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Solanum Tuberosum Leaf Disease Classification

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Abstract: Farmers cultivating solanum tuberosum often experience significant financial setbacks due to plant diseases that adversely affect crop health and yield. Early blight and late blight are particularly destructive diseases that, if not detected and managed early, can reduce crop productivity. Here we will use machine learning approach, Convolutional Neural Networks (CNNs), that detects and classifies these diseases, on its own, through image analysis of Solanum Tuberosum leaves. The developed system offers a rapid, accurate, and user-friendly diagnostic tool that enables farmers to take prompt action to manage and mitigate disease spread effectively. The primary goal is to reduce crop losses and enhance disease management, ultimately contributing to improved agricultural efficiency. Early disease detection through this technology allows for more effective disease control, leading to healthier crops and improved yields. The solution not only enhances crop monitoring but also provides an affordable way to protect farmers' livelihoods, fostering greater sustainability and productivity in Solanum Tuberosum farming.

Keywords- Solanum Tuberosum Disease Detection, Image Processing, Neural Network

I. Introduction

Solanum Tuberosumes play an essential role in human diets, providing a substantial source of carbohydrates, which are a key component of daily nutrition. However, Solanum Tuberosum farming faces significant challenges, particularly in the form of diseases that affect the health and productivity of the crops. Among these, diseases that target Solanum Tuberosum leaves are especially concerning, as they can lead to considerable reductions in yield and financial losses for farmers if not addressed promptly. The impact of these diseases extends beyond just the farmers; it can disrupt food production and availability on a broader scale. Therefore, timely and correct detection of Solanum Tuberosum leaf disease is critical for disease management and prevention. This allows farmers to implement appropriate interventions, reducing the spread of disease and maintaining the health of their crops. Early detection is particularly important because it provides the opportunity to control diseases before they become widespread, thereby minimizing the potential damage.

Old methods of disease detection, which primarily rely on visual inspection, are often slow, prone to human error, and require expert knowledge. As a result, many farmers are unable to diagnose the specific blight in time to take the necessary measures, leading to widespread crop loss and significant economic damage. To address this challenge, this research aims to develop a machine learning-based solution using Convolutional Neural Networks (CNNs) to automatically detects early and late blight from images of Solanum Tuberosum leaf.

The most familiar and damaging diseases that affects Solanum Tuberosum plants is early blight and late blight. The diseases primarily attack the leaves, which are vital for the plant's photosynthesis and overall growth. Early blight, caused by the fungus *Alternaria solani*, typically begins with the appearance of small, circular spots on the leaves, usually in the middle or near the edges. As the disease progresses, these spots enlarge, and the surrounding leaf tissue turns brown, ultimately leading to leaf deterioration. On the other hand, late blight, caused by the microorganism *Phytophthora infestans*, is an even more aggressive disease. It causes dark, water-soaked lesions on the leaves that quickly expand, potentially spreading throughout the entire plant. Late blight can be particularly devastating in cold, damp environments, where its spread is accelerated. If left unchecked, these diseases can severely affect crop yield, making early diagnosis and intervention crucial for farmers to protect their livelihoods and ensure consistent food production. Fig 1 (a) is showing early blight disease (alternaria solani fungus), whereas Fig 1 (b) exhinits the late blight (phytophthora infestans micro-organism).



Fig.1.Solanum Tuberosum(a)Premature(b) Late Blight Leaf

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Our system presented provides farmers with a fast, dependable, and easy-to-use tool for diagnosing plant diseases, allowing for early and precise detection. This enables timely actions to be taken, reducing the risk of significant crop losses and improving overall disease management strategies. As a result, it supports greater agricultural productivity and long-term economic stability. Utilizing image analysis paired with advanced deep learning methods, this system can transform how farmers monitor and protect the health of Solanum Tuberosum crops. It offers a highly effective solution to address the challenges posed by these harmful diseases, helping to safeguard yields and sustain farming operations.

Related Work

Different ML methods have been proposed during past years for classifying the of Solanum Tuberosum diseases. Early research predominantly used traditional image processing methods combined with machine learning classifiers. For instance, a study by [1] employed a combination of support vector machines (SVMs) to classify Solanum Tuberosum leaf diseases, demonstrating moderate accuracy. Another approach was presented by [2], where color and texture features were extracted from leaf images and fed into an artificial neural network (ANN) to identify early and late blight, achieving an improved performance over earlier methods. More recently, deep learning models have gained prominence due to their superior accuracy in image classification tasks. The authors in [3] used a deep convolutional neural network (CNN) to automatically detect Solanum Tuberosum blight from leaf images, reporting significant improvements in classification accuracy compared to traditional methods. Similarly, [4] developed a CNN-based architecture, which utilized pre-trained models for feature extraction and classification of Solanum Tuberosum diseases, further improving the performance. Other studies, such as [5], explored hybrid approaches by integrating CNNs with transfer learning techniques to address challenges in small, labeled datasets, thus enhancing the model's generalization capabilities.

Despite the advancements made by these approaches, several limitations remain. Traditional machine learning models [1], [2] often require extensive feature engineering and expert knowledge, which limits their scalability and robustness. Deep learning models, while offering higher accuracy [3], [4], typically require large labeled datasets for training, which are not always readily available for specific agricultural applications. Moreover, the computational resources needed for training CNNs [5] can be prohibitive for farmers in remote or under-resourced regions. Additionally, most existing systems do not incorporate real-time capabilities, reducing their applicability in fast-paced agricultural environments. Therefore, there remains a need for a system that balances accuracy, computational efficiency, and real-time diagnostic capabilities in Solanum Tuberosum disease classification.

II. Proposed Method

In this paper, we have presented the several stages of the project which is briefly visualised in the working diagram mentioned below.

Working Diagram

There are many important steps that have been taken to detect the leaf disease. The Fig. 2 is the model block diagram for the overview of the project and how it proceeds.

At first, the images are collected for pre-processing.After data augmentation, the CNN model is fabricated to train and then eventually, test. The trained followed by tested model finally detects and displays the desired results. Further mentioned steps are the more detailed version of how exactly deach and every step was fabricated and implemented to successfully identify and classify the leaves of solanum tuberosum.

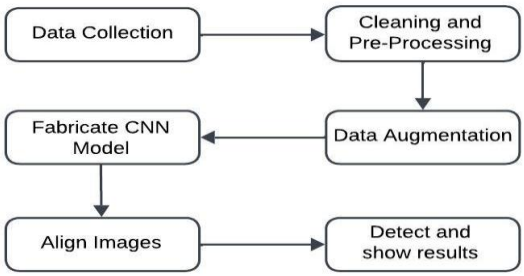


Fig.2. Block Diagram

Pseudocode

Step 1 : Load Dataset

- Import PlantVillage Dataset with "Healthy," "Early Blight," and "Late Blight" categories.

- Split data: 80% training, 20% testing.

Step 2 : Data Augmentation - For each training image:

- Apply transformations (rotation, flipping, cropping, scaling).

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- Resize to 252 x 252 pixels.

Step 3 : Define CNN Model Architecture

- Initialize a Sequential CNN model.

- Add layers:

Layer setup:

- Convolutional Layer 1: 32 filters, 3x3 kernel size, activated with ReLU
- Pooling Layer 1: 2x2 MaxPooling
- Convolutional Layer 2: 64 filters, 3x3 kernel, activated with ReLU
- Pooling Layer 2: 2x2 MaxPooling
- Convolutional Layer 3: 64 filters, 3x3 kernel, activated with ReLU
- Pooling Layer 3: 2x2 MaxPooling
- Convolutional Layer 4: 64 filters, 3x3 kernel, activated with ReLU
- Pooling Layer 4: 2x2 MaxPooling
- Flatten the output and add a Dense layer with 64 units, using ReLU activation.
- Final Output Layer: Dense layer with SoftMax activation for 3 output classes.

Step 4 : Compile Model

- Use Categorical Cross-Entropy as loss function.

- Set Adam optimizer, track accuracy.

Step 5 : Train Model

- Train on augmented training data for 10 epochs, batch size = 32.

- Track training and validation accuracy and loss.

Step 6 : Evaluate Model

- Test on 20% test data.

- Record final accuracy, loss, and prediction time per image.

Step 7 : Analyze Results

- Compare training vs. validation metrics across epochs.

- Report final model performance and efficiency.

Dataset Collection

The dataset utilized in this research consists of images of Solanum Tuberosum plant leaves, categorized into three groups: healthy leaves (Figure 3), leaves affected by early blight (Figure 3), and leaves with late blight (Figure 3). This dataset, titled "PlantVillage Dataset," was sourced from Kaggle, originally uploaded by Tairu Oluwafemi Emmanuel, with the most recent update in October 2018. The dataset includes 1000 samples of late blight, 1000 samples of early blight, and 152 samples of healthy leaves. A breakdown of it is presented in Table 1.

Table 1 : Dataset Details

S.no.	**Classes**	**Number of Images**
1.	Healthy	152
2.	Early Blight	1000
3.	Late Blight	1000
	Total	2152

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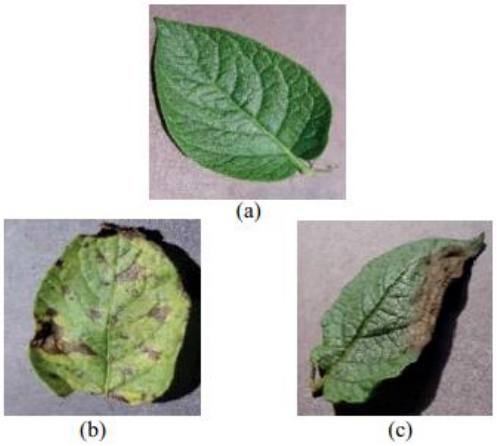


Fig.3.Image Data (a) healthy leaf (b) early (c) late blight

Data Preprocessing

- Data Augmentation in machine learning is the method of altering the versitality of a training dataset by applying various changes and transformations to the existing data. This is particularly useful in image processing and natural language processing tasks, where having more varied data helps improve model generalization and performance. By creating modified versions of the original data, models can become more robust to variations and reduce overfitting.
- This can be done by various methods such as rotation, flipping, cropping, translation, scaling and resizing. We have resized all the images to 252 x 252 in order to maintain uniformity.

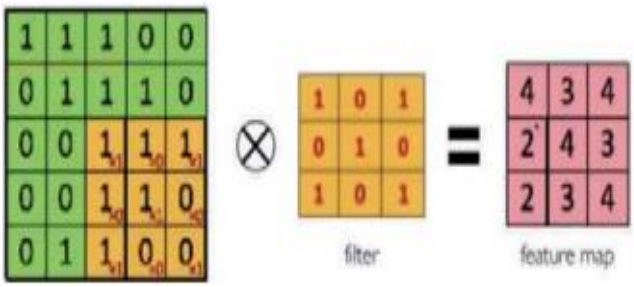
The details of the dataset chosen are mentioned below. The distribution of the dataset is 80:20 as, this split is often preferred over the 70:30 split for training and testing datasets because it provides a better balance between having enough data for training the model and sufficient data for testing. With 80% of data is used for training, the model has more information to learn from, which helps improve its performance and reduce the risk of overfitting. Meanwhile, 20% of the data reserved for testing is typically enough to accurately evaluate the model's generalization ability. This split ensures that the model can learn well while still being tested on a representative portion of the data, leading to more reliable and robust results.

table 2 : dataset details

S.no.	Classes	Number of Images	Training Samples	Test Samples
1.	Healthy	152	122	30
2.	Early Blight	1000	800	200
3.	Late Blight	1000	800	200
	Total	2152	1722	430

Convolution

Convolutional layers utilize filters to identify key features in the leaf images. During this convolution process, matrix multiplication occurs between the filter and specific regions of the image. As depicted in Fig. 4, the pixel values in the image are multiplied by the corresponding filter values. In this study, four convolutional layers will be applied. Convolutional neural network, is special case of ANN -artificial neural network, is commonly used for image segmentation and classification. It comprises of 3 rudimentary layers: the convolutional layer, the pooling layer, and fully linked pictures. Filters (shown as 'K' in Fig. (4)) slide over the image to collect important information at various processing stages since images are represented as matrices filled with numerical values (shown as 'I' in Fig. 4).



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Figure 4 : Convolution Process

Pooling

CNN's ability to learn and model complex relationships is build by applying activation function to it. In this case, the output layer uses the SoftMax activation function, while the hidden layers use the ReLU activation function. By choosing the maximum value from a N × N matrix, max pooling lowers the dimensionality of the input data as shown in Fig. 5. After the convolution process, pooling is performed, typically using MaxPooling. This step involves reducing the image size by selecting the highest pixel value within a defined area, as illustrated in Fig. 5. The benefit of this process is that it compresses the image data while preserving important information, thereby accelerating the classification process by reducing computational complexity.

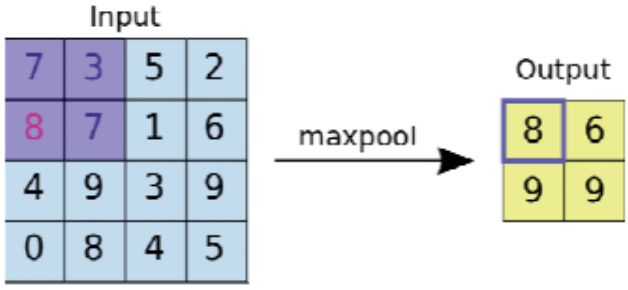


Fig. 5 : Max Pooling

Classification

The subsequent step involves classifying images using the Convolutional Neural Network (CNN) architecture, a technique from deep learning. CNN is a supervised learning method, where the model is trained on labeled image data to identify and categorize target image variables. The convolutional layers within the CNN architecture enable the network to recognize Solanum Tuberosum leaves by detecting specific features in the images. The network identifies these leaves based on pixel patterns in the images. In this study, images of size 252x252x3 are used, meaning the images are 252x252 pixels with three color channels: red, green, and blue (RGB). Initially, the images undergo convolution with a filter, followed by a pooling process to reduce resolution while preserving essential details, using Max Pooling for downscaling. The next stage is the fully connected layer, where the output from pooling is flattened. Flattening converts the pooled feature maps into a one-dimensional vector for final processing. The overall CNN architecture is illustrated in Fig. 6.

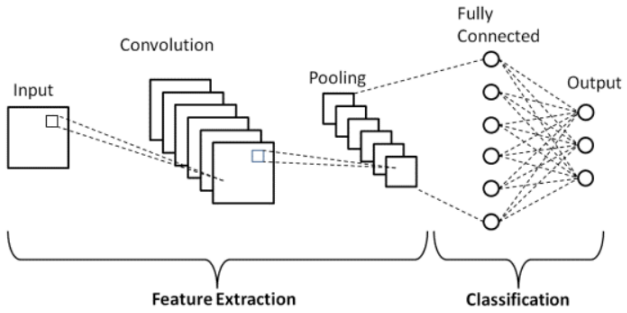


Figure 6 : Convolutional Neural Network Architecture

Table 3 : Convolutional Neural Network Model

Layer (type)	Output Shape	Param#
sequential_3 (sequential)	(32, 256, 256, 3)	0
sequential_4 (sequential)	(32, 256, 256, 3)	0
conv2d_6 (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d_6 (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_7 (Conv2D)	(32, 125, 125, 64)	18,496
max_pooling2d_7 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_8 (Conv2D)	(32, 60, 60, 64)	36,928

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max_pooling2d_8 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_9 (Conv2D)	(32, 28, 28, 64)	36,928
max_pooling2d_9 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_10 (Conv2D)	(32, 12, 12, 64)	36,928
max_pooling2d_10 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_11 (Conv2D)	(32, 4, 4, 64)	36,928
max_pooling2d_11 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten_1 (Flatten)	(32, 256)	0
dense_2 (Dense)	(32, 64)	16,448
dense_3 (Dense)	(32, 3)	195

Total params : 551,243 (2.10 MB)

Trainable Params : 183,747 (717.76 KB)

Non-Trainable Params : 0 (0.00 KB)

Optimizer Params : 367,496 (1.40 MB)

III. Result And Outcome

Table 4 shows the high performance, consistent accuracy, and low loss of the CNN-based Solanum Tuberosum leaf disease detection and classification model across training, validation, and test sets. Strong generalization and dependable performance on unknown data are demonstrated by the model's 99.35% accuracy on the training set, 99.25% accuracy on the validation set, and 99.65% accuracy on the test set. The model has successfully reduced errors without overfitting, as evidenced by the low loss values (0.011 for the training set, 0.012 for the validation set, and 0.010 for the test set).These results confirm the model's robustness and effectiveness in accurately identifying and classifying Solanum Tuberosum leaf diseases.

Table 4 : Model Accuracy and Loss

Metric	**Training Set**	**Validation Set**	**Test Set**
Accuracy	99.35 %	99.25 %	99.65 %
Loss	`	0.012	0.010

The training results of the Solanum Tuberosum leaf disease detection and classification model using CNN show a clear improvement in accuracy and reduction in loss over 10 epochs, as given in Table 5. Initially, the model had a training accuracy of 46.35% and validation accuracy of 45.31%, with higher loss values. However, by the third epoch, the accuracy improved significantly, reaching 73.90% for training and 80.21% for validation. As training progressed, the model continued to perform better, achieving a training accuracy of 91.26% and validation accuracy of 91.66% by the final epoch, with corresponding losses decreasing to 0.22 and 0.23, respectively. These results tell that the model effectively learned to detect and classify Solanum Tuberosum leaf diseases, achieving high accuracy and low error rates, making it reliable for future applications.

Table 5 : Result from Fit Model 80:20

Epoch	**Training Accuracy**	**Training Loss**	**Val Accuracy**	**Val Loss**
1	0.463542	0.917001	0.453125	0.881327
2	0.572338	0.84776	0.53125	0.951938
3	0.7390050	0.630454	0.802083	0.505657
4	0.811921	0.442026	0.864583	0.350816
5	0.861111	0.346077	0.885417	0.325677
6	0.888889	0.293531	0.84375	0.367892
7	0.890625	0.276371	0.90625	0.228104
8	0.902778	0.254628	0.916667	0.208956

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9	0.909144	0.237405	0.911458	0.249015
10	0.912616	0.220126	0.916667	0.23102

The performance analysis of the Solanum Tuberosum leaf disease detection and classification model using CNN includes an evaluation of prediction speed. The model demonstrates efficient processing, with the total average time for batch prediction being 0.100041 seconds, as shown in Figure 7. On an individual image basis, the average time taken for prediction is 0.003126 seconds per image.

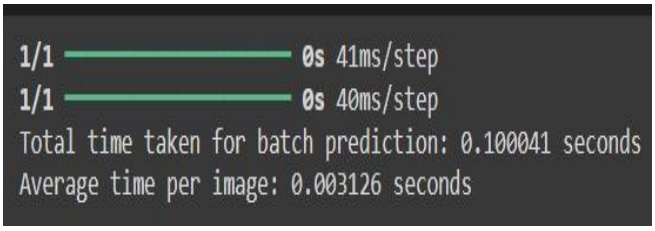


Figure 7 : Average Time Taken for Batch and Image

Below mentioned image, that is Figure 8, is an example screenshot from the model prediction process. It took the time of 142 millisecond, to predict the disease correctly with 100% accuracy, which is highly efficient.

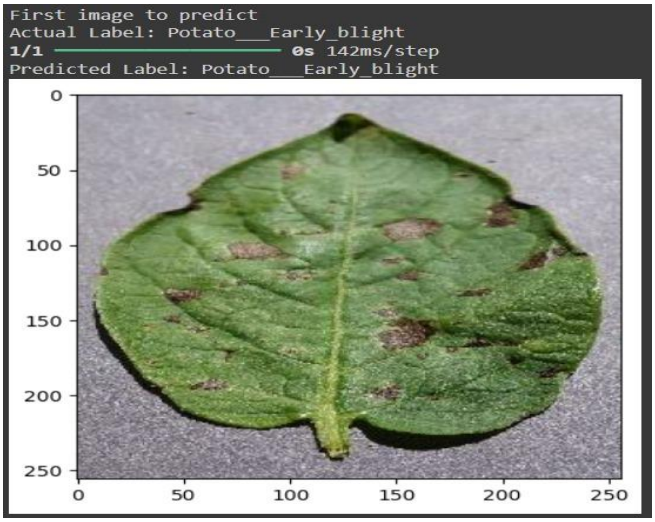


Figure 8 : Example that took 142 ms to predict

Figure 9 shows performance of our CNN model in forms of accuracy and loss over the training process. Both the training and validation data accuracy graphs are shown in Figure 9(a), with the orange line denoting the validation data and the blue line the training data. A similar illustration of the training and validation loss over epochs can be found in Figure 9(b). The model's consistent improvement in accuracy and loss reduction with each epoch shows that it is indeed learning well.

As accuracy represents the proportion of correct predictions out of the total, the rising accuracy across epochs reflects the model's improving ability to make accurate predictions. On the other hand, loss, which measures the error in the model's predictions, steadily decreases, demonstrating the model's success in minimizing errors over time. The downward trend in loss and upward trend in accuracy suggest that the model is well-optimized for high-performance prediction, making it reliable for classifying Solanum Tuberosum leaf diseases.

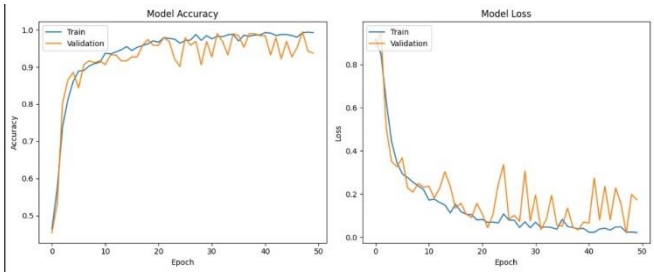


Fig.9.: Model Accuracy and Model Loss

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The confusion matrix visually represents the results of a classification algorithm, showing both correct and incorrect predictions. It helps evaluate the performance by highlighting where the model makes accurate or inaccurate assumptions. The classification accuracy and error rate equations are outlined below to quantify the model's precision and errors :

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Where,

TN = True Negative, TP = True Positive, FP = False Positive, FN = False Negative.

$$ERROR = 1 - Accuracy$$

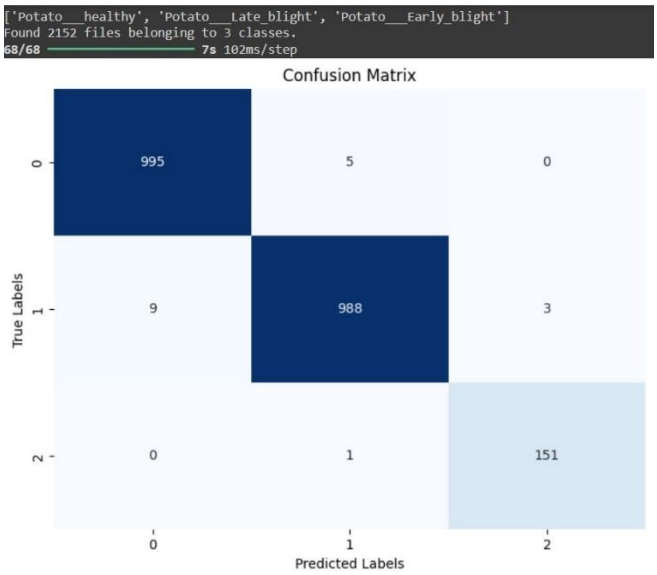


Fig. 10 : Confusion Matrix

Where, 0 – healthy, 1 – early blight, 2 – late blight

Fig. 10 shows the confusion matrix. It highlights that diagonal values are the highest in each row, indicating that our proposed algorithm achieves optimal accuracy.

X-axis (Predicted Classes): This axis shows the classes predicted by your model.

Y-axis (True Classes): This axis shows the actual classes (ground truth) of the dataset.

Below mentioned Table 6 shows the accuracy of our work while comparing it with other renowed methods earlier done by other people, around the globe.

Table 6: Comparision with other works

Reference	Technique	Plant	Accuracy(%)
This work	CNN,Data Augmentation	Solanum Tuberosum	99.48
Islam et al. 2017 [3]	RGB	Solanum Tuberosum	95
Hu et al. 2016 [13]	Hyperspectral Imaging	Solanum Tuberosum	95
Asfarian et al. 2013 [14]	Texture Analysis and PNN	Rice	83
Xu et al. 2011 [15]	K-Nearest Neighbour	Tomato	82

IV. Conclusion

The conclusion drawn is, that this study successfully developed a model that detects and classifies Solanum Tuberosum leaf diseases using Convolutional Neural Networks (CNN), achieving an impressive accuracy of 99.48%. By utilizing an 80:20 split for training and testing, we ensured the model is trained on a sufficient portion of the data while maintaining an enough evaluation process. This dataset division proved to be highly effective, outperforming other potential splits such as 70:30 and 90:10 splits, which may not provide the same level of model generalization. The high accuracy of our model demonstrates the superiority of CNN over traditional techniques in image-based disease detection, making it a reliable and efficient tool for early

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identification of Solanum Tuberosum leaf diseases. The approach enhances agricultural productivity by enabling timely intervention and reducing crop losses. Future work could explore further optimizations and expand this method to detect diseases in other crops, making it a versatile solution for precision agriculture.

Future Work

Predicting diseases in Solanum tuberosum (Solanum Tuberosum) is a complex challenge, but our research has yielded promising results that pave the way for effective disease detection systems. Based on our findings, we plan to develop a comprehensive system capable of determining whether a Solanum Tuberosum leaf is healthy or affected by disease. This project encompasses both software and hardware components, ensuring that we can achieve optimal performance and real-time outputs.

In our future work, we aim to integrate these elements, utilizing a diagram that illustrates the export of the trained model to disk, followed by the implementation of ML Ops. A TensorFlow (tf) server will be established to host the trained models, enabling seamless interaction with FastAPI for real-time disease detection. Additionally, we will extend our system to include the detection of diseases in other vegetables, such as tomatoes and bell peppers, thereby enhancing its versatility and applicability in agricultural settings. By leveraging this technology, we strive to provide farmers with efficient tools for early disease identification, ultimately contributing to improved crop management and yield.

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