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# Disease Detection of Bangladeshi Crops using Image Classification based on Deep ResNet-50 Model towards Smart Farming Prediction System

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**Abstract**: "The Smart Farming Prediction System using Deep Learning Method through Web Interface in Bangladesh" represents an innovative approach to agriculture, utilizing cutting-edge technologies like image processing and machine learning to optimize farming operations and enhance crop yields. This project focuses on developing a sustainable and efficient smart farming system that employs image processing and machine learning techniques to optimize crop growth and yield. It incorporates a crop health checking feature to promptly identify and diagnose plant diseases, offering appropriate treatment options to minimize crop loss. The system generates real-time data on environmental factors such as temperature, humidity, and nutrient levels, empowering farmers to make data-driven decisions and improve global food security. It used the ResNet-50 model, trained using TensorFlow with a dataset comprising of 38 class labels for crop disease prediction. By leveraging this powerful model, aimed to enhance the accuracy and effectiveness of disease identification in crops it obtained an impressive overall accuracy of 99.34%. Given that Bangladesh predominantly relies on traditional subsistence farming methods, our project endeavors to introduce a smart farming system that brings about significant improvements and sustainability. This system aims to provide farmers in Bangladesh with advanced farming techniques, leading to better agricultural practices and outcomes.

**Keywords:** Deep learning, Crop Diseases, ResNet-50, Digital farming.

## Introduction

Smart farming is an inventive approach to agriculture that leverages state-of-the-art technologies such as image processing, the Internet of Things (IoT), and machine learning to optimize farming operations and improve crop yields. With the world population projected to reach 9.7 billion by 2050, the need to improve food production and ensure food security has never been greater. Smart farming systems are designed to help farmers achieve these goals by providing real-time data on soil moisture, nutrient levels, and plant health, as well as automating many of the tasks involved in farming. In this project, it is proposed the development of a smart farming system that utilizes image processing and AI-driven farming techniques to optimize crop growth and yield. The system will be equipped with a network of sensors and cameras that will capture data on different environmental factors such as humidity, temperature, and light intensity. These data will be processed using machine learning algorithms to deliver insights into the health and growth of crops. Overall, this project aims to

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advance the field of agriculture by developing a smart farming system that is sustainable, efficient and scalable.

By leveraging the power of image processing and AI-driven techniques, it is believed that it could help farmers increase their yields, reduce their environmental impact, and contribute to global food security.

Smart farming is a managing idea concentrated on delivering the agricultural initiative with the infrastructure to leverage state-of-the-art technology – including the cloud, big data, and the Internet of Things (IoT) for monitoring, tracking, automating, and analyzing operations. Smart farming is undoubtedly a supreme enabler in growing more food with less effort for an incredibly growing world population. In certain, smart farming allows expanded yield via more efficient usage of natural resources and inputs and enhanced land and environmental management. While this is essential to sustainably feeding the world's increasing population, there are additional advantages that smart farming delivers to farmers communicating all around the world.

Smart Farming System using deep learning in Bangladesh is transforming the ways that farmers make decisions on farms. They have tremendous insight into the probable challenges, opportunities, and constraints. Some features are available to the Farmer as normal users-farmers view their Basic Information, observe land locations on Google map, check the weather temperature in their field area, identify their crops' diseases through uploading an image, and, can also get instant solutions for the diseases of crops. The system's use case model (Figure 1) shows the activities of a farmer in our project.

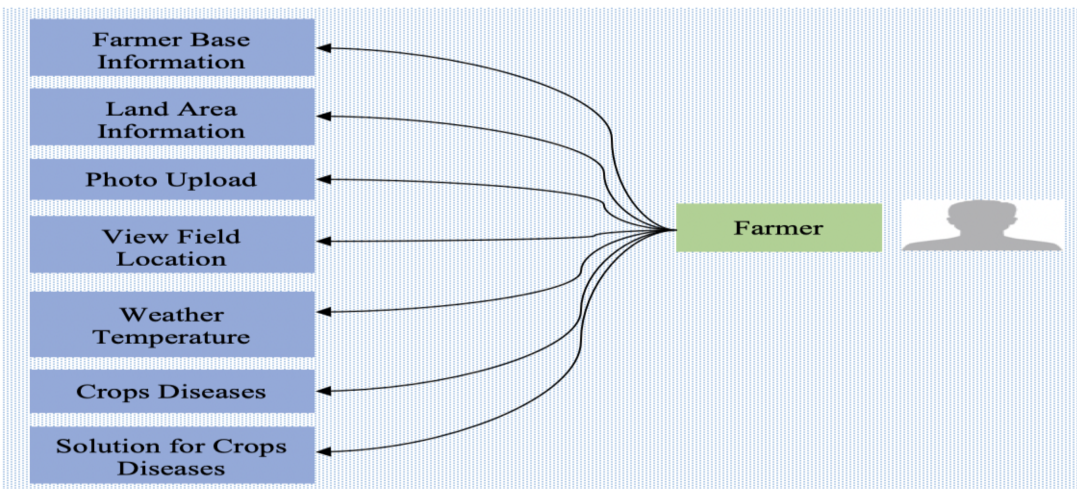


**Figure 1: System use case model.**

A really good thing about this branch of farming is that it permits soil sensing. This factor of smart farming provides space for us as a farmer to experiment with our soil for details and also estimate it for a vast range of important and nutritional constituents crucial in ensuring the good health of our farm produce.

In this project, we have utilized the ResNet-50 model to address the limitations of conventional CNN models and ensure accurate test results. A comparative study titled "Comparison of CNN vs. ResNet-50 for small data sets"[13] conducted by researchers has demonstrated the superior performance of ResNet-50, achieving 98% accuracy compared to 77% accuracy achieved by CNN models. the dataset have been considered comprising of 38 class labels. Here we accomplished a great overall accuracy of 99.34% for ResNet50 model where the testing size was 20%. Our contribution part is listed as follow:

- Introduced a smart farming system for the farmer.
- For predicting diseases, we have applied deep learning model (ResNet-50) and achieved outstanding performance.
- User interface for this project to help the farmer detecting crop diseases, getting suggestion against the diseases.
- Generated huge functionalities for the farmer to digitalize them in irrigation.

The sections that follow provide an overview of this article's specifics. Literature Review section provides an explanation on disease detection in plants, crops, and smart farming research. Definition of the suggested methodology is provided in the Methodology section. Analysis and findings the result of the experiment is presented in the Experimental Result and Discussion section. Finally, the summary and illustration of the study's result as well as the direction for future research is provided in the Conclusion section.

## Literature Review

The detection and classification of crops and plants diseases are remarkable research in the recent era. Many researchers are worked with various technique to obtain better performance. But some exertions have been done on reviews of plants and crops diseases prediction that have some limitations.

T. V. Klompenburg et al [1] introduced a great review on 50 machine learning (ML) related studies of crop yield prediction (features being temperature, rainfall and soil type), with artificial neural networks (ANNs) which are classified as part of the classifier type, among the highest performing algorithms. In a similar vein to a different group of researchers reviewing 30 deep learning-based papers, they have found that Convolutional Neural Networks is the most used algorithm, followed by Long-Short Term Memory and Deep Neural Networks. In the domain of agriculture likewise, R. Akhter et al [2] demonstrated how IoT, data analytics, and machine learning can revolutionize agriculture using an Apple disease prediction model in orchards of Kashmir. Yet it raises the real-world challenge of how to ENBAR this technology within traditional farming and amplifies the urgency to develop implementation-focussed research on the farmer adoption pathway. An innovative proposal developed by M. M. Rahman et al. [3] aims to present a study that explores the applicability of using deep learning algorithms, such as MobileNet, for an automated fruit identification system in supermarkets, given that an accuracy of 99.21% is achieved. Despite some challenges associated with fruits' diverse characteristics and the fact that data collected in Bangladesh contributed to the final accuracy. However, it should be specified that these may be considered as local data and are not representative of a wider range of fruits. In turn, another study by A. Khamparia et al. [4] presents a hybrid approach to crop disease detection, which involves the use of convolutional neural networks and autoencoders in combination with leaf images. The study has achieved a

100% level of accuracy using 3×3 convolution filters, which outperforms classical methods. At the same time, it is important to continue investigating the vision-related side of the topic to address challenges experienced in the area. T. R. Gadekallu et al [5] addressed the urgent need for proactive measures against agricultural crises due to population growth and economic dependence on agriculture. It proposes a novel approach utilizing machine learning, specifically a hybrid PCA-WOA algorithm for feature extraction and a deep neural network for tomato disease classification. While promising, the study lacks an exploration of alternative methodologies and broader datasets for comprehensive evaluation. R. Sujatha et al [6] introduced various machine learning (ML) and deep learning (DL) methods that were compared for citrus plant disease detection, indicating the superior performance of DL over ML, with VGG-16 achieving the highest classification accuracy (CA) at 89.5%. However, the study acknowledges the limitations of RF achieving the least CA among the methods tested. A. Darwish et al [7] proposed an ensemble of pre-trained CNNs (VGG16 and VGG19), this study addressed plant disease diagnosis via leaf image classification, leveraging deep learning. The orthogonal learning particle swarm optimization (OLPSO) algorithm optimizes hyperparameters, overcoming manual tuning challenges. However, the study's reliance on specific pre-trained CNNs and limited dataset balancing methods warrants further exploration for broader applicability. A. Rajbongshi et al [8] introduced an online machine vision-based expert system to recognize cauliflower diseases, aiming to aid farmers in timely actions. Utilizing 776 images, it employs K-means clustering for segmentation and six classification algorithms. While achieving an 89.00% accuracy with Random Forest, the absence of real-time implementation remains a limitation. S. Ramesh et al [9] addressed the challenge of crop disease identification by employing Random Forest on leaf images, utilizing Histogram of Oriented Gradients for feature extraction. While showing promising results, it highlights the ongoing infrastructure limitations hindering rapid disease detection in global agriculture. M. M. H. Matin et al [10] proposed a system on rice leaf disease detection has explored various techniques, with AlexNet showing promising results in detecting bacterial blight, brown spot, and leaf smut with over 99% accuracy. However, the study lacks comprehensive comparison with other deep learning models and may benefit from broader datasets to assess its generalizability.

From the above outline, it has been used that very rare analysis works have been studied related to crops and plant disease detection. While some corresponding work has been established, most of the research is accomplished with conventional approaches, while our work is presented with a noble approach along with a large number of datasets.

## Methodology

In this area, It has been explained the data collection process, data preprocessing, applying deep learning models for predicting disease, and web interface and application. There are three categories first presentation tier, second application tire & third data tier [12]. In Figure 2, the architecture of our project is shown-

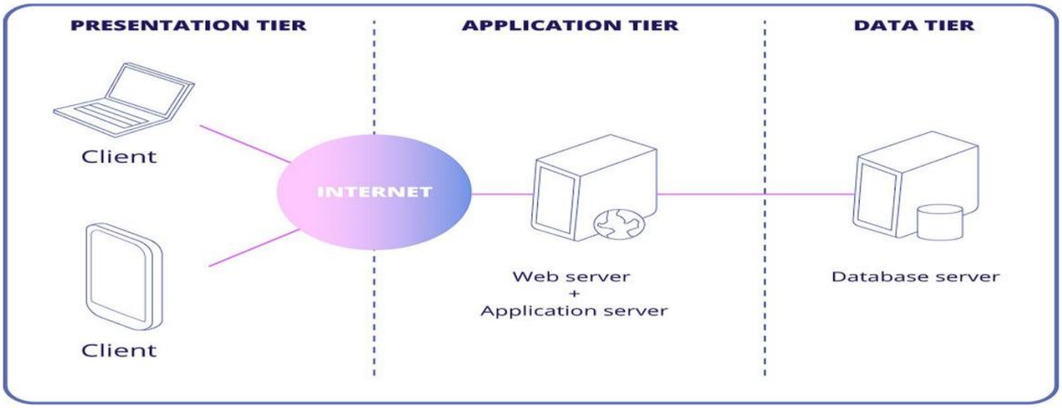


**Figure 2: Project Architecture.**

**Dataset**

In this analysis, the dataset has been examined of 54,306 plant leaf images, encompassing 38 different crop-disease pairs. Our objective is to predict the specific crop-disease pair based solely on the image of the plant leaf. To accomplish this, PlantVillage dataset [14] is utilized, which provides the relevant crop-disease pairs. In our approach, the images were resized to 256 × 256 pixels, optimizing and conducting predictions on these downscaled images. Figure 3 shows the sample leaf images from the dataset.

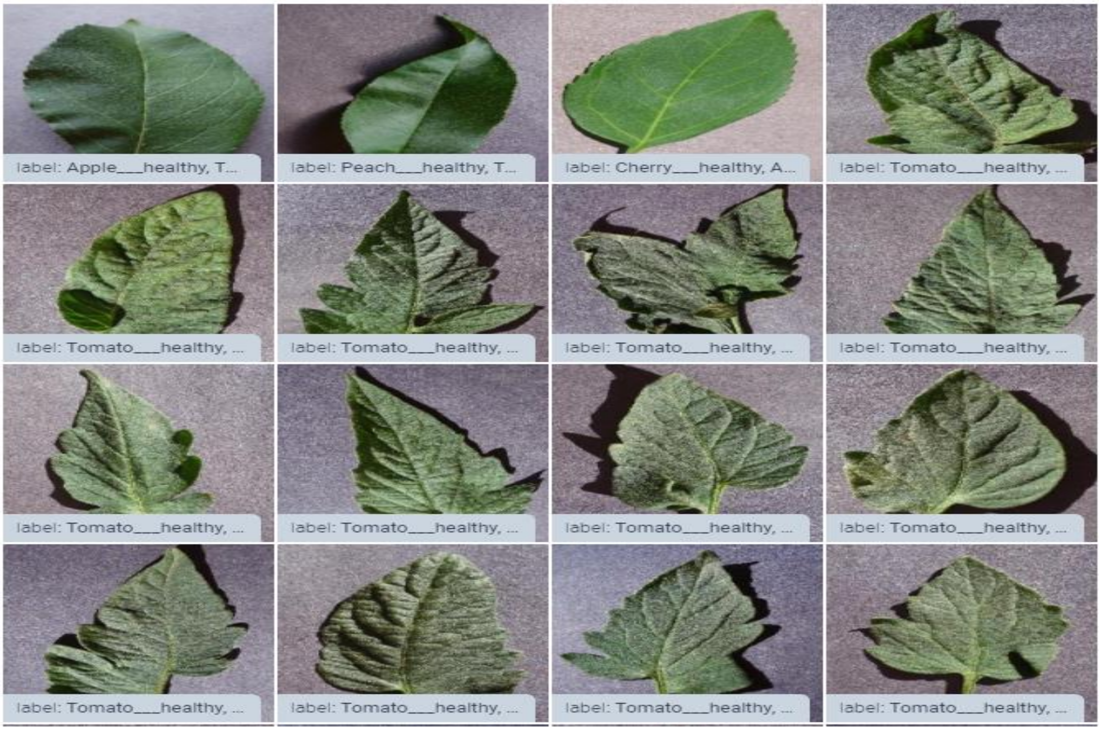


**Figure 3: Sample leaf images from the dataset.**

## Data Preprocessing

To prepare the images for training, several pre-processing steps are applied. These include center cropping, resizing, normalization, and labeling. For center cropping, the image is focused around its central area to highlight the leaf object and reduce the impact of noise. After cropping, all images are uniformly resized to dimensions of 256 × 256 pixels to meet the input size requirements of the ResNet-50 model. The experiments are conducted using different train-test set splits, with an 80-20 ratio (80% for training and 20% for testing) applied to the entire dataset. In Figure 4, sample of a pre-processed leaf image is shown-

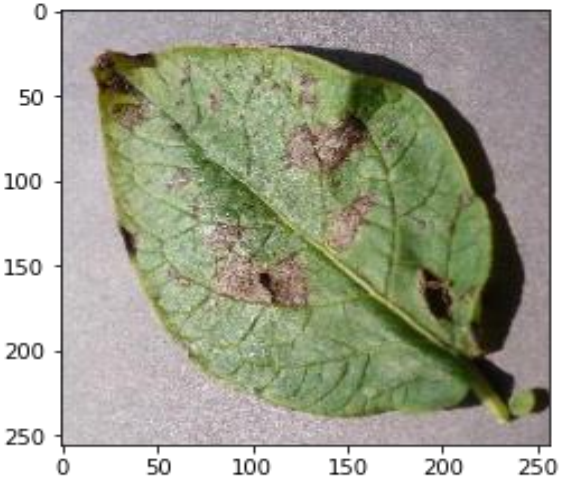


**Figure 4: Sample of a pre-processed leaf image.**

## Deep learning models

Deep Learning has been confirmed to be a very helpful strategy over the previous few decades due to its capability to handle a huge amount of data. The desire to use hidden layers has surpassed traditional techniques, especially in pattern recognition. Convolutional Neural Networks (CNNs or ConvNets) are one of the most prominent deep neural networks in deep learning, especially for computer vision applications.

- Convolutional Neural Network (CNN)

  A convolutional neural network (CNN/ConvNet) is a type of deep neural network that is often accustomed to evaluate graphical imagery. When assuming a neural network, matrix multiplications were usually considered, but ConvNet is not like that. It utilizes a specialized procedure known as Convolution. In mathematics, convolution is a mathematical procedure of two procedures that results in a third procedure that describes how the figure of one is modified by the other. Figure 5 shows an image classification based on no CNN model.

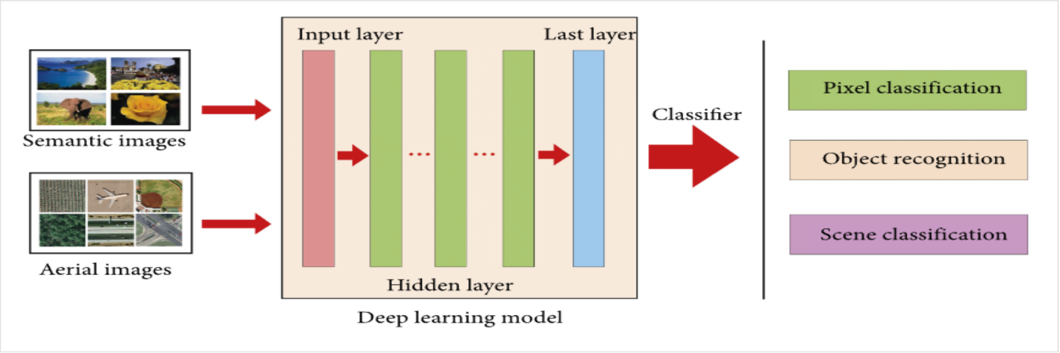


**Figure 5: Image classification based on CNN model.**

- Residual Neural Network (ResNet-50)

  ResNet-50 directs to a 50-layer convolutional neural network (CNN). The ImageNet database includes a pre-trained version of the network that has been trained on over a million images. The pre-trained network can classify photos into 1000 different object categories, such as animals, keyboards, mice, and pencils. Figure 6 shows picture classification based on the ResNet-50 model.

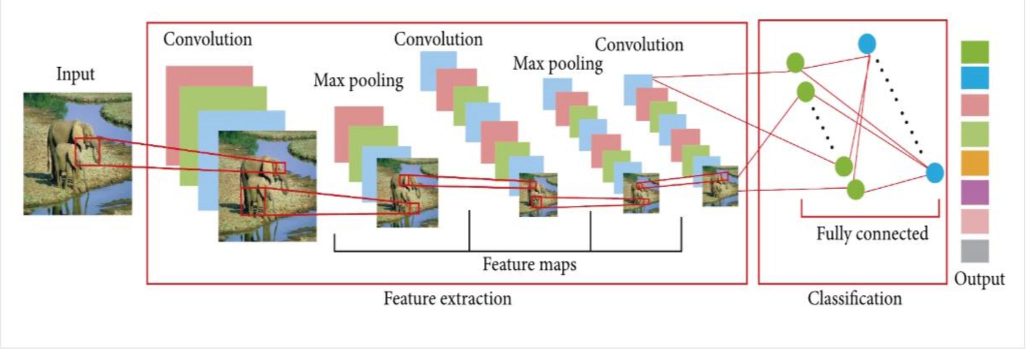


**Figure 6: Image classification based on ResNet-50 model.**

However, CNNs have significant disadvantages that restrict their performance and utility. One of the most significant limitations of CNNs is that they require a huge amount of labeled data to train well, which may be expensive and time-consuming to gather and annotate. Furthermore, Convolutional Neural Networks have a significant disadvantage: the 'Vanishing Gradient Problem'. During backpropagation, the gradient value reduces dramatically, therefore weights change very little. To address this issue, ResNet-50 is utilized.

**Web interface and application**

Here, we have discussed about the web application version and mobile application version.

- Web version

  Web application architecture summarizes how databases, servers, and applications interact in a system. It handles how a system's functionality and logic are spread between the server and client sides. Figure 7 illustrates the web application architecture as follows:

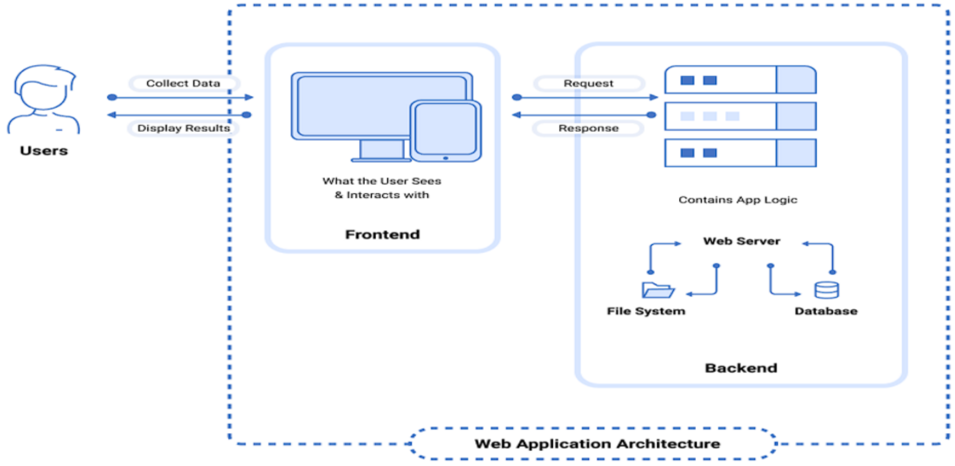


**Figure 7: Web Application Architecture.**

- Mobile application version
  A set of rules, techniques, procedures, and patterns used in the development of mobile applications is referred to as mobile app architecture. These rules assist developers in producing applications that satisfy industry standards and business requirements. The mobile application architecture for this step is displayed in Figure 8.

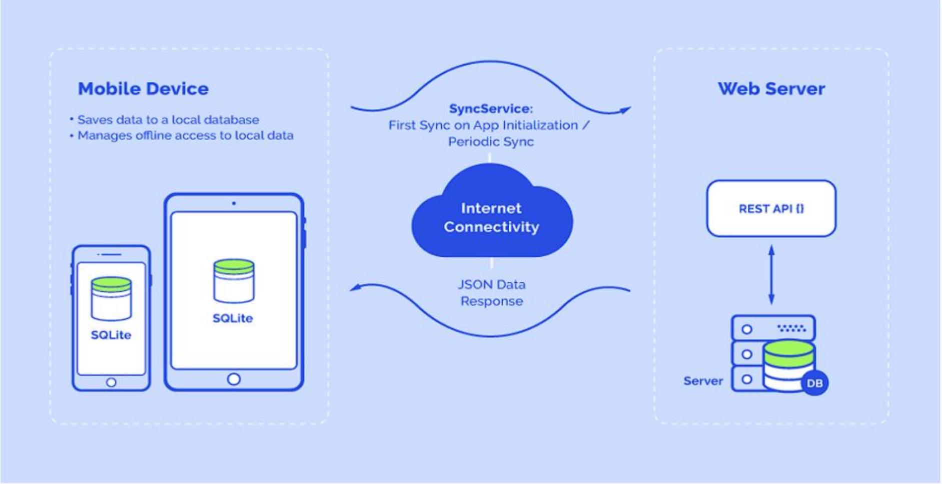


**Figure 8: Mobile Application Architecture.**

The sustainable and efficient farming system poses the crops yields. A user must register into this site for using this application. One has to go setting panel and fills up this information. As a farmer one should add one's field's information, so that one can use this application. A user can add multiple field areas. New field information would be filled up by the farmers who have a bit of tech knowledge.

## Experimental Result and Discussion

For evaluating the employed models, the accuracy has been chosen for crop disease detection as the criterion. Our suggested method automatically determines the issue, comes up with a solution, and gives the user feedback. Figure 9 displays the accuracy for the ResNet-50 model over 10 epochs. The model's training accuracy was represented by the blue line, while its validation accuracy was displayed by the orange line. Figure 9 shows that the accuracy of both training and validation has grown during the epochs, indicating a beneficial attribute of a well-designed model.

The loss for the ResNet-50 model during ten epochs is shown in Figure 10. The orange line represents the validation loss, and the blue line represents the training loss. A strong model exhibits the positive trait of decreasing train and validation loss throughout the course of the epochs, as seen in this picture.

At the outset, it is important to highlight that when considering the dataset comprising of 38 class labels, It was achieved an impressive overall accuracy of 99.34% (with an 80%–20% train-test split). This remarkable accuracy demonstrates the significant potential of the deep learning approach in addressing crop-disease prediction challenges.

The Table-1 shows the summary of related works on plants diseases. As studied several research papers tried to find out the accuracy, research topics, applied model on different plant diseases.

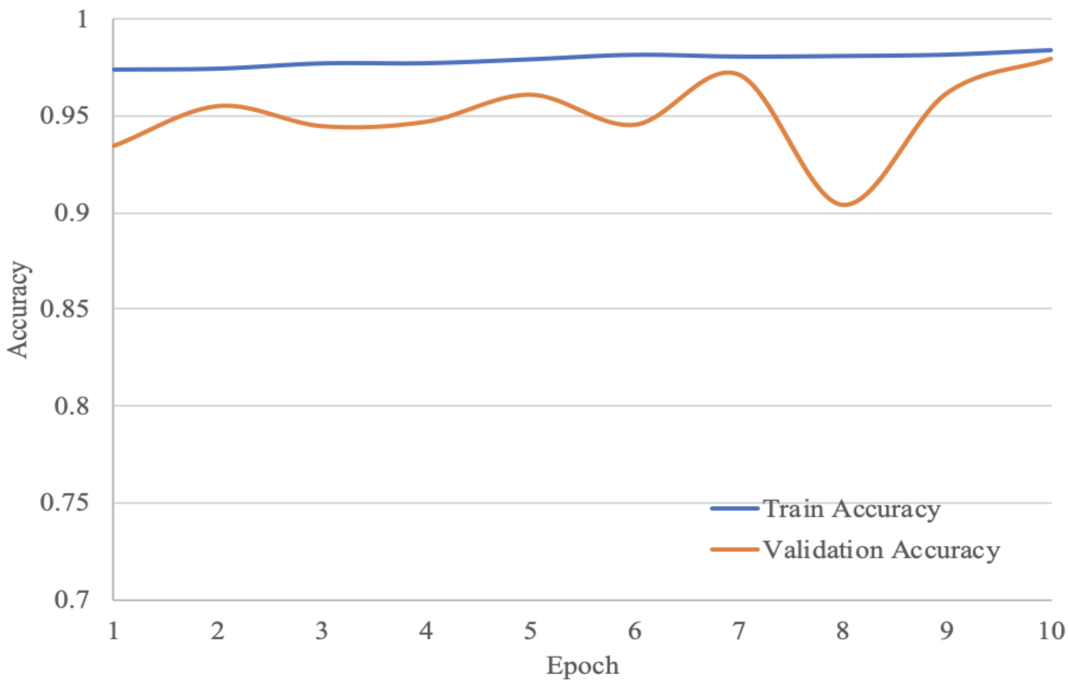


**Figure 9: Accuracy over the epochs for the ResNet-50 model.**

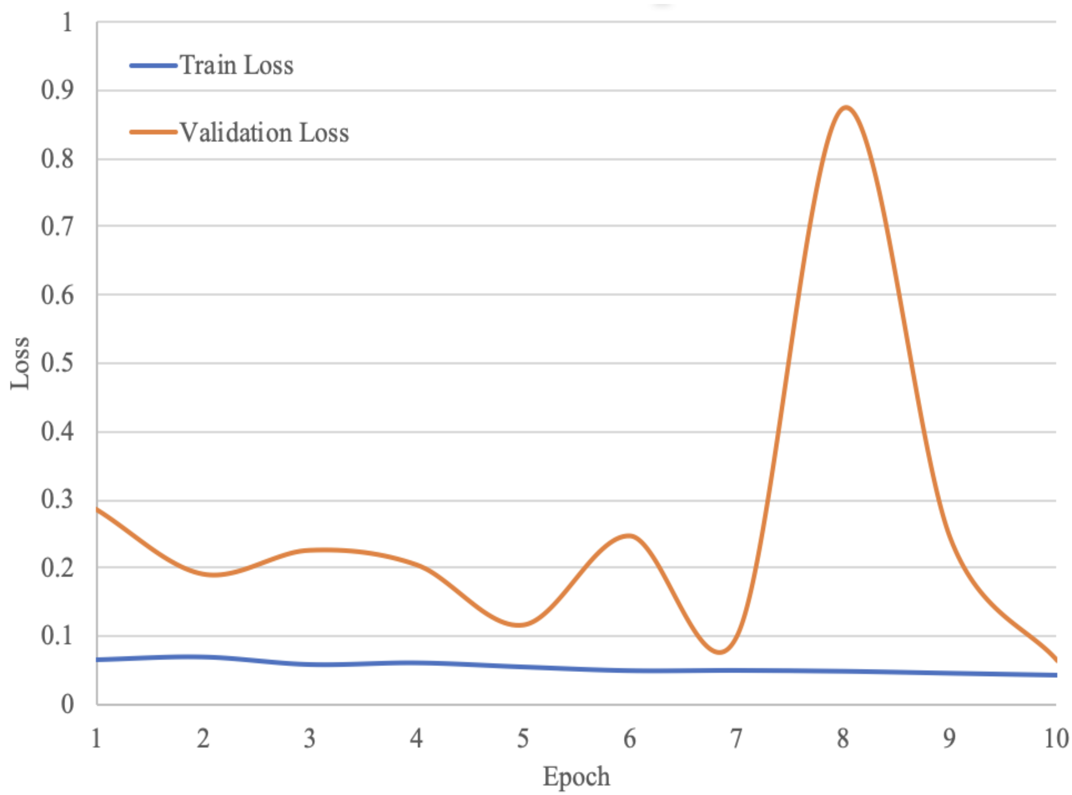


**Figure 10: Loss over the epochs for the ResNet-50 model.**

From Table-1, It is observed that our proposed system worked excellent by the ResNet-50 model and obtained highest accuracy of 99.34%.

**Table 1:** Comparing Accuracy of Related Works.

| Author | Topics | Model | Accuracy |
|---|---|---|---|
| M. M. Rahman et al [3] | Local Fruits | CNN | 99.21% |
| Khamparia et al [4] | Crops Disease | CNN | 97.50% |
| T. R. Gadekallu et al [5] | Tomato plant disease | DNN | 94.00% |
| R. Sujatha et al [6] | Plant leaf | VGG-16 | 89.50% |
| Darwish et al [7] | Plant Disease | AE | 98.20% |
| Rajbongshi et al [8] | Cauliflower Diseases | RF | 89.00% |
| S. R. Maniyath et al [9] | Plant Diseases | RF | 70.00% |
| M. M. H. Matin et al [10] | Rice Leaf | AlexNet | 99.00% |
| J. Chen et al [11] | Plant Diseases | Transfer learning | 98.63% |
| M. A. Islam et al [15] | Paddy Leaf Disease | Inception-ResNet-V2 | 92.68% |
| **Proposed Algorithm** | **Plant Diseases** | **ResNet-50** | **99.34%** |

## Conclusion

Smart Farming System is an innovative and cutting-edge solution that leverages the power of image processing and AI-driven farming techniques to enhance the productions and growth of agricultural crops. With its prediction abilities to detect different crop diseases, provide detailed data of the disease, and suggest suitable solution of treatments. This is how the system empowers farmers to make data-driven decisions and take proactive measures to prevent crop loss due to regular predictable diseases. Moreover, it aims to improve the efficiency, productivity, and sustainability of agriculture practices while reducing the environmental impact of farming. With its rich feature set and user-friendly interface, the system has the potential to transform the ways that farmers operate and drive significant improvements in crop yields and enhance profitability.

In future, to enhance the productivity of this project it needs to improve the quality of dataset for better and reliable outcomes and will apply latest explainable AI to find the exact effected region. Finally, the web interface need to be updated with more features and more user friendly manner using latest UX/UI technology.

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