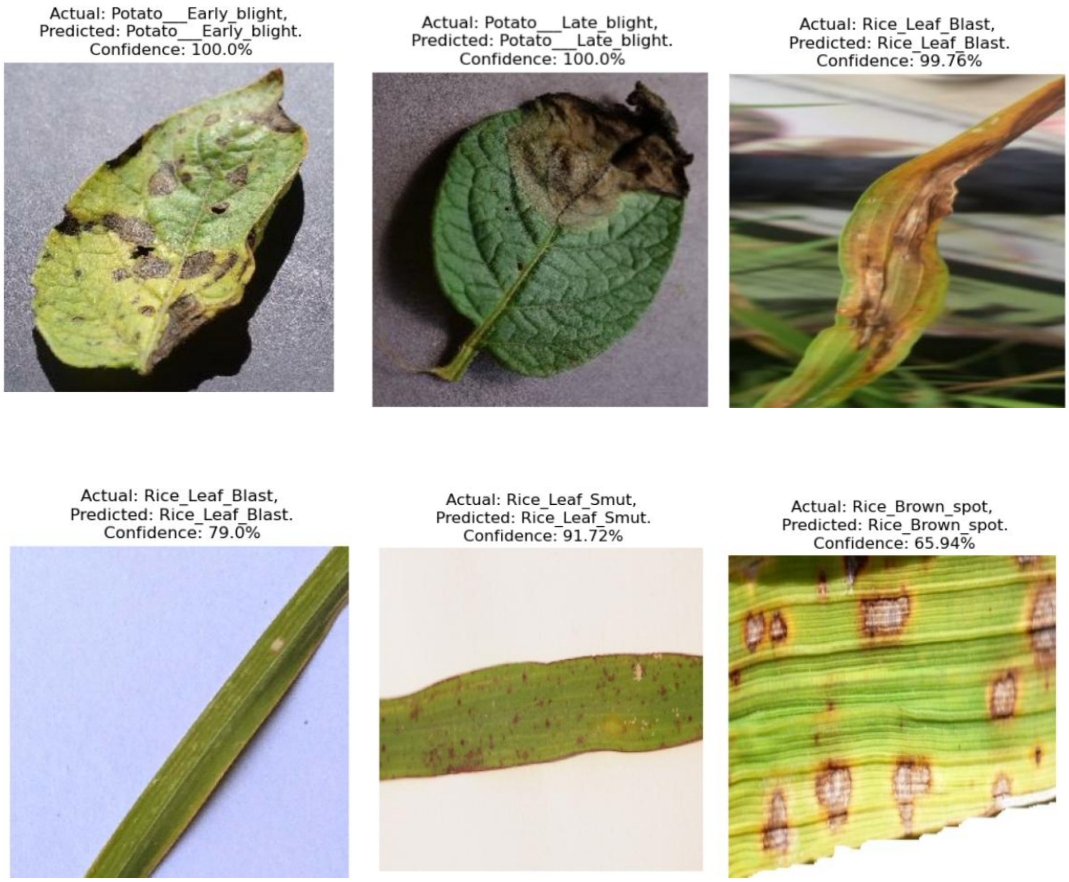

Fig. 7 Results of the CNN model's performance in disease detection

Streamlit UI application performance evaluation

Further, a Streamlit web-based application was developed for interactive disease detection and tested with 15 images per disease category. Fig. 8 depicts the interface of the web application while performing the test. The model yielded an average accuracy of 92.84% (Table 2) on average for all of the detected diseases, validating its practical application potential.

In order to evaluate the performance of the current model in Streamlit web-based application, 15 test images of each disease were provided to detect and provide the result with a confidence percentage.

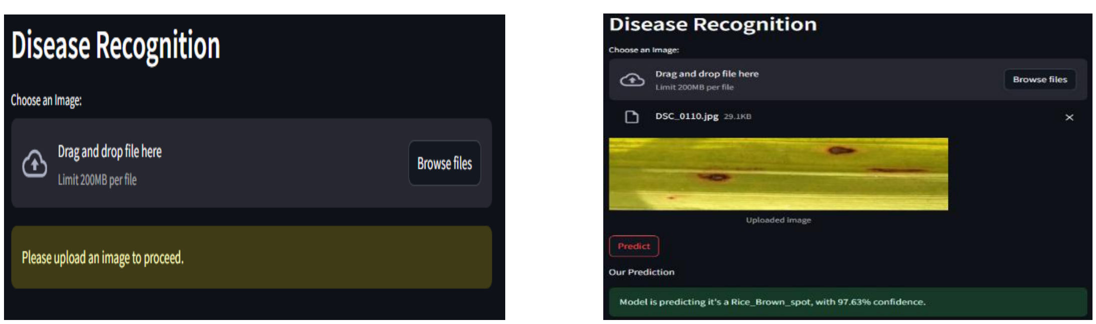

Fig. 8. Streamlit user interface of plant disease recognition system

Table 2 Performance of the system on 15 field test images analyzed in Streamlit UI

Diseases	Accuracy	Correct	Incorrect
Potato Early Blight	99.96%	14	1
Potato Late Blight	99.14%	14	1
Rice Bacterial Leaf Spot	86.98%	12	3
Rice Brown Spot	93.63%	13	2
Rice Leaf Blast	89.59%	12	3
Rice Leaf Smut	87.76%	12	3

Confirmation through lab test

Out of the six diseases studied, the causal agents of two: *Magnaporthe oryzae* and *Xanthomonas oryzae* were identified under an electron microscope in the lab environment.

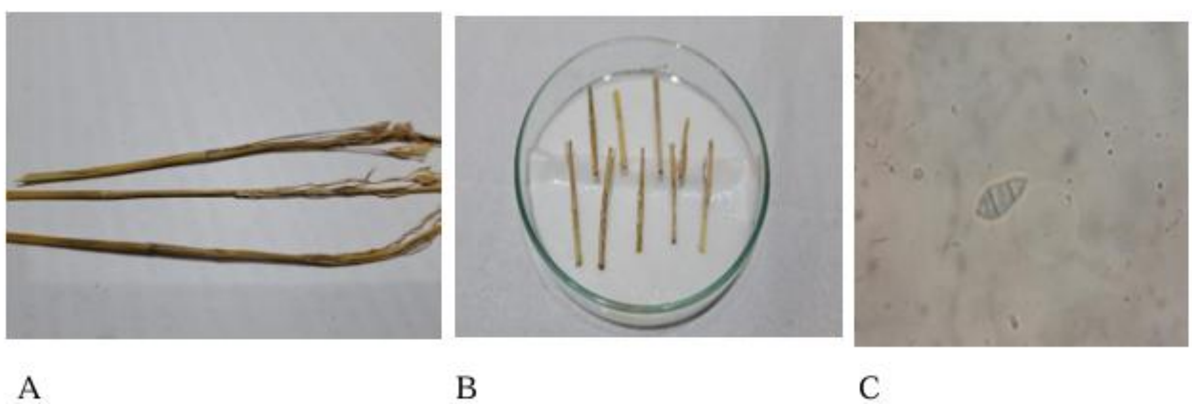

Fig. 9 Isolation and identification of Magnaporthe oryzae. **a** Infected neck. **b** Infected neck placed on moist filter paper and **c** Conidium (100x).

Laboratory tests conclusively identified the causative pathogen of two prominent rice diseases: *Magnaporthe oryzae* was confirmed as the cause of rice blast based on the morphological observation of its distinctive three-celled pyriform conidia grown on PDA medium; and *Xanthomonas oryzae* pv. *oryzae*, the bacterial leaf blight pathogen, was validated based on successful reproduction of symptoms within five days following leaf-clip inoculation. (Fig. 9, 10)

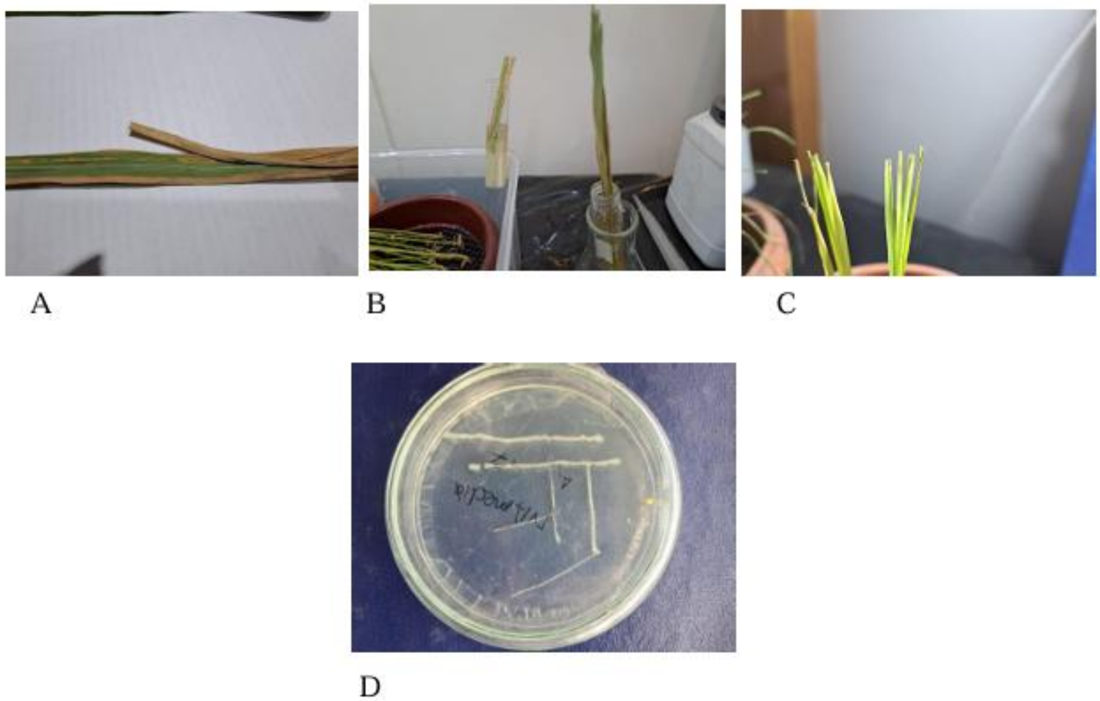

Fig. 10 Isolation and identification of *Xanthomonas oryzae* pv. *oryzae*. **a** infected leaf observing BLB symptom. **b** Leaf clipping of infected leaf and placed in sterile distilled water. **c** Isolation of *Xanthomonas oryzae* pv. *oryzae* by streaking method from a water sample. **d** Development of BLB after leaf clipping method using sterile scissors emerged in the *Xanthomonas oryzae* pv. *oryzae* water suspension.

Discussion

This study demonstrates that TensorFlow-based Convolutional Neural Networks (CNNs) can be harnessed in the identification of rice and potato plant diseases through picture recognition. It generated accuracies consistently above 90% during training and validation, in line with the research reports stating that CNN-based approaches for classifying rice and potato diseases generally achieved accuracies ranging from 93% to 99% (Afzaal et al., 2021; Liang et al., 2019; Anim-Ayeko et al., 2023). It was selected because it is very popular in agricultural image studies and for its proven scalability and strong prowess in complex deep learning tasks (Ahad et al., 2023). CNNs were used to detect a spatial hierarchy in images that would particularly pertain to the disease-related patterns on the leaves with a view to early detection. (Jelali, 2024; Falaschetti et al., 2022). The findings supported prior research that deep learning models surpass traditional image processing and manual diagnosis in precision and speed (Chakraborty et al., 2022; Mokhtar et al., 2015). Although hybrid models integrating CNNs with other architectures may yield superior performance and interpretability, the present study demonstrates that a simple CNN framework, implemented using TensorFlow, is capable of achieving high accuracy in detecting diseases (Anim-Ayeko et al., 2023; Afzaal et al., 2021).

The gradual increase in accuracy and decrease in loss during training and validation indicate effective learning and minimal overfitting of this model (Afzaal et al., 2021; Lee et al., 2021; Anim-Ayeko et al., 2023). The development and deployment of the web-based application Streamlit bridges the gap between the development of theoretical models and easy-to-use tools for extension workers and farmers. This approach addresses a significant drawback of earlier studies, which frequently lacked field-based or real-time implementation practices that are important for effective disease management (Lu et al., 2017; Sudhesh et al., 2023). However, literatures state that due to computational limitations and the requirement for lightweight models, deployment on mobile or edge devices is still a challenge (Latif et al., 2022; Gogoi et al., 2023). Previous studies have reported that resource-optimized CNN models such as MobileNetV2 can achieve accuracies up to 97.5% while reducing computational costs, making them suitable for resource-limited scenarios (Nugroho et al., 2024).

Lab-confirmed pathogen identification complements wet lab methods by affirming causal agents through classical morphology and inoculation techniques. This multidisciplinary verification enhances confidence in the model predictions while setting up an integrated framework for the management of the disease.

A key limitation in both this and prior studies is the diversity and size of available datasets. Whereas many researchers worked with different numbers of datasets. For example, Hughes et al. (Hughes & Salathe, 2015) utilized a dataset of 54,306 images for identifying 26 diseases across 14 crop types. Their study recognized the complexity of extracting relevant features from the images as a constraint. However, prior studies suggest that the best validation and test accuracy is obtained with moderately sized and diverse datasets (2,800 to 5,600 images). Going beyond that size, especially without proper diversity, may lead to overfitting or limit generalization capacity (Ali et al., 2021; Rezasefat and Hogan, 2023). In this study, A dataset of 4,809 images was used. While the model performed well on the available dataset, accuracy may be hampered in the actual scenario due to image quality and other variations brought on by the environment or the diversity of disease symptoms (Gogoi et al., 2023; Nugroho et al., 2024). Further enhancement of model robustness and generalizability may be attained by expanding the size of the dataset with more varied field images, as suggested by recent research (Sethy et al., 2020; Gogoi et al., 2023; Nugroho et al., 2024). Additionally, an explainable AI approach could be implemented using saliency maps in order to improve model transparency along with user trust, which is increasingly emphasized in the literature (Anim-Ayeko et al., 2023; Gao et al., 2023).

Conclusion

The study developed a CNN model capable of predicting most significant rice and potato diseases, achieving over 90% accuracy in both testing and training phases. This demonstrates the practical potential of machine learning to reduce time and cost in disease diagnosis. The current model, showcasing its effectiveness. A user-friendly web-based application was also developed using the Streamlit framework, allowing users to upload leaf images and receive disease predictions with confidence scores. Future improvements can enhance performance by expanding the training dataset and continuously updating the platform.

Author Contributions

A.A.J. designed the experiment and conducted the research, M.Y.H. analyzed the data, A.A.J., M.Y.H. and M.S. wrote this manuscript, M.R.I., F.M.A. and S.O.N. reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Data availability statement

Some of the datasets used in this study was obtained from Kaggle (https://www.kaggle.com/datasets). Additional datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request. More image data can be found at https://www.plantvillage.org/en/plant_images

Conflict of Interest Statement

The authors declare no competing interests.

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