DEPARTMENT OF COMPUTER ENGINEERING

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IMAGE AND VIDEO PROCESSING PROJECT REPORT ON

PLANT DISEASE CLASSIFICATION USING CNN MODEL

Submitted By

Roll No: – B033
Name - Saakshi Jain

Under The Guidance of

Dr. Supriya Agrawal

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INTRODUCTION

Agriculture is the backbench of food production around the globe and also a source of livelihood for millions worldwide. Apart from being a food source, plants supply all essential nutrition and oxygen needed to support human and animal life. Governments and other agricultural experts are trying in every way to enhance the production of food, but the most significant issue encountered is the plant diseases challenging crop yields and food security. They all infect various parts of a plant-from leaves and stems-and cause high degrees of damage. Most are influenced by climatic change; therefore, changing climatic conditions can also make complicated crop growth patterns and increased food insecurity worse. Effects of climatic change compound all these problems to threaten crops as well as global food security.

For most crop losses to be curtailed and prevented from extensive spread, diseases must be timely and accurately diagnosed. It allows targeted pesticides for early diagnosis that minimize harmful chemicals for overuse while damaging the crops and even the quality of the soil. The progress of certain diseases remains invisible until at an advanced stage, so they might diminish crop health and eventually reduce yield. Automated disease detection systems have come out as a powerful solution, providing quick and accurate results for small and large-scale farms.

The recent advances in deep learning and neural networks, particularly in the form of Convolutional Neural Networks (CNNs), have changed the paradigm of plant disease identification. These models, trained on images of both healthy and infected plant leaves, offer precise classification, which leads to early detection and targeted intervention.

These are among the most important and most widely cultivated and nutritious crops in the world, packed with essential vitamins and minerals, such as potatoes, tomatoes, and peppers. Still, they are easily infected by diseases such as late blight, which is caused by Phytophthora Infestans, and early blight, caused by Alternaria Solani, and are dangerous for crop yields and quality. Traditionally, crop diseases are detected through human skill, which is labor intensive, time consuming, and not practical for farmers farther from the urban centers. The application of image processing and machine learning offers an efficient, scalable alternative with higher accuracy in identifying symptoms of diseases and quicker decision making in disease management.

This paper introduces a classification framework that leverages the powers of image processing together with deep learning, for example, CNNs, in disease detection in various diseases afflicting pepper, potato, and tomato crops. The paper aims to exploit the potential of automated image analysis towards helping farmers in good-time detection of the disease so that crop health will be better protected while yield maximized.

LITERATURE SURVEY

Reference	Summary	Key Points
SpringerOpen(2021) [1]	This paper surveys deep learning concepts, specifically focusing on convolutional neural networks. Their applications, challenges, and future directions of further research are described here.	DL and CNN: Extremely important for machine learning Challenges:Overfitting, vanishing gradient issues are discussed along with suggested solutions.
ResearchGate(2018)[2]	This paper shall discuss how CNNs are applied to images for detection and recognition and describe their effectiveness and application	Detection Techniques: Discuss various techniques for object detection and recognition by CNNs. Performance Metrics: Analyzes the performance of CNNs by accuracy, precision, and recall metrics.
Frontiers(2022)[3]	This research focuses on the suitability of deep learning and computer vision in the early detection of plant diseases, thereby improving agricultural production and sustainability.	AI and Deep Learning for Plant Disease Detection Focus on early identification using leaf images Potential to decrease crop losses
ScienceDirect(2020)[4]	This work exploits deep learning algorithms in classifying plant leaf diseases with high precision, thus offering a great breakthrough for advancing agricultural health and productivity.	Application of deep learning to detect plant diseases Focus on leaf image analysis Improved Diagnostic Sensitivity Crop health and production benefits Scalable solution for agriculture
Ieeexplore (2020)[5]	This work proposes a deep learning-based approach for the accurate identification of crop diseases based on the analysis of images, which are exciting tools for enhancing agricultural efficiency.	Deep learning for crop disease detection Uses advanced image processing .It is accuracy- and efficiency-oriented. An opportunity to help farmer

Nature (2022)[6]	This paper develops an advanced deep learning model for disease identification and localization in tomato plants with a focus on agricultural efficiency.	The model delivered an accuracy rate of 99.97 percent. Performs perfectly under varying conditions for imaging. Aims at reducing the dependency on manpower inspection.
ASP journals(2019)[7]	A deep learning architecture has been developed to detect and localize disease in tomato plants to improve efficiency in agriculture.	The model delivered an accuracy rate of 99.97 percent. Performs perfectly under varying conditions for imaging. Aims at reducing the dependency on manpower inspection.
ScienceDirect(2020)[8]	This paper presents a CNN-based model for the detection and classification of diseases in tomato leaves with improved performance compared to pre-trained models at 91.2% accuracy.	Main Crop Tomato Problem: To identify disease on yield quality. Dataset: PlantVillage, 10 classes 9 diseases + healthy Model: ConvNet, 3 convolution + max pooling layers
ResearchGate(2021)[9]	To establish various architectures of CNNs in differentiating and classifying diseases on a tomato plant, measures of accuracy and applicability will be highlighted.	Comparison:Performance across different models Objective: Improve diagnostic accuracy Application:Field-use adaptability by the farmers
Ieeexplore (2022)[10]	Introduces innovative methods in the differentiation of CNN techniques using leaves of a bell pepper, tomatoes, and potatoes toward improving agriculture productivity.	It uses image processing and deep learning. Improving the sensitivity of disease diagnosis. Impact: Supports Sustainable Agriculture by Improving Plant Health Management.
MECS Press (2023)[11]	This paper proposes a custom CNN model that is used to accurately identify potato leaf diseases and hence provides an automated way to help farmers manage their crops.	Potato leaf disease detecting CNN model customized It deals with early blight, late blight, and healthy leaves. Achieved 99.22% accuracy Data augmentation and transfer learning used Potential applications in agricultural practice

PROBLEM STATEMENT

Plant diseases have severe impacts on agriculture productivity and cause huge loss globally. Most crops, peppers, potatoes, and tomatoes especially, are susceptible to all kinds of diseases that affect the quality or quantity of their yield. It is of paramount importance to identify such diseases in time and to do so accurately so proper management of crops and more prevention of the spread can be done. Traditional inspections are laborious, and prone to errors, and require experts to evaluate. This paper proposes an AI-based system to identify diseases in plants by classifying the leaves into the following categories:

This paper introduces an AI-driven plant disease detection system that classifies leaves into the following categories:

1. **Pepper**: Bacterial spot, healthy.
2. **Potato**: Early Blight, healthy, Late Blight.
3. **Tomato**: Target Spot, Tomato mosaic virus, Tomato Yellow Leaf Curl Virus, Bacterial spot, Early Blight, healthy, Late Blight, Leaf Mold, Septoria leaf spot, Spider mites (Two-spotted spider mite).

Leveraging Computer Vision, Image Processing, and Machine Learning (AIML), the system classifies leaves using image analysis. It will use visual disease indicators in the leaves to categorize them. The steps in the proposed system architecture involve image collection, data preprocessing, feature extraction, and model training. The Convolutional Neural Networks will be the core of this classification process.

The automated system is far much more efficient and reliable when compared to manual inspection methods based on speed, consistency, and reliability. Experimental results yield excellent accuracy in the detection and classification of multiple diseases, validating potential value to farmers for appropriately timely decisions. These huge benefits in disease prevention and reduced crop loss leading to increased agricultural productivity would then be realized.

PROPOSED SYSTEM

The proposed system aims to combine advanced image processing and deep learning techniques with the objective of identifying plant diseases across crops such as peppers, potatoes, and tomatoes.

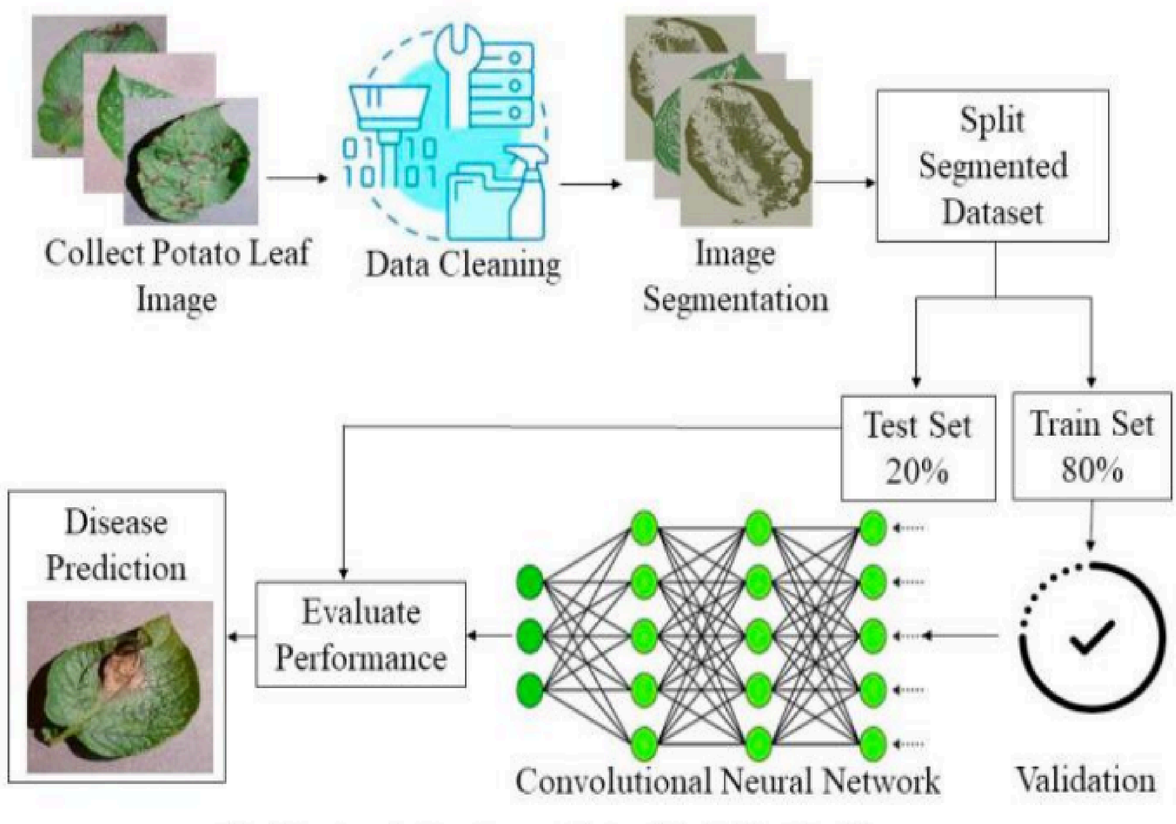


Figure 1: AI-Powered Deep Learning System for Predicting Potato Leaf Diseases

1. Dataset Compilation

This research utilizes the PlantVillage dataset from Kaggle, comprising images categorized as follows:

- **Peper:** Bacterial spot, healthy.

- **Potato:** Early blight, healthy, Late blight**.**
- **Tomato:** Target Spot, Tomato mosaic virus, Tomato Yellow Leaf Curl Virus, Bacterial spot, Early blight, healthy, Late blight, Leaf Mold, Septoria leaf spot, Spider mites (Two-spotted spider mite).

The dataset was divided into training (80%) and testing (20%) sets to ensure robust model performance. Sample distributions varied, ensuring adequate representation of each class.

2. Pre-processing

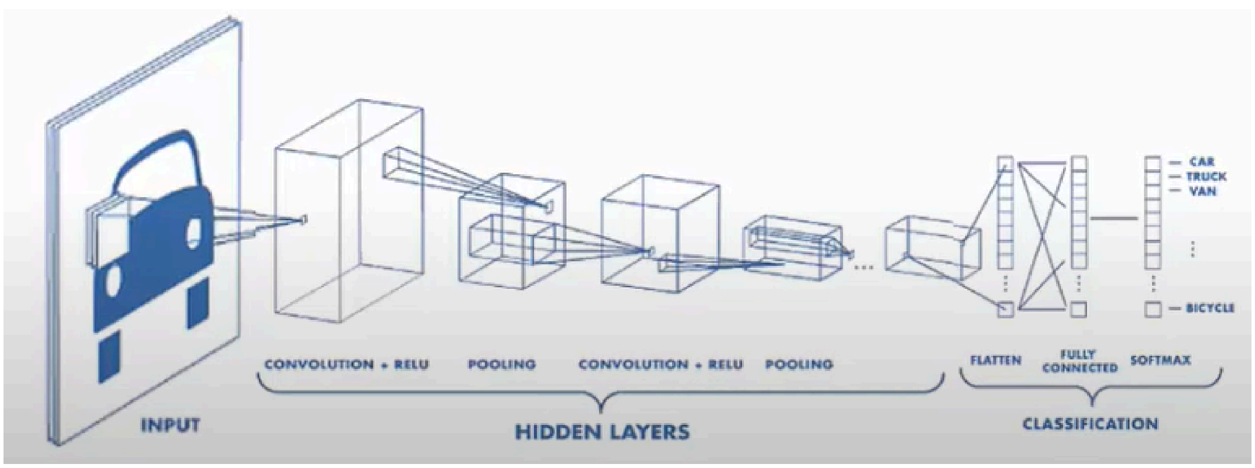
Pre-processing involved a series of steps to standardize the images and enhance their quality for better classification. Key image processing techniques applied include:

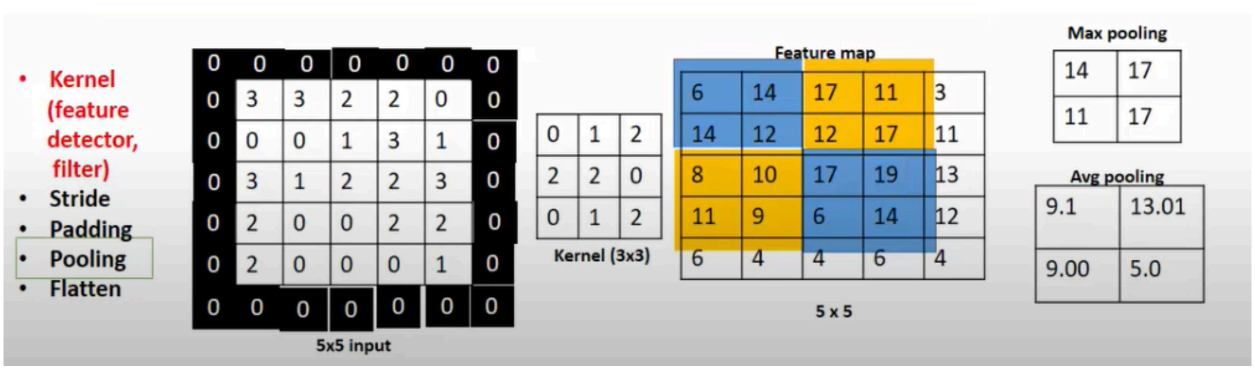
- **Thresholding Visualization**: Converts images to binary format to emphasize disease regions.
- **Grayscale Image Conversion**: Reduces image complexity by limiting color channels.
- **Spatial Resolution Adjustment** - adjusts image resolution to ensure resolution consistency within the dataset.
- **Digital Negative Transformation**: Inverts image colors to highlight disease details.
- **Smoothing and Sharpening:** noise removal, revelation of critical features, identification of significant differences between abnormality and normality.
- **Histogram Equalization:** improves contrast and spreads intensities so disease characteristics become easier to appreciate.
- It is applied for the purpose of data compression in an image, retaining significant frequency components for good features to be extracted.

- **Morphological Processing**: Dilation and erosion techniques refine the image structures in order to remove small noise elements and enhance the shapes of disease.
- **Edge Detection**: Applies either Canny or Sobel algorithms to identify edges of objects. This then defines disease spots.

3. Classification Using the CNN Model

The CNN is the main building block of the classification module. It uses a series of layers of convolution to extract the features and pooling layers for reducing the dimensionality and retaining important information. A fully connected layer does the final classification and provides the output category of the disease, for example, healthy, Early Blight, Late Blight, etc. It was trained on the preprocessed images and then its performance was verified using the test set.





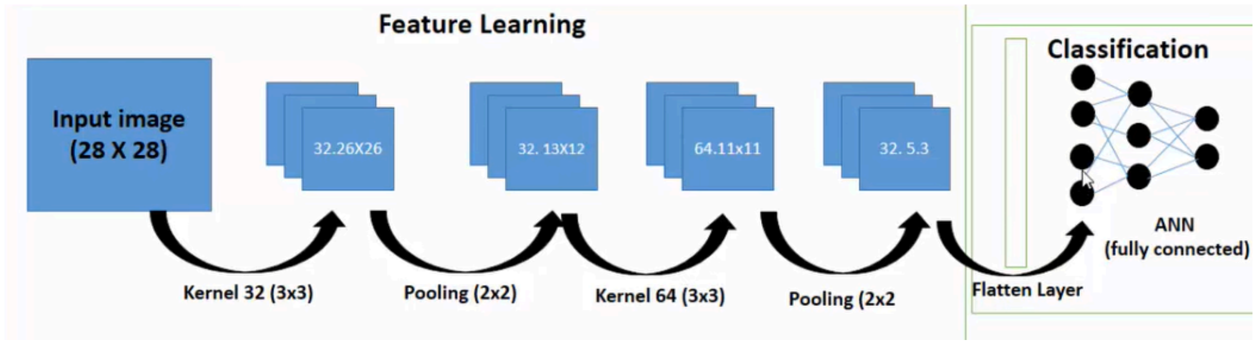


Figure 2: CNN Architecture

4. System Evaluation

The system's efficacy was assessed using metrics such as accuracy, precision, recall, and F1-score. The combination of deep learning and advanced image processing contributed to improved model reliability and accuracy. Prior methods, including Random Forests and SVMs, yielded positive results, but the deep learning approach enhanced performance through its capacity to handle complex visual patterns and higher-dimensional data.

System Workflow (Sequence Diagram)

The operational flow begins when the user uploads an image through a Flask-based web interface. The Flask application processes the request, saves the image, and conducts pre-processing. The pre-processed image is then input into the CNN model for prediction, which returns the classified disease type and a confidence score. The final output is displayed on an HTML page rendered by Flask. Fig. 7 illustrates the complete interaction, covering user input, image handling, and model prediction.

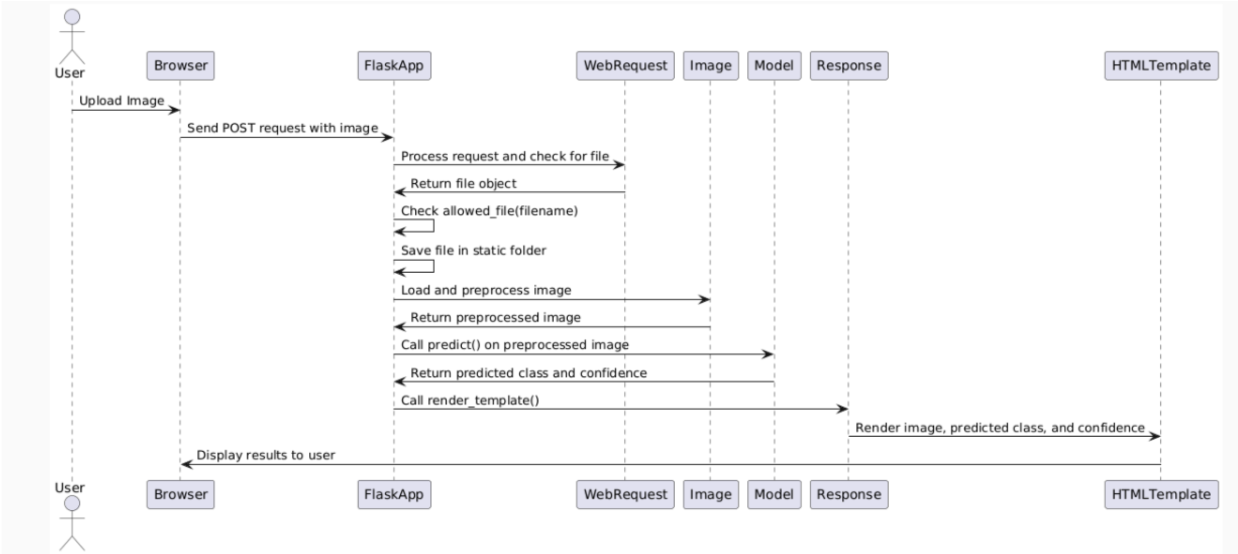


Figure 3: Pictorial Representation of the Architecture(Sequence Diagram)

Index Terms—Plant disease detection, Pepper diseases, Potato diseases, Tomato diseases, Computer Vision, AIML, Image classification, CNN, Agricultural productivity, Disease diagnosis.

IMPLEMENTATION

```
input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNEL)
n_classes = 15

model = models.Sequential([
    resize_and_rescale,
    layers.Conv2D(32, kernel_size = (3,3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    # ANN starts
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),
])
# ANN does not understand 2d
# flatten - 2d ko 1d convert
#
model.build(input_shape=input_shape)
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
sequential_6 (Sequential)	(32, 255, 255, 3)	0
conv2d_12 (Conv2D)	(32, 253, 253, 32)	896
max_pooling2d_12 (MaxPooling2D)	(32, 126, 126, 32)	0
conv2d_13 (Conv2D)	(32, 124, 124, 64)	18,496
max_pooling2d_13 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_14 (Conv2D)	(32, 60, 60, 64)	36,928
max_pooling2d_14 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_15 (Conv2D)	(32, 28, 28, 64)	36,928
max_pooling2d_15 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_16 (Conv2D)	(32, 12, 12, 64)	36,928
max_pooling2d_16 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_17 (Conv2D)	(32, 4, 4, 64)	36,928
max_pooling2d_17 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten_2 (Flatten)	(32, 256)	0
dense_4 (Dense)	(32, 64)	16,448
dense_5 (Dense)	(32, 15)	975

Figure 4: Model Architecture

```
Epoch 1/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 467s 777ms/step - accuracy: 0.2228 - loss: 2.3250 - val_accuracy: 0.4429 - val_loss: 1.6751
Epoch 2/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 374s 713ms/step - accuracy: 0.4893 - loss: 1.5469 - val_accuracy: 0.6455 - val_loss: 1.0424
Epoch 3/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 352s 682ms/step - accuracy: 0.6879 - loss: 0.9336 - val_accuracy: 0.6821 - val_loss: 0.9550
Epoch 4/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 351s 679ms/step - accuracy: 0.7683 - loss: 0.6672 - val_accuracy: 0.7915 - val_loss: 0.5787
Epoch 5/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 351s 679ms/step - accuracy: 0.8233 - loss: 0.5167 - val_accuracy: 0.8418 - val_loss: 0.4677
Epoch 6/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 347s 671ms/step - accuracy: 0.8509 - loss: 0.4371 - val_accuracy: 0.8325 - val_loss: 0.4806
Epoch 7/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 356s 689ms/step - accuracy: 0.8623 - loss: 0.4114 - val_accuracy: 0.8892 - val_loss: 0.3210
Epoch 8/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 347s 671ms/step - accuracy: 0.8837 - loss: 0.3411 - val_accuracy: 0.8921 - val_loss: 0.3059
Epoch 9/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 350s 675ms/step - accuracy: 0.8950 - loss: 0.3058 - val_accuracy: 0.8726 - val_loss: 0.3619
Epoch 10/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 350s 677ms/step - accuracy: 0.8891 - loss: 0.3291 - val_accuracy: 0.9150 - val_loss: 0.2533
Epoch 11/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 346s 670ms/step - accuracy: 0.9079 - loss: 0.2633 - val_accuracy: 0.8984 - val_loss: 0.2995
Epoch 12/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 349s 675ms/step - accuracy: 0.9018 - loss: 0.2816 - val_accuracy: 0.8901 - val_loss: 0.3134
Epoch 13/50
...
Epoch 49/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 333s 645ms/step - accuracy: 0.9718 - loss: 0.0890 - val_accuracy: 0.9780 - val_loss: 0.0674
Epoch 50/50
516/516 ━━━━━━━━━━━━━━━━━━━━ 339s 656ms/step - accuracy: 0.9730 - loss: 0.0813 - val_accuracy: 0.9673 - val_loss: 0.0802
```

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Figure 5: Model Compiling

```
scores = model.evaluate(test_ds)
```

```
65/65 ━━━━━━━━━━━━━━━━━━━━ 77s 201ms/step - accuracy: 0.9698 - loss: 0.0898
```

```
model.save("ALLmodel.h5")
```

Figure 6: Model Accuracy and loss

OUTPUT-Project Images

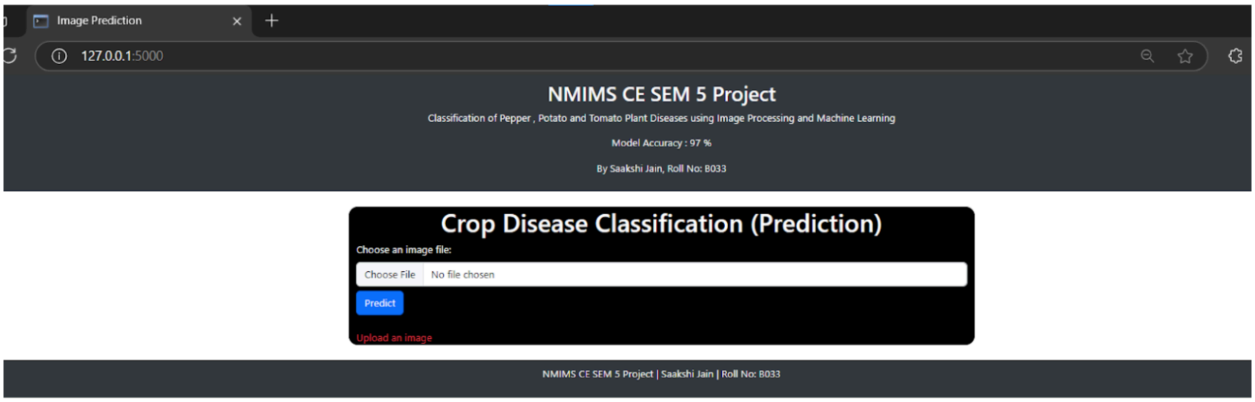

Figure 7: Output image 1

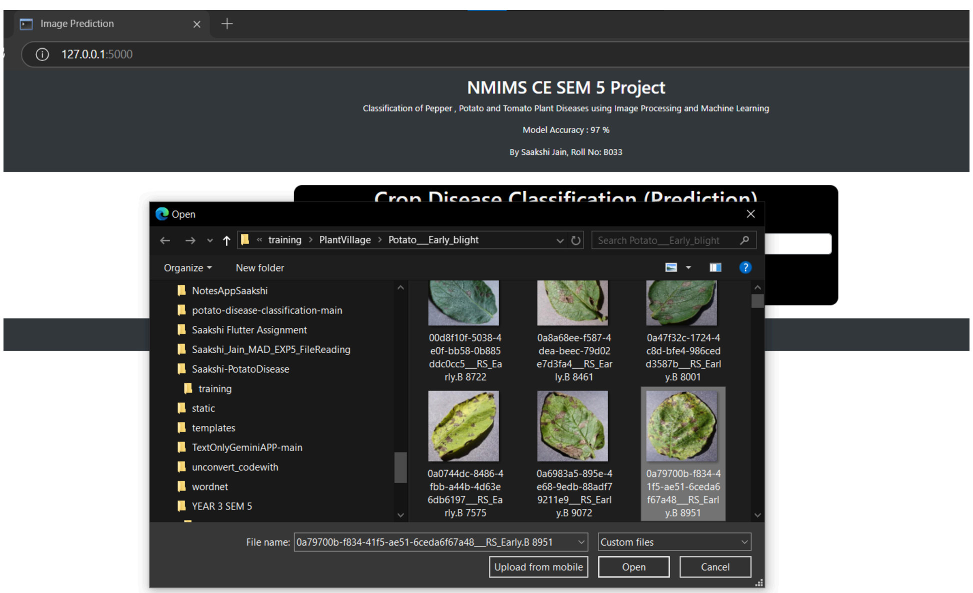

Figure 8: Output image 2

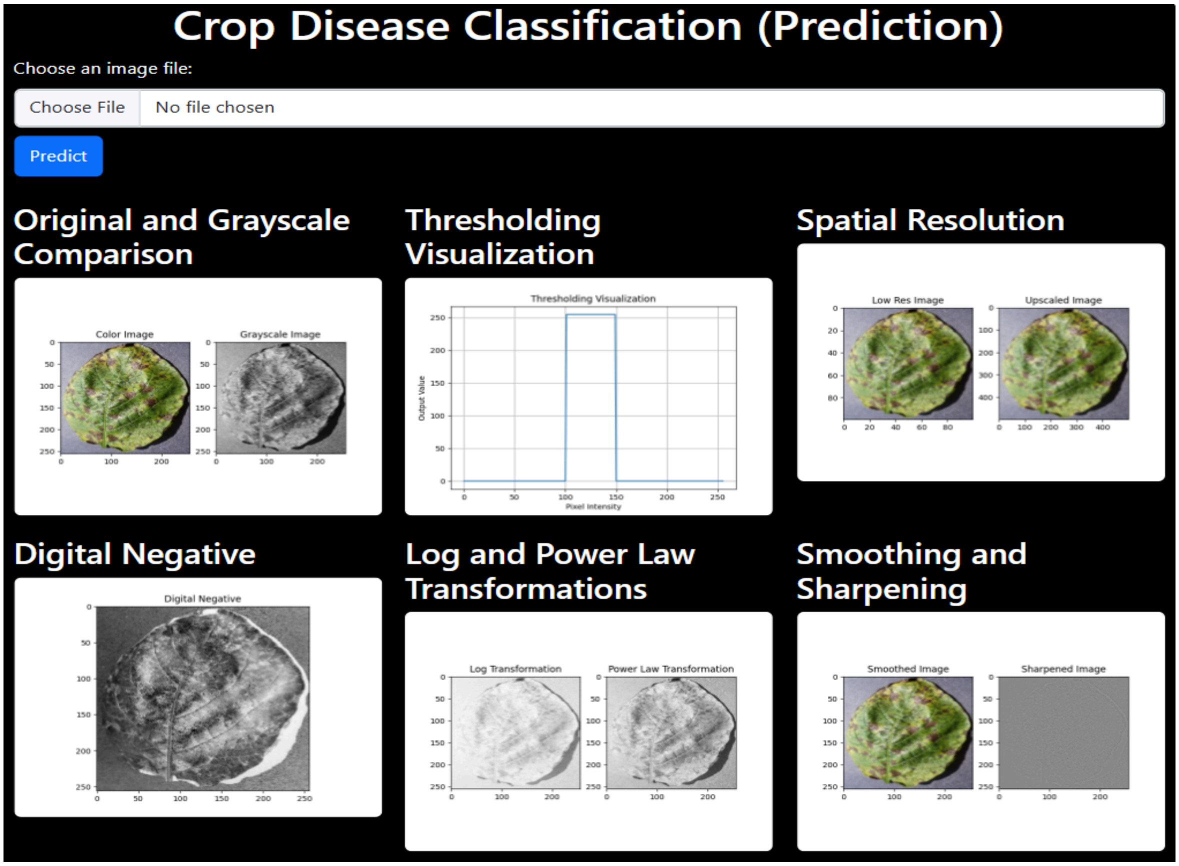

Figure 9: Output image 3

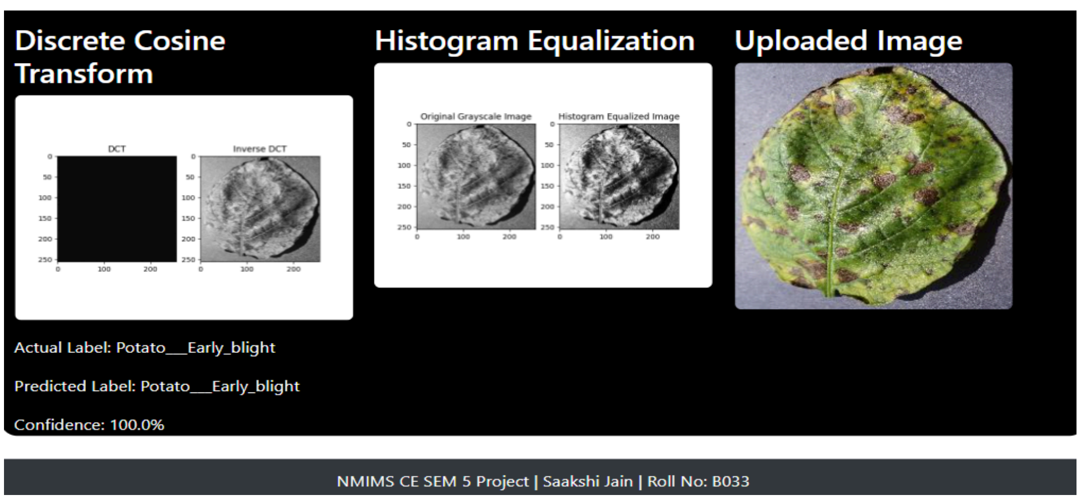

Figure 10: Output image 4

CONCLUSION

In this paper, an AI system for classifying the diseases of peppers, potatoes, and tomatoes has been designed using image processing techniques and deep learning methods. The proposed system was constructed based on CNNs for distinguishing well between healthy leaves and infected leaves in classes like early blight, late blight, bacterial spot, and more. The model achieved 96.69 percent accuracy and a minimum loss value of 0.0898, which might ensure great reliability in its practical applications and robustness.

These advanced methods of image processing that were integrated into the system-the thresholding visualization, histogram equalization, morphological processing, and edge detection-all improved the capture of critical features of disease cases, thus enhancing classification. Integration of pre-image processing with CNN-based deep learning is a very robust approach toward timely and precise disease detection.

The high accuracy and low loss indicate that such a model could be a very useful tool for farmers, enabling early plant disease detection, thus allowing for time-sensitive interventions to prevent the loss of crops. Such a system would empower even farmers in remote or resource-poor areas by avoiding dependence on manual inspection and expert consultation. In the long term, deploying such automated disease detection systems may lead to increased productivity in agriculture, food security, and sustainability in farming.

Future work may include expanding the dataset with a more diversified plant species and diseases as well as further optimizing the model for real-time deployment through mobile or IoT-based applications, which may reach more users.

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