World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

WJAETS World Journal of Advanced Engineering Technology and Sciences

(Review Article)

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Potato disease detection and control measure recommendation using CNN

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World Journal of Advanced Engineering Technology and Sciences, 2024, 13(01), 229–239

Publication history: Received on 20 July 2024; revised on 09 September 2024; accepted on 12 September 2024

Article DOI: https://doi.org/10.30574/wjaets.2024.13.1.0399

Abstract

Potato cultivation will continue to be a crucial agricultural endeavor, significantly enrich to global food supply. and economic prosperity. However, the ongoing vulnerability of potatoes to diseases, particularly named early Blight and late Blight, will persist as a substantial threat to crop yield and quality. Traditional disease identification methods, reliant on expert visual inspection, are expected to remain time-consuming, error-prone, and inadequate for timely intervention. This paper will outline to find Potato diseases and recommend effective control measures using convolutional Neural-Networks (CNN). The project will adopt an object-oriented methodology to ensure modularity and maintainability, leveraging TensorFlow for comprehensive dataset collection, data cleaning, and model training. TensorFlow Lite will be applied to optimize and quantify the developed model, enhancing the efficiency of the deployment process. The frontend will be crafted with React Native to facilitate user accessibility and seamless interaction. The resulting deep learning technique is anticipated to exhibit high accuracy in identifying early-blight and late-blight in potato plants, enabling users to receive prompt and reliable disease predictions and actionable control suggestions. This innovative approach aims to downgrade crop losses, improve productivity, and foster sustainable agricultural practices, thereby bolstering global food security in the future.

Keywords: Early Blight; Late Blight; Convolutional-Neural- Networks (CNN); TensorFlow; Data augmentation; Real-time

1. Introduction

Potato cultivation is the fundamental agricultural activity that significantly contributes to global food security and economic stability. As one of the-most widely consumed staple crops, potatoes are an essential source of nutrition for millions of people around the world. However, the productivity and quality of potato crops are continually threatened by various diseases, with Early-Blight and Late-Blight being the most destructive. These diseases, caused by the fungi Alternaria solani and the oomycete Phytophthora infestans respectively, can direct to severe crop losses if not detected and managed promptly.

Traditional methods of disease identification and management of potato farming primarily rely on the expertise of farmers and agricultural specialists who visually inspect the plants for symptoms. While effective to-some-extent, these methods are time-consuming, labor-intensive, and prone to human error. The variability in disease presentation and the subjective nature of visual assessment further complicate accurate and timely diagnosis, often resulting in delayed intervention and increased crop damage. Moreover, the scarcity of agricultural experts in remote and underserved regions exacerbates the challenge of early disease detection, leaving many farmers without the necessary support to manage outbreaks effectively.

The advent of advanced technologies, particularly in the field of Artificial-intelligence (AI) and Machine-learning (ML), presents a promising solution to these challenges. convolutional Neural Networks(cnn), a class of deep learning

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algorithms, have demonstrated remarkable success in image Recognition and Classification tasks. By leveraging CNNs, it is possible to develop automated systems capable of accurately identifying diseases from images of potato plants, thereby enabling timely and precise intervention.

This project will involve the implementation of CNNs in the creation of a Potato disease detection mechanism and the recommendation of controls. In this case, the application is meant to enable farmers to access an easy to use, reliable and efficient early disease detection tool for minimizing crop losses and increasing agricultural yield. To ensure modularity, and hence maintainability, the project shall follow an object oriented paradigm.

This paper proposes a method for farmers and other users to submit photos of potato plant leaves via a website to diagnose early or late blight with greater accuracy and confidence. The system uses Deep Learning and a convolutional-neural-network to detect the disease. This paper's significant contributions are as follows: Utilizing a deep Cnn to accurately identify whether potato leaves are affected by early blight or late blight diseases.

Developing a frontend built with React, hosted on a local server, where farmers or any user can upload photos of potato leaves and quickly determine if they are affected by early or late blight diseases.

Simulating a React Native frontend as an end to-end solution for farmers to identify blight diseases in potato leaves.

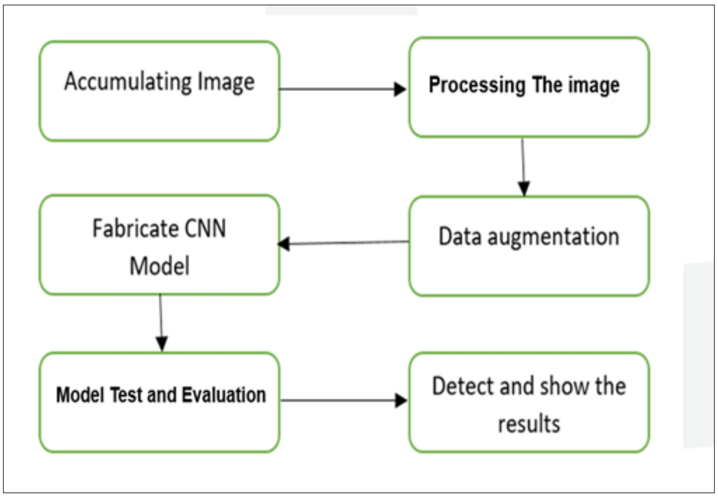


Figure 1 Diseases detection Block Diagram

2. Literature Review- Statistics

The motivation of our paper is to developing a pragmatic, end to-end deep learning-based solution architecture that enables farmers for detecting blight diseases in potato plants with greater accuracy and confidence. We conducted a thorough literature review before deciding on our model architecture. We examined previously published works on plant blight disease identification and classification in which the authors used many deep learning techniques and their applicability in the agricultural sector in this part of the literature review.

2.1. Using Convolutional Neural Networks Potato Leaf Disease Classification

This study proposes a classification-based strategy to iden tify late-blight, early-blight, and healthy leaf photos of potato plants using deep learning techniques and convolution neural networks. It was discovered that CNN works well for this kind of item categorization. This method predicts with validation accuracy of 99%. This kind of undertaking, in general, will be extremely important for the agriculture industry. The majority of the farmers in the Indian community are illiterate and have incomplete knowledge about the illness. We are believe that our effort has the potential to improve the lot of Indian potato farmers. In order-to accomplish classification, studies have been done on photos of both healthy and infected leaves. The suggested approach successfully differentiate between three different forms of potato leaf diseases, it is determined.

2.2. Hyperspectral-Based Identification of Disease Spots on Potato Leaves Using Locally Adaptive 1D-CNN

The approach described in this paper seeks to actively detect local disease sites on potato leaves by means of hyperspectral imaging. It starts from labeling the data along with the rough calibration and then fine calibration. 1D-CNN is then used to identify regions with the disease or any other abnormality in the patient's skin. The key findings are as follows:

- The basic SVM algorithm takes a very long time for analysis of a particular decision data whereas, the identification time in the present study by using 1D-CNN takes approximately fifteen seconds to recognize thus improving on the recognition time remarkably.
- The case of misclassified pixels in distinguishing areas detected by the 1D-CNN is fewer than that of the SVM algorithm. Further, the present average accuracy of 1D-CNN model is higher by about 2 per cent as compared with SVM algorithm and total accuracy enhancement by about 2. 1%.

2.3. CNN Approach for Disease Detection on Potato Leaves

Hence, we employed a CNN based on the sequential model to diagnose potato diseases. Particularly, the identification of these drugs passed through a two-tier testing process to guarantee utmost accuracy. Different potato diseases were studied intensively and a big number of field images of the potato plant were used for analysis. Due to this, we used various algorithms when continuing the performance optimization of the used CNN architecture. The type of model proposed here manages to achieve a rather good distinction between diseased and healthy plants. Step, primarily, it is rather important and relevant to develop a model, dedicated to two particular diseases, however, taking into account the crucial necessities of farmers and other people, who work in the sphere of agriculture, the plan is to broaden a list of diseases and enlarge the given image dataset to make a model more reliable. Further, we plan to create an frontend to ensure people can have easier access to this solution.

2.4. Potato Leaf Disease Detection Survey Using CNN

This paper is a review of papers done on the use of deep neural networks for the identification of potato leaf diseases. The diseases are classified into two types: there are two types of blights; Early Blight and Late Blight. From the research study, CNN produces the best results in diagnosing and differentiating these diseases, and inategorizing non-affected leaves from the actual diseases ails compared to other deep neural networks. Actually, the Artificial Neural Networks (ANN) accomplished an accuracy rate of 85%, and Support Vector Machines (SVM) accomplished 88% accuracy. 89% while programme CNN attained a 99. 07%. Hence, CNNs are identified to offer the greatest extent of accuracy and characteristic differentiation for image recognition and the next-generation deep-learning technique in artificial intelligence.

2.5. Potato Leaf Disease Identification with Multi-Stage Approach: A Comparative Study

The study presents an approach that utilizes Deep-learning techniques and CNN for classification of late blight potato, early blight potato, and healthy potato. Moreover, it also classifies whether a plant leaf considered is a potato leaf or not. Through our experimentation, we discovered that the VGG16 model was the most efficient when integrated with a Raspberry Pi and camera module. While other models also performed well, their output had a considerable latency which was a significant drawback. This project has the potential to be highly beneficial for the agriculture industry. By identifying diseases in the earliest stages, farmers can take appropriate preventive measures to mitigate crop damage and increase the overall yield. The leaves classification was done in our experiments with both healthy and diseased leaves, providing a comprehensive dataset for the training and evaluation. Overall, this study contributes to the development of the potential tool for the early detection.

2.6. Potato Blight: Multi-Class Classification using Deep Learning Model

A PB disease detection system has been developed using a CNN-based DL model on a real-time collected image dataset from Ludhiana province of Punjab state, India. Total of 900 images of healthy and PB disease crop has been collected for binary and multi-classification of the PB disease images. Binary classification has been done based on the healthy and diseased crop which results in detection accuracy of 90.77% while multi-classification has been taken place based on four different severity levels of PB disease crop that resulted in the best detection accuracy of 94.77% in case of the middle severity level of PB disease. In the future, we will focus to perform the same experiment using more severity levels and by developing a hybrid classification model which will focus to show some improvement in detection accuracy of PB disease using a big number of the image dataset.

2.7. Automated Detection of Potato Leaf Blight Diseases Using Deep Learning Based on Optical Images

Chakraborty et al. explored the use of deep learning mod els, including VGG16, VGG19, ResNet50, and MobileNet, for classifying potato leaf blight infections. They selected the best-performing model and fine-tuned its parameters to improve performance [7]. Lee et al. investigated the effec tiveness of various transfer learning approaches using VGG16, GoogLeNetBN, and InceptionV3 network architectures [9]. They found that VGG16 outperformed inception-based mod els, thanks to the limited variation in the potato leaf dataset.

2.8. Automated and Accurate Leaf Disease Detection Using Deep Learning Techniques

chowdhury tested various CNN architectures and compared their model predictions to ground truth images for tomato blight disease classification tasks [3]. Aravind et al. provided an overview of deep learning for disease detection and explored the Squeeze Net model using the Plant Village dataset.

2.9. Potato Disease-Detection Using Image Segmentation and Machine Learning

In this particular research, image processing was employed and from which a model that could readily diagnose diseases on potatoes through analyzing the leaves was constructed. Different methods were experimented, and the best yields noted were achieved by the CNN model regarding image segmentation. Five algorithms were employed. there are many algorithm are there. Specifically, the model was proposed for the identification of images of healthy and infected potato leaves. The above images were classified as normal and unhealthy potato plant leaves using the above proposed algorithms. The developed model's precision rate was of 97 % which was considered on rather high standard.

2.10. Enhanced Detection of Potato Blight diseases in Complex field based Backgrounds Using Deep Learning

Dasgupta et al. demonstrated the effectiveness of pre-trained models on unknown datasets [2]. Johnson et al. highlighted the importance of rapid and automated identification of potato blight infections for farmers to protect their crops [6]. They presented an automated approach for recognizing blight dis ease areas on potato leaves using the Mask R-CNN architec ture, which employs transfer learning and works well with limited datasets.

3. Proposed Methodology

The proposed methodology for developing a real-time potato disease detection using Convolutional Neural Networks (CNNs) encompasses several key phases. Initially, the project planning and requirements analysis phase involves defining the project scope, objectives, and technical requirements, ensuring a comprehensive understanding of stakeholder needs and project feasibility. Following this, the dataset collection and preparation phase focuses on acquiring high-quality images of potato plants exhibiting symptoms of Early-Blight, Late-Blight, and healthy conditions from various sources, followed by meticulous annotation, cleaning, and augmentation to enhance dataset robustness.

The model development phase entails designing an CNN architecture, training it using TensorFlow, and optimizing hyperparameters to achieve high classification accuracy. Subsequent model evaluation ensures the model's performance through metrics like accuracy, precision, recall, and F1-score, validating its effectiveness on a separate test set. For deployment, the model is optimized using TensorFlow Lite to reduce its size and improve inference speed, making it suitable for mobile devices. The frontend is developed using React Native to ensure cross-platform compatibility, with an intuitive user interface for easy image capture, disease prediction, and control recommendations.

The testing and validation phase involves rigorous testing to ensure functionality, usability, and reliability, with field trials providing practical validation.

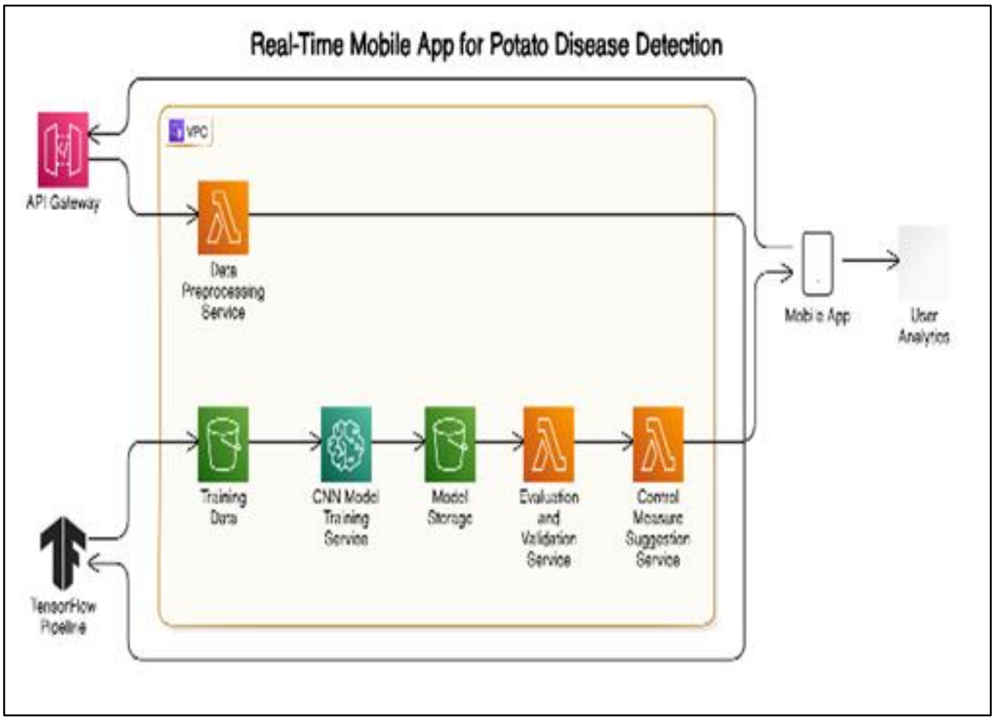


Figure 2 Proposed work Diagram

4. Algorithm

Input: Potato leaf image data

Output: diseases detection

< ----------- START—--------->

- Data Collection
- Data Pre-Processing
- Model Building
- Model Evaluation
- Frontend and deployment

< —---------END——------->

4.1. Data Collection

The data collection phase aims to gather a comprehensive and high-quality dataset of potato plant images to train and evaluate the convolutional-neural network (CNN) algorithm model for disease detection. The dataset will include images of healthy potato plants as well as those affected by Early Blight and Late Blight. We used the ”Plant Village” dataset from Internet for this research work.The dataset is 327 MB and contains 15 directories include many other plant leaf's. We focused only on the three potato directories, which include:

- Potato Early Blight Images (1000 Images)
- Potato Late Blight Images (1000 Images)
- Potato Healthy Images (152 Images)

Total images = 2152 images

TABLE 1, contains a summary of the Data Samples used from the ”Plant Village” Dataset.

Table 1 Summary of used data samples from the ”plant village” dataset

Plant Village Dataset	
Class Labels	**Samples**
EarlyBlight	1000
LateBlight	1000
Healthy	152
Total Samples	2152

4.2. Data Pre-processing

Data preprocessing is a critical step in preparing the dataset for Training a ConvolutionalNeuralNetwork (CNN) algorithm model for potato disease detection. This phase involves using TensorFlow's input pipeline for efficient data handling and implementing data augmentation techniques to enhance the quality of the model. Here Utilized TensorFlow's Dataset API to create a pipeline for loading and preprocessing images. Then normalize pixel values to a range between 0 and 1 by dividing them by 255.0 and standardize the image sizes to a consistent dimension (e.g., 256 X 256 pixels). The length of the-dataset is equal to 68 as every element of a dataset is a batch of 32 images. We also visualize some of the samples of the datasets that we used. By seeing Figure 1. We can visualize the datasets.

Then, in an 8:1:1 ratio, we divided the dataset into Training, Validation, and Testing datasets. We used TensorFlow’s get datasets partitions tf function for splitting and 1000 shuffles to ensure randomness. In Figure 3, we can observe a segment of the dataset that includes samples of potato leaves affected by early blight, and those affected by late blight. Our datasets were segmented down as follows:

Figure 3 Visualizing the datasets

- Dataset used for Training (80%)
- Dataset used for Validation (10%)
- Dataset used for Testing (10%)

Then We did data preprocessing to make the data ready for model building. Some data preprocessing techniques which we used before building the model are:

- Data Prefetching and Data Caching
- Data Augmentation
- Resizing

To improve the data pipeline's performance, we used prefetching and caching in the training datasets, as caching will read the image from the desk. Then for the next iteration, when you need the same image, it will keep that image in the memory and improve the performance. Furthermore, prefetching will improve the performance by loading the next set of a batch of images from the desk when the GPU is busy with training. Prefetching helps to improve performance when we use both the GPU and the CPU. We also used the resizing function to convert every input image to a 256*256 size, which will provide the best accuracy. After all of these pro cesses of Data Preprocessing, we did another step called Data Augmentation, which makes the model robust. We used data augmentation because if someone provides rotated, flipped, or high-contrast images, our model will know how to identify them and correctly predict the results.

4.3. Model Building

We developed a Convolutional_neural_Network (CNN) to train on our preprocessed datasets, subsequently evaluating its performance and measuring its accuracy using test datasets. The trained model was then extracted to a file on our disk for later use in a FastAPI-based server to make real-time predictions. Our CNN architecture is composed of two primary parts: feature Extraction and Classification. The feature extraction component leverages Convolutional layers with the Rectified-Linear-Unit (ReLU) activation function, along with Max_Pooling layers, to efficiently identify and extract essential feature from the input images. The classification component comprises dense layers, a flattened layer, and a robust deep neural thick hidden layer, facilitating the accurate categorization of these extracted features into the respective disease classes. Our proposed model's structure is summarized in Table II, highlighting the use of five various types of layers in total. This architecture is meticulously designed to balance feature Extraction and classification, ensuring high accuracy and performance in detecting potato diseases.

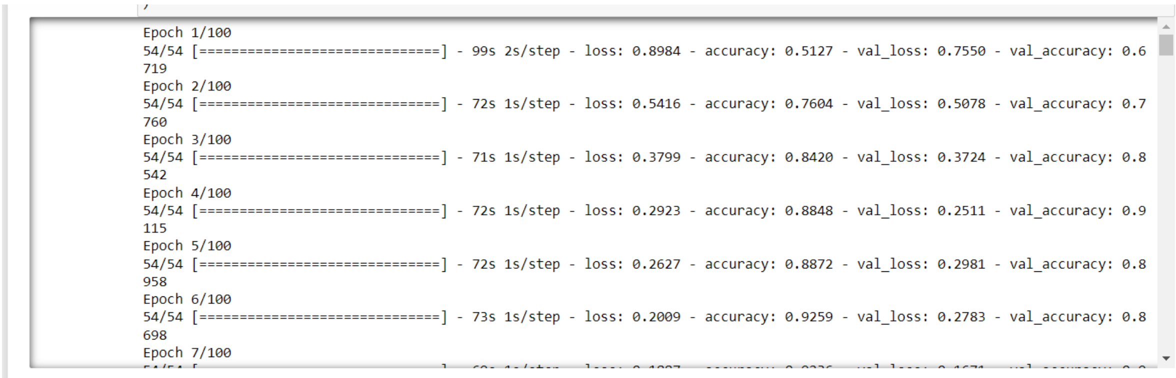
4.4. Proposed model summary

We used a model compiler to put the model together after we finished it. To accomplish this, we selected an optimizer, a loss_function, and a method of measuring success. We used Adam as the optimizer. Sparse Categorical Crossentropy was chosen as the loss function. We also tracked our model's accuracy to assess how well it was performing. To track the progress of our training, we use accuracy as a metric. It mostly allows us to monitor how effectively the gradient descent method is performing.

4.5. Model Evaluation

During the model evaluation process, we train-our convolutional neural network over 50 epochs, monitoring key metrics at each epoch to assess its performance on the Training and validation datasets. Using TensorFlow's History parameter, we tracked the following metrics:

- **Training Accuracy**: This metric indicates the percentage of correctly classified samples from the training dataset during each epoch. It helps us understand how well the model is learning from the training data.
- **Training Loss**: The training loss quantifies the difference between the predicted output and the actual target values for the training dataset. Lower training loss values indicate the model is converging towards optimal performance.
- **Validation Accuracy**: Validation accuracy measures the model's accuracy on a separate validation dataset that it hasn't seen during training. It serves as a proxy for how best the model generalizes to unseen data.
- **Validation Loss**: Validation loss represents difference in between predicted value and actual values on the validation dataset. It helps in monitoring overfitting; increasing validation loss while training loss decreases may indicate overfitting.



```
Epoch 1/100
54/54 [==============================] - 99s 2s/step - loss: 0.8984 - accuracy: 0.5127 - val_loss: 0.7550 - val_accuracy: 0.6
719
Epoch 2/100
54/54 [==============================] - 72s 1s/step - loss: 0.5416 - accuracy: 0.7604 - val_loss: 0.5078 - val_accuracy: 0.7
760
Epoch 3/100
54/54 [==============================] - 71s 1s/step - loss: 0.3799 - accuracy: 0.8420 - val_loss: 0.3724 - val_accuracy: 0.8
542
Epoch 4/100
54/54 [==============================] - 72s 1s/step - loss: 0.2923 - accuracy: 0.8848 - val_loss: 0.2511 - val_accuracy: 0.9
115
Epoch 5/100
54/54 [==============================] - 72s 1s/step - loss: 0.2627 - accuracy: 0.8872 - val_loss: 0.2981 - val_accuracy: 0.8
958
Epoch 6/100
54/54 [==============================] - 73s 1s/step - loss: 0.2009 - accuracy: 0.9259 - val_loss: 0.2783 - val_accuracy: 0.8
698
Epoch 7/100
```

Figure 4 Results of the EPOCHS

4.6. Results, model deployment

4.6.1. Plotting the Accuracy and Loss Curves

We got the loss, accuracy, validation, validation loss, etc. a Python list containing values of loss, accuracy, etc. the end of each epoch. After 50 Epochs we got:

- Training data accuracy: 1.0000
- Training data loss: 1.0724e-05
- Validation data precision: 1.0000
- Validation data loss: 1.0023e-05

As we can see from Figure 4, the number of-epoch increases, the accuracy of model gradually increases and the loss de creases.

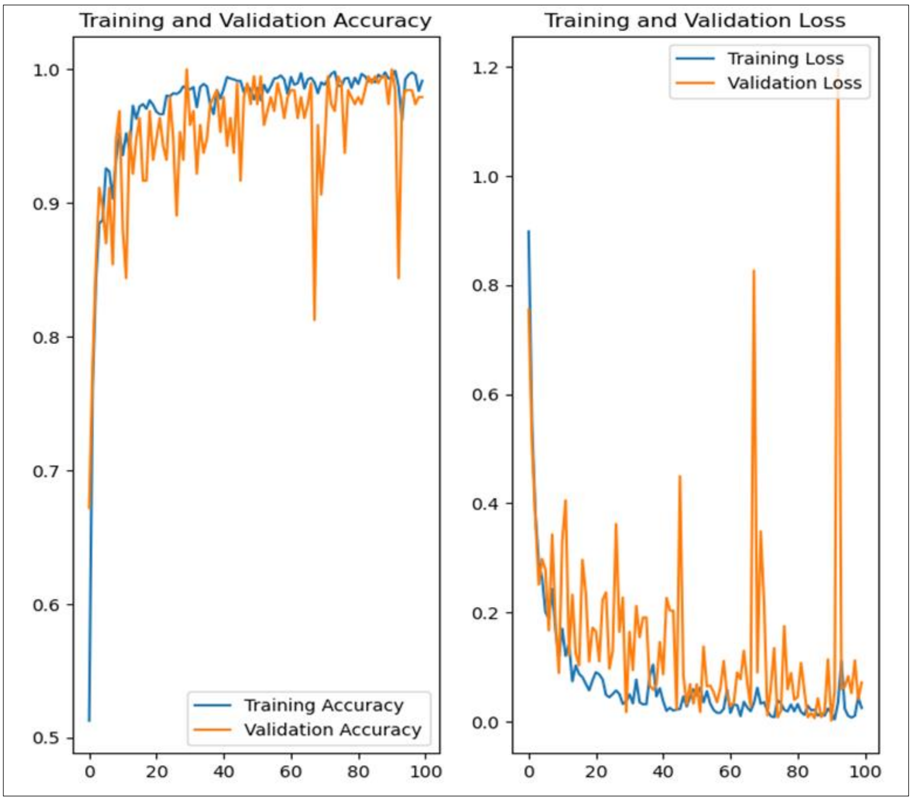


Figure 5 Accuracy and loss curves

4.6.2. Predictions on Single Image and Multiple Images

After getting the accuracy vs loss curve, then we run the prediction on a sample image and in Figure 6 where we can see the prediction class and confidence level for a sample image.

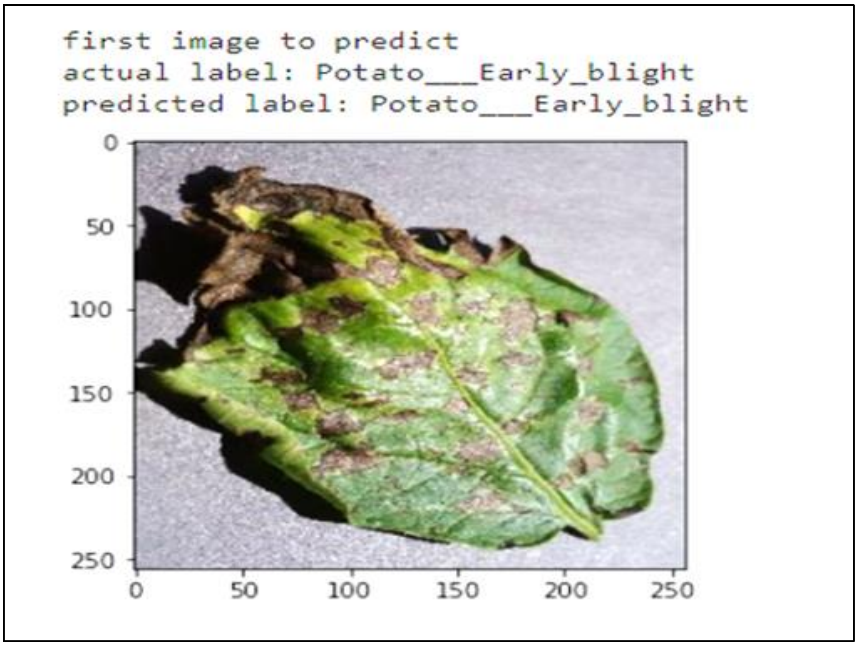


Figure 6 Prediction on a sample image

After that, we wrote a function for inference and ran inference on a few sample images. In Figure 7, We can see the prediction class and confidence level for multiple images which are showing the highest accuracy. After measuring the performance of our model on test data, we saved the model for further deployment.

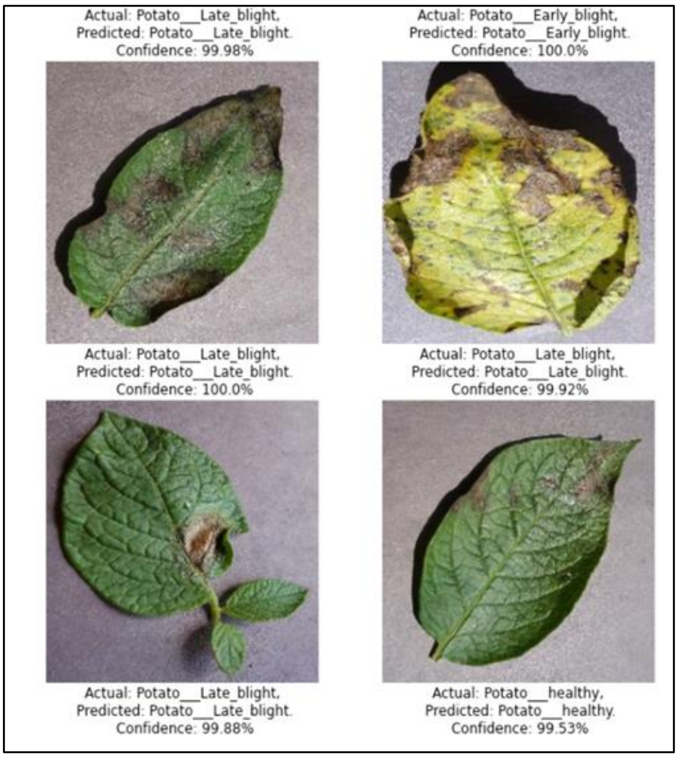


Figure 7 Prediction on Multiple Images

4.6.3. Application Development

At first, we needed to convert the model into a TF-lite model using quantization. Quantitation is being used to reduce the model's size so that the model occupies less memory and can be deployed on cell phones and edge devices. Also, the inference speed is much faster. After exporting the TF lite model, the lite model will be deployed to Google Cloud. We have used the Google Cloud Function, which is like the AWS Lambda Function. And this function will be included in front end development, and the application can predict Blight disease. We have the application user interface, and from that a farmer clicks a picture of the leaves of his potato plant, the potato disease prediction app can accurately predict blight disease of the potato plants with the highest accuracy.

Our study primarily discussed on developing a user-friendly system utilizing TensorFlow for detecting and recognizing Early and Late stages of potato plant diseases. We accomplish this by creating a unique form of network known as a convolutional neural network, which assists us in precisely recognizing and categorizing all these diseases in potato plants.

5. Overall Outcomes

The completion of this project on developing a real-time front end for potato disease detection and control measures using Convolutional-Neural-Networks (CNNs) is expected to yield several significant outcomes. The application will enhance disease detection accuracy, enabling timely intervention strategies and mitigating crop losses, thereby improving agricultural productivity and promoting sustainable farming practices. Its user-friendly interface, developed with react native for cross-platform compatibility, ensures accessibility for farmers, including those in remote areas, empowering them with advanced technological solutions. The application educates farmers with insights and tailored control recommendations, enhancing their decision-making abilities and resilience against disease outbreaks. Rigorous testing and validation through field trials ensure practical applicability and reliability in real-world settings, contributing to advancement of agricultural technology research. The scalable and adaptable design allows for future enhancements, accommodating new disease types and integrating emerging technologies. By improving disease management practices and enhancing crop resilience, the project contributes to global food security and aligns with sustainable development goals. It also sets a precedent for leveraging AI and mobile technology in agriculture, fostering innovation and collaboration across the sector, ultimately impacting agricultural communities and industry stakeholders positively.

6. Feature Work

The work for this research work will focus on several enhancements to improve functionality, performance, and overall impact. Plans include expanding the CNN model to detect additional potato diseases, implementing real-time disease monitoring, and introducing multi-language support to cater to diverse farming communities. The application will integrate decision support systems for personalized disease management recommendations and develop offline functionality for areas with low connectivity. Geolocation and mapping features will be added to track disease spread and visualize crop health data. A community platform will be established for knowledge sharing among farmers, and the user interface will be continuously improved based on feedback. Long-term data analytics capabilities will be implemented to predict disease outbreaks and provide proactive recommendations. Integration with agricultural IoT devices will enhance data collection and automate processes, while advanced AI techniques will be explored to improve model accuracy. Additionally, the application architecture will be designed for scalability and cloud integration to handle growing user adoption and ensure real-time updates. These enhancements aim to create a comprehensive tool that aids in disease detection and management, empowers farmers with actionable insights, promotes sustainable practices, and fosters resilience in agricultural communities.

7. Conclusion

we propose our developed architecture based on a deep-learning model that is convolutional_neural-networks to identify potato plant blight diseases, specifically early blight, and late blight. Data preprocessing was performed to prevent overfitting and achieve high prediction accuracy. After constructing the model, we saved it for future deployment. We then built the TensorFlow Lite model using quantization and developed a React Native-based front end for farmers so they can drag and drop the potato images and also they can click a real time photos of the potato leaf to predict potato blight diseases. This application can significantly aid individual farmers and potentially reduce the economic loss associated with crop diseases.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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