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# LEAF DISEASE PREDICTION

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**ABSTRACT**

Leaf diseases are a major problem in agriculture, causing significant losses in crop yield and quality. Early detection of leaf diseases is essential for effective management, but it can be difficult and time-consuming to do manually. In recent years, there has been growing interest in the use of machine learning and computer vision techniques for leaf disease prediction. These techniques can be used to automatically extract features from leaf images that are indicative of disease, and then use these features to train a classifier that can distinguish between healthy and diseased leaves. Several studies have shown that machine learning-based methods can achieve high accuracy in leaf disease prediction. For example, one study reported an accuracy of 98% for detecting 10 different types of leaf diseases in tomato plants. The development of accurate and reliable leaf disease prediction methods has the potential to revolutionize the way that plant diseases are managed. By enabling early detection of diseases, these methods can help to reduce crop losses and improve crop yields

**Keywords**

CNN, Image processing, Convolution operations, Fully connected layer, Machine learning,
Computer vision

## 1. Introduction

One of the major sources of yield in India is the product of crops. It's of enhancing the technological advancement in the fields related to crop productivity. Then growers cultivate a maximum diversity of shops and crops. further studies are erected with the important sphere of qualitative and effective husbandry is concentrated on enhancing the yield and food crop productivity at a minimal time with a lesser outgrowth. The discovery of factory complaint by mortal visualization is a more delicate task and at the same time, less effective, and it’s done with a limited set of splint images and takes further time. Whereas the automatic identification fashion will take lower trouble and time and a more accurate program. Then we use image processing to descry the conditions. We can put the image into a system and a computer can perform colorful phases for identification and descry the affiliated classes to which that image belongs. This work aims to make a splint recognition fashion grounded on the specific characteristics deduced from images.

The CNN model is designed to suit both healthy and sick leaves; prints are used to train the model, and the affair is determined by the input splint. A working model for splint complaint vaticination generally uses a machine literacy algorithm to classify images of factory leaves into healthy or diseased orders.

The most common machine learning algorithm used for this task is a convolutional neural network( CNN). CNNs are a type of deep literacy algorithm that are specifically designed for image bracket tasks. A CNN- grounded working model for splint complaint vaticination works by first collecting a dataset of images of healthy and diseased factory leaves. The images are also preprocessed to remove noise and regularize the size. also trained on the preprocessed images.

The CNN learns to identify the features that are characteristic of healthy and diseased leaves. These features can include the shape of the splint, the color of the splint, and the presence of any spots or lesions. Once the model is trained, it can be used to classify new images of factory leaves. Model workshop by applying a series of complication operations to the input image. The complication operations excerpt features from the image that are applicable to the task of bracket. These features are also passed through a series of pooling operations that reduce the size of the point maps while conserving the most important features. The features are also smoothed and passed through a completely connected subcaste that classifies the image as either healthy or diseased. Applicable fungicides and diseases are suggested to help the conditions The CNN- grounded working model for splint complaint vaticination is a important tool that can be used to identify and manage factory conditions. The model can be used by growers to ameliorate crop yields and reduce crop losses.

The utilization of CNN-based models in the field of agriculture holds immense potential for revolutionizing crop management practices. By employing advanced technologies such as image processing and machine learning, we can create efficient and accurate systems for the early detection of plant diseases. This proactive approach enables farmers to take timely measures, such as targeted pesticide application or crop rotation, to mitigate the impact of diseases and pests. The CNN model's ability to discern subtle differences in leaf characteristics allows for precise identification, contributing to the overall health and productivity of crops.

Furthermore, the scalability of CNN models makes them adaptable to diverse agricultural settings and crop varieties. As agriculture plays a crucial role in the livelihoods of millions of people in India, embracing such technological advancements can lead to sustainable farming practices. The integration of

CNN-based systems into precision agriculture not only enhances yield prediction but also facilitates optimized resource allocation, minimizing environmental impact and maximizing resource efficiency.

In addition to disease detection, CNN models can also be employed for monitoring overall crop health. By analyzing images of plant growth patterns and leaf structure over time, these models can provide valuable insights into the developmental stages of crops. This information aids farmers in making informed decisions related to irrigation, fertilization, and other agronomic practices, ultimately contributing to improved crop management strategies.

The continuous refinement of CNN models through ongoing research and development is essential for keeping pace with evolving agricultural challenges. This includes expanding the dataset used for training to encompass a wide variety of crops and geographical conditions, ensuring the model's robustness across different scenarios. Collaborations between researchers, technologists, and farmers can further enhance the effectiveness of these models by incorporating local knowledge and real-world insights.

In conclusion, the adoption of CNN-based models for crop disease prediction and overall plant health monitoring represents a significant leap forward in agricultural technology. This convergence of artificial intelligence and agriculture not only addresses current challenges but also sets the stage for a more resilient and sustainable future for Indian agriculture. By empowering farmers with cutting-edge tools, we pave the way for increased food security, reduced environmental impact, and improved livelihoods in the agricultural sector.

## 2. LITERATURE SURVEY

[1] This paper titled "Deep Learning for Image-Based Plant Disease Detection using Convolutional Neural Networks" by Prasanna Mohanty proposes an innovative approach utilizing Convolutional Neural Networks to detect diseases in plants. The model is trained to distinguish between healthy and diseased plants across 14 different species, employing the capabilities of CNNs in image processing and recognition. The proposed model achieves an accuracy of 31.4% when evaluated on a dataset obtained from reputable online sources. The need for automated plant disease detection is addressed through this CNN-based approach, showcasing the potential for future enhancements and optimizations to further improve accuracy and robustness in plant disease detection using deep learning

[2] This paper by Malvika Ranjan, titled "Detection and Classification of Leaf Diseases using Artificial Neural Network," presents a pioneering approach to identify and categorize leaf diseases in plants utilizing an Artificial Neural Network (ANN). The model is meticulously trained by selecting pertinent feature

values critical for distinguishing between healthy and diseased plants. Inspired by the human brain's structure and functioning, ANN is a foundational element in deep learning, widely applied in diverse machine learning tasks, including image and speech recognition. The proposed approach achieves an impressive accuracy of 80% in leaf disease detection and classification, underscoring the potency of ANNs in automated plant disease diagnosis. Future research should delve into optimizing the model, exploring additional features, and integrating advanced techniques to further refine accuracy and robustness in leaf disease detection and classification.

[3] In this paper titled "Plant Disease Identification and Classification using Image Processing" authored by E. Vamsidhar, an innovative approach is presented for the automated detection and classification of plant diseases through image processing techniques. The proposed methodology involves training an image classification model, a fundamental task in computer vision, to categorize images of plants into predefined disease classes. This approach leverages the potential of image processing and automation for plant disease diagnosis, achieving an impressive accuracy of 85.3%. The results highlight the promising prospects of image classification in this context, providing a significant step toward reliable and automated plant disease identification, with the potential to enhance agricultural practices and crop yields. Future research should focus on model refinement, dataset expansion, and advanced image processing techniques to further improve accuracy and robustness in plant disease detection and classification.

[4] In this work titled "Detection of Unhealthy Regions in Plant Leaves and Plant Leaf Disease Classification using Texture Features" authored by S. Arivazhagan, a novel method is proposed to identify unhealthy regions in plant leaves and classify plant leaf diseases through the application of texture feature algorithms. These algorithms are fundamental tools in computer vision, offering insights into the texture and patterns within leaf images. By characterizing diverse surfaces, patterns, or structures present in the images, these texture features play a pivotal role in automating disease diagnosis in plants. The proposed approach demonstrates a significant accuracy of 86.77% in disease detection and classification, highlighting the efficacy of utilizing texture features for automated plant disease diagnosis. This research showcases promising potential for practical implementation and suggests avenues for further exploration, focusing on enhancing accuracy and robustness in automated plant disease detection and classification.

[5] The paper titled "Paddy Leaf Disease Detection Using SVM Classifier" by S. Pavithra introduces an approach for plant disease detection, employing a Support Vector Machine (SVM) Classifier. SVMs are a well-established supervised machine learning algorithm known for their effectiveness in binary

classification tasks. This paper demonstrates that the SVM Classifier model achieves an 85% accuracy rate, showcasing its potential for identifying diseases in paddy leaves, which could be instrumental in crop health management.

[6] The paper by P. Sanyal, titled "Pattern Recognition Method to Detect Two Diseases in Rice Plants," introduces a novel approach for disease detection in rice plants using Pattern Recognition Method, a field within artificial intelligence and machine learning. This method specializes in identifying and interpreting patterns present in various types of data. The paper demonstrates the effectiveness of this approach by achieving an accuracy of 89% in disease detection using the support vector machines (SVM) model, highlighting its potential for accurate diagnosis of diseases in rice plants.

[7] The paper titled "Advances in Image Processing for Detection of Plant Diseases" by K. Jayamala introduces a novel approach to plant disease detection using image processing algorithms. Image processing involves techniques to manipulate and analyze images, enhancing their quality and extracting valuable information for subsequent analysis. The paper discusses the significance of image processing algorithms across various domains such as computer vision, medical imaging, remote sensing, and multimedia processing. The results presented in the paper demonstrate that employing image processing techniques yields an accuracy of 85% in disease detection, emphasizing the potential of this approach in plant disease diagnosis.

[8] The paper titled "Tomato Leaves Diseases Detection Approach Based on Support Vector Machines" by Usama Mokhtar proposes an effective method for plant disease detection utilizing support vector machines (SVM). SVM is a powerful supervised machine learning algorithm commonly employed for classification and regression tasks, with notable efficiency in binary classification and adaptability to multi-class classification. SVMs are renowned for their capability to discern an optimal hyperplane, maximizing the margin between classes, rendering them robust and versatile classifiers. The results presented in this paper demonstrate an accuracy of 78% when employing support vector machines for tomato leaf disease detection, showcasing the potential of SVM in this domain.

[9] The paper titled "A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network" by Stephen Gang Wu Proposes an approach to detect disease in plants by training a "Probabilistic Neural Network". A Probabilistic Neural Network (PNN) is a type of artificial neural network that falls under the category of pattern recognition and classification algorithms. PNN is particularly useful for

classification tasks, where it's primarily applied to pattern recognition problems. It's known for its simple and efficient training process and has found applications in various fields, including pattern recognition, medical diagnosis, finance, and fault diagnosis.

[10] The paper titled “Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight” by Sharath D M Proposed an approach to detect disease in plants by “Image Processing”. Image processing algorithms encompass a wide range of techniques used to manipulate, enhance, analyse, and interpret images. These algorithms play a critical role in various applications such as computer vision, medical imaging, remote sensing, and more. When using the Image processing model achieves an accuracy of 75%.

## 3. METHODOLOGY

The different factory conditions have an enormous effect on growing food crops. An iconic illustration is the Irish potato shortage of 1845 – 1849, which redounded in1.2 million deaths. The conditions of several common shops are shown in Table 1. Plant conditions can be totally divided into fungal, oomycete, hyphomycete, bacterial, and viral types. We've shown some filmland of factory complaint in Figure 1. The filmland in Figure 1 were taken in the hothouse of Chengdu Academy of Agriculture and Forestry lores. Experimenters and growers have noway stopped exploring how to develop an intelligent and effective system for factory complaint bracket. Laboratory test approaches to plant samples, similar as polymerase chain response, enzyme- linked immunosorbent assay, and circle-intermediated isothermal modification, are largely specific and sensitive in relating

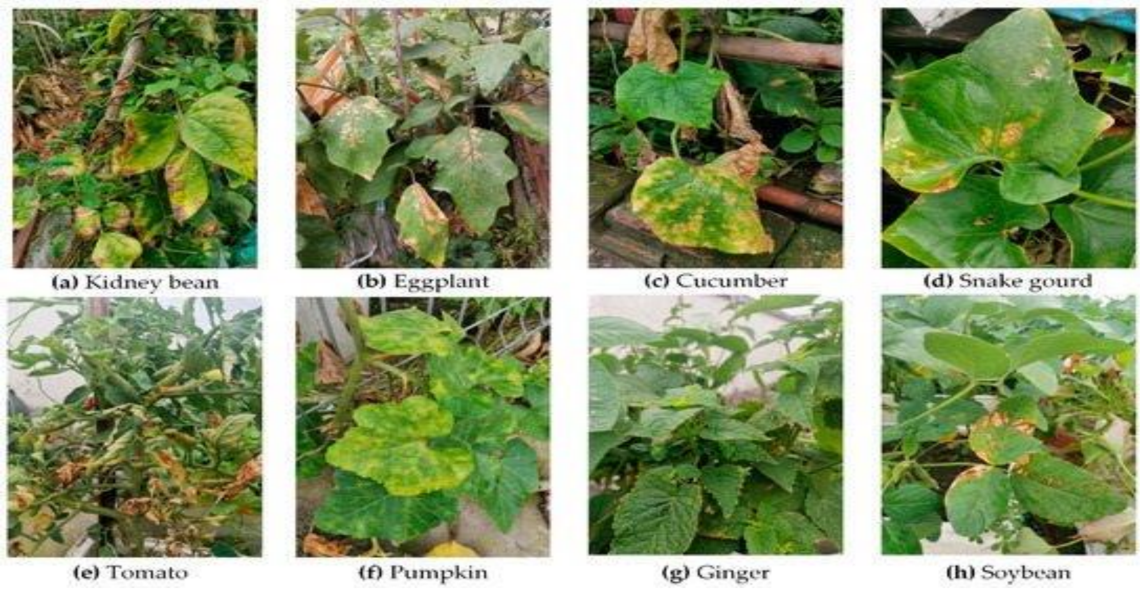


**Figure 1.** Leaf spot in eight common plants. We took these pictures in the greenhouse of Chengdu Academy of Agriculture and Forestry Sciences.

**Table 1.** Common diseases of several common plants.

| Plant | Major Types of Disease | | | Reference |
|---|---|---|---|---|
| | **Fungal** | **Bacterial** | **Viral** | |
| Cucumber | Downy mildew, powdery mildew, gray mold, black spot, anthracnose | Angular spot, brown spot, target spot | Mosaic virus, yellow spot virus | Kianat et al. (2021), Zhang et al. (2019), Agarwal et al. (2021) |
| Rice | Rice stripe blight, false smut, rice blast | Bacterial leaf blight, bacterial leaf streak | Rice leaf smut, rice black-streaked dwarf virus | Chen et al. (2021) Shrivastava et al. (2019) |
| Maize | Leaf spot disease, rust disease, gray leaf spot | Bacterial stalk rot, bacterial leaf streak | Rough dwarf disease, crimson leaf disease | Sun et al. (2021), Yu et al. (2014) |
| Tomato | Early blight, late blight, leaf mold | Bacterial wilt, soft rot, canker | Tomato yellow leaf curl virus | Ferentinos (2018), Abbas et al. (2021) |

still, conventional field gibing for conditions in crops still relies primarily on visual examination of the splint color patterns and crown structures. People observe the symptoms of conditions on factory leaves with the naked eye and diagnose factory conditions grounded on experience, which is time and labor consuming and requires technical chops. At the same time, the complaint characteristics among different crops are also different due to the variety of shops; this condition brings a high degree of complexity in the bracket of factory conditions. Meanwhile, numerous studies have concentrated on the bracket of factory conditions grounded on machine literacy. Using machine literacy styles to descry factory conditions is substantially divided into the following three way first, using preprocessing ways to remove the background or member the infected part; second, rooting the identifying features for farther analysis; eventually, using supervised bracket or unsupervised clustering algorithms to classify the features. utmost machine literacy studies have concentrated on the bracket of factory conditions by using features, similar as the texture, type, and color of factory splint images. The main bracket styles include support vector machines, K- nearest neighbor, and arbitrary timber. The major disadvantages of these styles are epitomized as follows

**3.1. Low Performance:** The performance they obtained was not ideal and could not be used for real-time classification.

**3.2 Professional database:** The datasets they applied contained plant images that were difficult to obtain in actual life. In the case of PlantVillage, the dataset was taken in an ideal laboratory environment, such that a single image contains only one plant leaf and the shot is not influenced by the external environment (e.g., light, rain).

**3.3 Requiring the use of segmented operation:** The plants must be separated from their roots to gain research datasets. Obviously, this operation is not good for real-time applications.

Most of the traditional machine learning algorithms were based on laboratory conditions, and the robustness of the algorithms is insufficient to meet the needs of practical agricultural applications. Nowadays, deep learning (DL) methods, especially those based on convolutional neural networks (CNNs), are gaining widespread application in the agricultural field for detection and classification tasks, such as weed detection, crop pest classification, and plant disease identification. DL is a research direction of machine learning. It has solved or partially solved the problems of low performance, lack of actual images, and segmented operation of traditional machine learning methods. The important advantage of DL models are that they can extract features without applying segmented operation while obtaining satisfactory performance. Features of an object are automatically extracted from the original data. Kunihiko Fukushima introduced the Neocognitron in 1980, which inspired CNNs. The emergence of CNNs has made the technology of plant disease classification increasingly efficient and automatic

**3.4 DEEP LEARNING**

DL is a branch of machine literacy and is substantially used for image bracket, object discovery, and natural language processing. DL is an algorithm grounded on a neural network for automatic point selection of data. It doesn't need a lot of artificial point engineering. It combines low- position features to form abstract high- position features for discovering distributed features and attributes of sample data. Its delicacy and conception capability are bettered compared to those of traditional styles in image recognition and target discovery. presently, the main types of networks are multilayer perceptron, CNN, and intermittent neural network( RNN). CNN is the most extensively used for factory splint complaint bracket. As for other DL networks, similar as completely convolutional networks( FCNs) and deconvolutional networks, they're generally used for image segmentation or medical opinion but aren't used for factory splint complaint bracket. CNN generally consists of convolutional, pooling, and completely connected layers. The convolutional subcaste uses the original correlation of the information in the image to prize features. The process of complication operation is shown in Figure 2. A kernel is placed in the top- left corner of the image. The pixel values covered by the kernel are multiplied with the corresponding kernel values, and also the products are added, and the bias is added at the end. The kernel is moved over by one pixel, and the process is repeated until all possible locales in the image are filtered, which is shown in Figure 2. The pooling subcaste selects features from the upper subcaste point chart by slice and contemporaneously makes the model steady to restatement, gyration, and scaling. The generally used one is maximum or average pooling. The process of the pooling operation is shown in Figure 3. Maximum pooling is to divide the input image into several blockish regions grounded on the size of the sludge and affair the maximum value for each region. As for average pooling, the affair is the normal of each region. Convolutional and pooling layers frequently appear alternatively in operations. Each neuron in the completely connected subcaste is connected to the upper neuron, and the multidimensional features are integrated and converted into one- dimensional features in the classifier for bracket or discovery tasks.

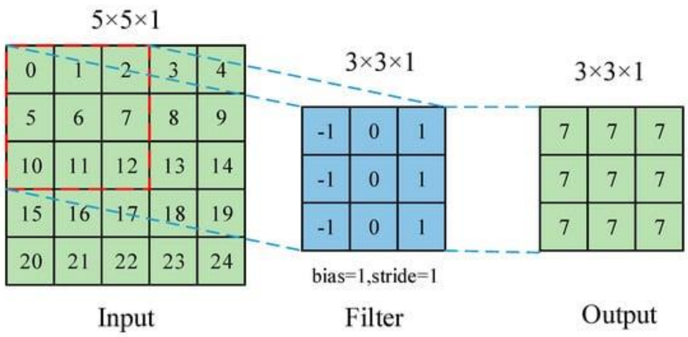


**Figure 2.** The process of convolution operation.

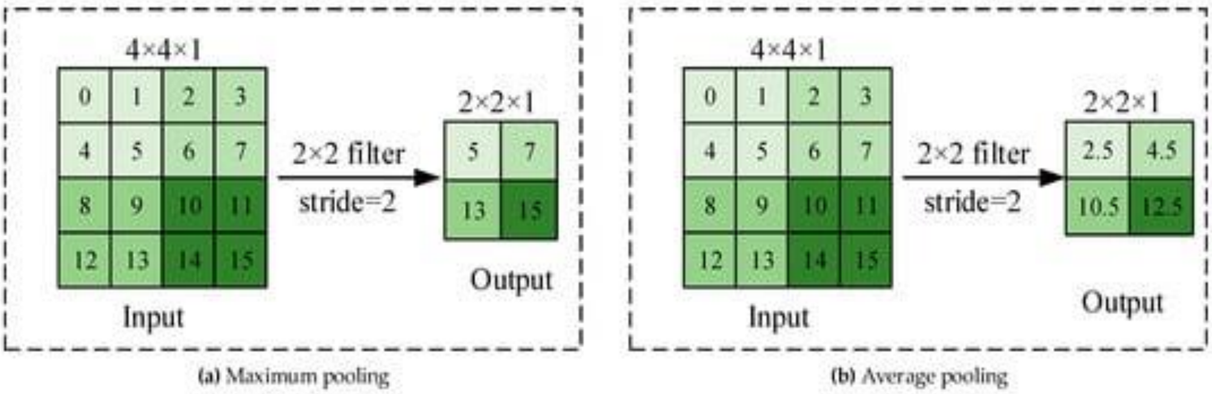


**Figure 3.** The process of pooling operation.

For bracket tasks, colorful CNN- grounded bracket models have been developed in DL- related exploration, including EfficientNet. AlexNet was proposed in 2012 and was the champion network in the AlexNet, VGGNet, GoogLeNet, ResNet, MobileNet, and ILSVRC- 2012 competition. This network contains five convolutional layers and three completely connected layers. AlexNet has the following four highlights( a) it's the first model to use a GPU device for network acceleration training;( b) remedied direct units( ReLUs) were used as the activation function;( c) original response normalization was used;( d) in the first two layers of the completely connected subcaste, the powerhouse operation was used to reduce overfitting. also, the deeper networks appeared, similar as VGG16, VGG19, GoogLeNet. These networks use lower piled kernels but have lower memory during conclusion. latterly, experimenters set up that when the number of layers of a deep CNN reached a certain depth, blindly adding the number of layers would not ameliorate the bracket performance but would beget the network to meet more sluggishly. Until 2015, Microsoft lab proposed the ResNet network and won the first place in the bracket task of the ImageNet competition. The network creatively proposed residual blocks and roadway connections, which solves the problem of grade elimination or grade explosion, making it possible to make a deeper network model. ResNet told the development direction of DL in academia and assiduity in 2016. MobileNet was proposed by the Google brigades in 2017 and was designed for mobile and bedded vision operations. In 2019, the Google brigades proposed another outstanding network EfficientNet. This network uses a simple yet largely effective emulsion measure to slightly gauge all confines of depth/ range/ resolution, which won't arbitrarily gauge the confines of the network as in traditional styles. As for factory complaint bracket tasks, it isn't necessary to use deep networks, because simple models, similar as AlexNet and VGG16, can meet the factual delicacy conditions.

The rapid-fire increase of DL is thick from the wide development of GPU. The perpetration of deep CNN requires GPUs to give calculating power support, else it'll beget the training process to be relatively slow or make it insolvable to train CNN models at all. At present, the most used is CUDA. When NVIDIA launched CUDA( Computing Unified Device Architecture) and AMD launched Stream, GPU computing started, and now, CUDA is extensively used in DL.

Image bracket is a introductory task in computer vision. It's also the base of object discovery, image segmentation, image reclamation, and other technologies. The introductory process of DL is shown in Figure 4, taking the task of bracket of conditions on the face of snake gourd leaves as an illustration. In Figure 4, we use a CNN- grounded armature to prize features, which substantially include convolutional, maximum- pooling, and full connection layers. The convolutional subcaste is substantially used to prize features of snake gourd factory splint images. The shallow convolutional subcaste is used to prize some edge and texture information, the middle subcaste is used to prize complex texture and part of semantic information, and the deep subcaste is used to prize high- position semantic features. The convolutional subcaste is followed by a maximum- pooling subcaste, which is used to retain the important information in the image. At the end of the armature is a

classifier, which consists of full connection layers. This classifier is used to classify the high- position semantic features uprooted by the point extractor.

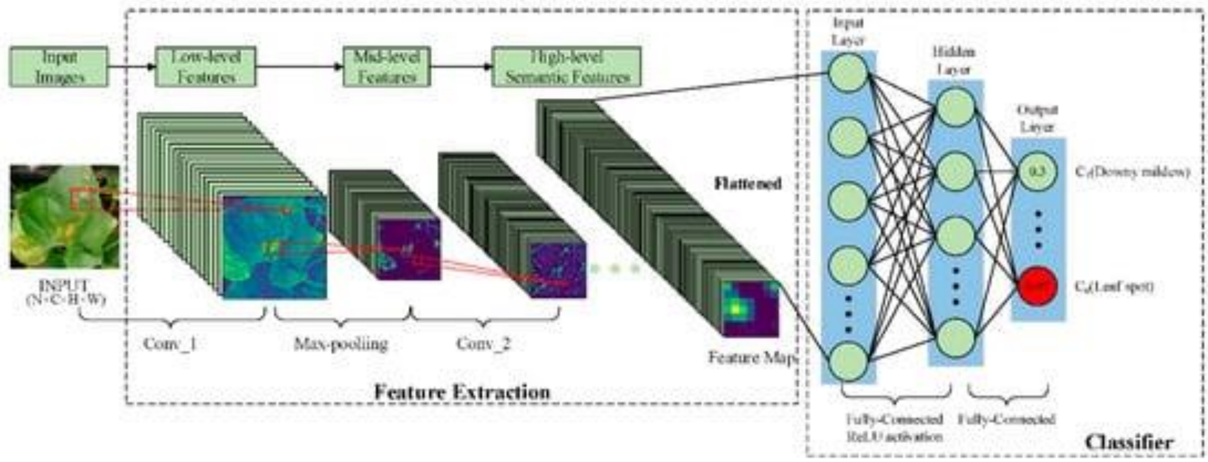


**Figure 4.** Convolutional neural networks for snake gourd leaf disease classification.

In Figure 4, we input a batch of images into the feature extraction network to extract the features and then flatten the feature map into the classifier for disease classification. This process can be roughly divided into the following three steps.

- Step 1. Preparing the Data and Preprocessing
- Step 2. Building, Training, and Evaluating the Model
- Step 3. Inference and Deployment

### 4. DATA PREPARATION AND PREPROCESSING

Data are important for DL models. The results are bound to be inaccurate no matter how complex and perfect our model is as long as the quality of the input data is poor. The typical probabilities of the original dataset intended for training, confirmation, and test are 702010, 801010, and 602020. A DL dataset is generally composed of a training set, a confirmation set, and a test set. The training set is used to make the model learn, and the confirmation set is generally used to acclimate hyperparameters during training. The test set is the sample of data that the model has not seen ahead, and it's used to estimate the performance of the DL model. We collected some public factory datasets from the websites Mendeley data and Bifrost

**Table 2.** Some public plant datasets from Mendeley data and Bifrost.

| **Name** | **Number of Images** | **Classes** | **Task** | **Type of View** | **Source** |
|---|---|---|---|---|---|
| New Plant Diseases Dataset | 87,000 | 38 | Image classification | Field data | Mendeley data |
| PlantVillage Dataset | 162,916 | 38 | Image classification | Uniform background | Mendeley data |
| Flowers Recognition | 4242 | 4 | Image classification | Field data | Mendeley data |
| Plant Seedings Dataset | 5539 | 12 | Target detection | Field data | Bifrost |
| Weed Detection in Soybean Crops | 15,336 | 4 | Target detection | Uniform background | Mendeley data |

For snake gourd splint complaint bracket, we need a large number of splint images of different complaint orders. Meanwhile, the complaint image data of each order were roughly balanced. However, also the neural network will be poisoned toward this complaint, If one complaint with a particularly large number of image data is considered. piecemeal from sufficient data on order balance, it also needs data to preprocess including image resize, arbitrary crop, and normalization. The shape of the data varies according to the frame used. Figure 5 shows the tensor shape of the input for the neural network, where H and W represent the height and range of the preprocessed image, C represents the number of image channels( argentine or RGB), and N represents the number of images input to the neural network in a training session.

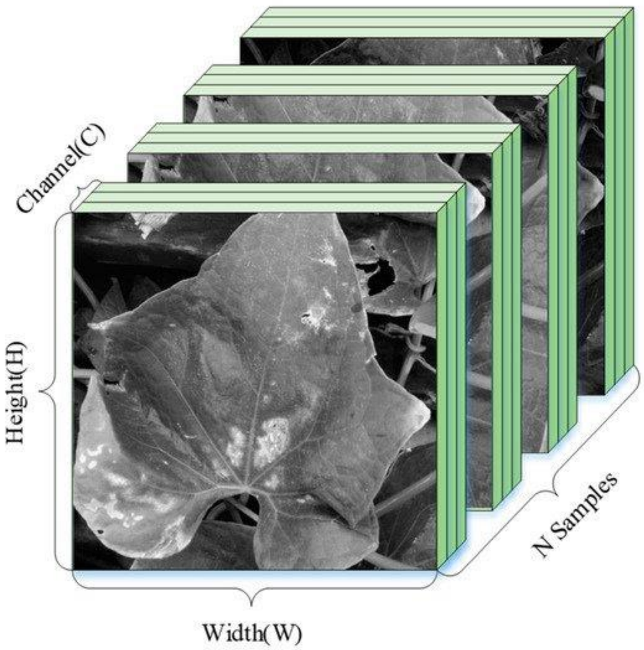


**Figure 5.** The tensor shape of the input neural network in PyTorch.

**5. INFERENCE AND DEPLOYMENT**

The conclusion is the capability of the DL model to snappily apply the literacy capability by the trained model to new data and snappily give the correct answer grounded on data that it has noway seen. After the training process is completed, the networks are stationed into the field for inferring a result for the handed data, which they've noway seen ahead. Only also can the trained deep literacy models be applied in real agrarian surroundings. We can emplace the trained model to the mobile terminal, pall, or edge bias, similar as by using an operation on the mobile phone to take prints of factory leaves and judge conditions. In addition, in order to use the trained model more in the field, the conception capability of the model needs to be bettered, and we can continuously modernize the models with the new labelled datasets to ameliorate the conception capability.

**6. BUILDING MODEL ARCHITECTURE, TRAINING, AND EVALUATING THE MODEL**

Before training, a suitable DL model armature is demanded. A good model armature can affect in more accurate bracket results and more rapid-fire bracket speed. presently, the main network types of DL are CNN, RNN, and generative inimical networks( GAN). Among colorful workshop, CNN is the most extensively used point birth network for the task of factory complaint discovery and bracket After the model armature is established, different hyperparameters are set for training and evaluation. We can set some parameter combinations and use the grid hunt system to reiterate through them to find the stylish one. When training the neural network, training data are placed into the first subcaste of the network, and each neuron updates the weight of the neuron through back- propagation according to whether the affair is equal to the marker. This process is repeated until new capability is learned from being data. still, whether the trained model has learned new capabilities is unknown. The performance of the model was estimated by criteria, similar as delicacy, perfection, recall, and F1 score.

**7. PROPOSED SYSTEMS**

We propose an innovative automated splint complaint vaticination system exercising Convolutional Neural Network( CNN) and image processing ways. Leaf conditions represent a significant trouble to agrarian productivity, causing substantial crop yield and quality losses. Timely complaint discovery is pivotal for effective operation, yet homemade identification styles are frequently laborious and time-consuming. using machine literacy and computer vision advancements, our system excerpts complaint-reflective features from splint images and trains a CNN classifier to distinguish between healthy and diseased leaves. The CNN model undergoes training on a comprehensive dataset of preprocessed splint images, learning distinctive features similar as splint shape, color, spots, and lesions. latterly, the system can directly classify new splint images into" healthy" or" diseased" orders, abetting growers in early complaint discovery. likewise, the system provides precious recommendations for suitable fungicides and diseases, enabling visionary complaint forestallment. By automating this pivotal aspect of husbandry, our proposed system offers an effective, accurate, and accessible result, promising to significantly reduce crop losses and enhance overall agrarian yields.

**7.1.System Overview and Architecture**

- The proposed automated splint complaint prediction system utilizes Convolutional Neural Network (CNN) and image processing techniques to classify splint images into "healthy" or "diseased" categories. The system comprises three main components:
- Image Preprocessing: This module preprocesses the input splint images to ensure consistency and enhance feature extraction. Preprocessing steps may include resizing, noise reduction, and color normalization.
- Feature Extraction: The CNN model extracts relevant features from the preprocessed images. These features capture the essential characteristics of the splint, such as shape, color, spots, and lesions.

- Classification: The extracted features are fed into the trained CNN classifier, which determines whether the splint is healthy or diseased. The classifier outputs a probability score for each class, indicating the likelihood of the splint being diseased.

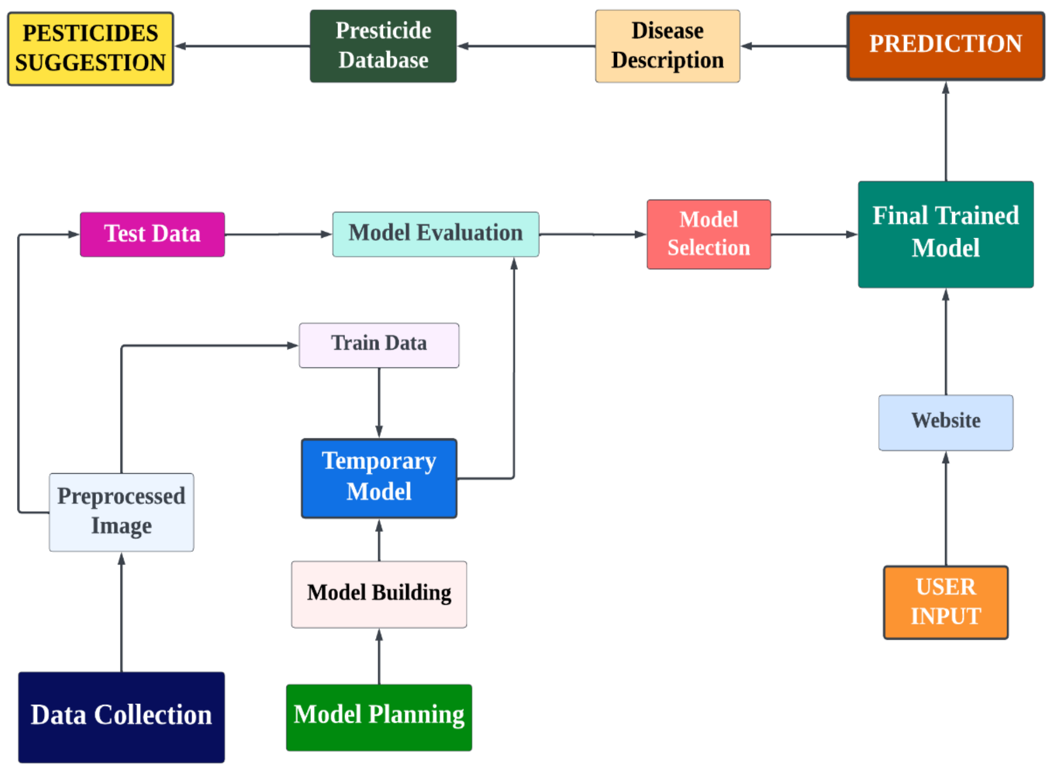


**Figure 6**.The System Architecture of proposed system

### 7.2.System Advantages

- The proposed system offers several advantages over traditional manual splint disease identification methods:
- Early Disease Detection: The system can detect diseases at an early stage, enabling timely intervention and preventing significant crop losses.
- Improved Accuracy: CNN-based classification can achieve high accuracy in distinguishing between healthy and diseased splints, reducing misclassifications.
- Automation: The system automates the disease identification process, saving time and labour for growers.
- Accessibility: The system can be easily integrated into existing agricultural practices and requires minimal technical expertise.

### 7.3.Algorithm Used

The system employs a Convolutional Neural Network (CNN) algorithm for image classification. CNNs are particularly well-suited for image recognition tasks due to their ability to extract hierarchical features from images. The CNN model is trained on a large dataset of prelabelled splint images, allowing it to learn the distinguishing features of healthy and diseased splints.

### 7.4.System Design

The system is designed to be modular, scalable, and user-friendly. The image preprocessing, feature extraction, and classification modules can be independently optimized and adapted to different splint types. The system's user interface is designed to be intuitive and easy to navigate, allowing growers to easily upload splint images and receive disease classification results.

The proposed automated splint complaint prediction system has the potential to revolutionize the way that splint diseases are managed in agriculture. By enabling early detection and providing timely recommendations, the system can help to reduce crop losses, improve crop yields, and enhance overall agriculture productivity

## 8.RESULTS


**Figure 7.** various types of plants available

### User-Friendly Interface for Image Upload and Plant Selection

The proposed leaf disease prediction system features a user-friendly web interface that allows users to easily upload images of plant leaves and specify the type of plant. This feature is crucial for accurate disease prediction, as different plant species exhibit distinct leaf characteristics and are susceptible to different diseases.

### Plant Selection Option

To enhance the accuracy of disease prediction, the system incorporates a plant selection option. Users can choose from a comprehensive list of plant species, providing the system with valuable context about the leaf image being analyzed. This information allows the deep learning model to consider plant-specific characteristics, leading to more precise disease classification results.

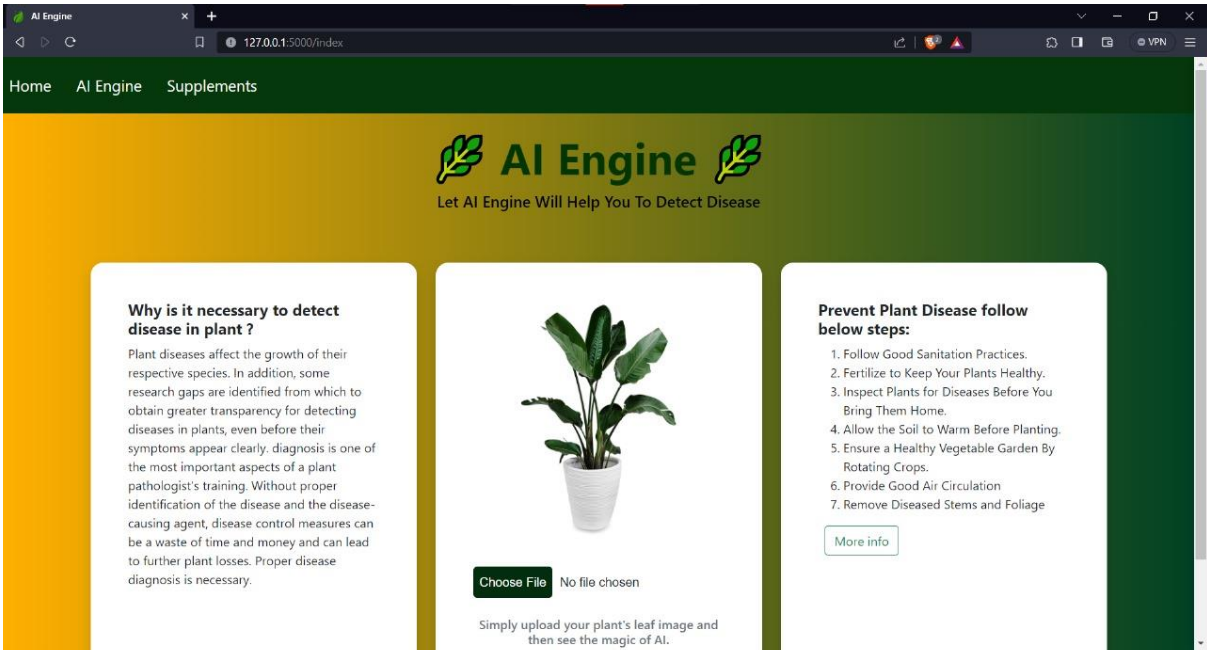


**Figure 8.** User input page

### Image Upload Mechanism

The web interface provides a straightforward image upload mechanism, enabling users to select images from their local storage or directly capture images using their device's camera. The system supports various image formats, ensuring compatibility with a wide range of devices and user preferences.

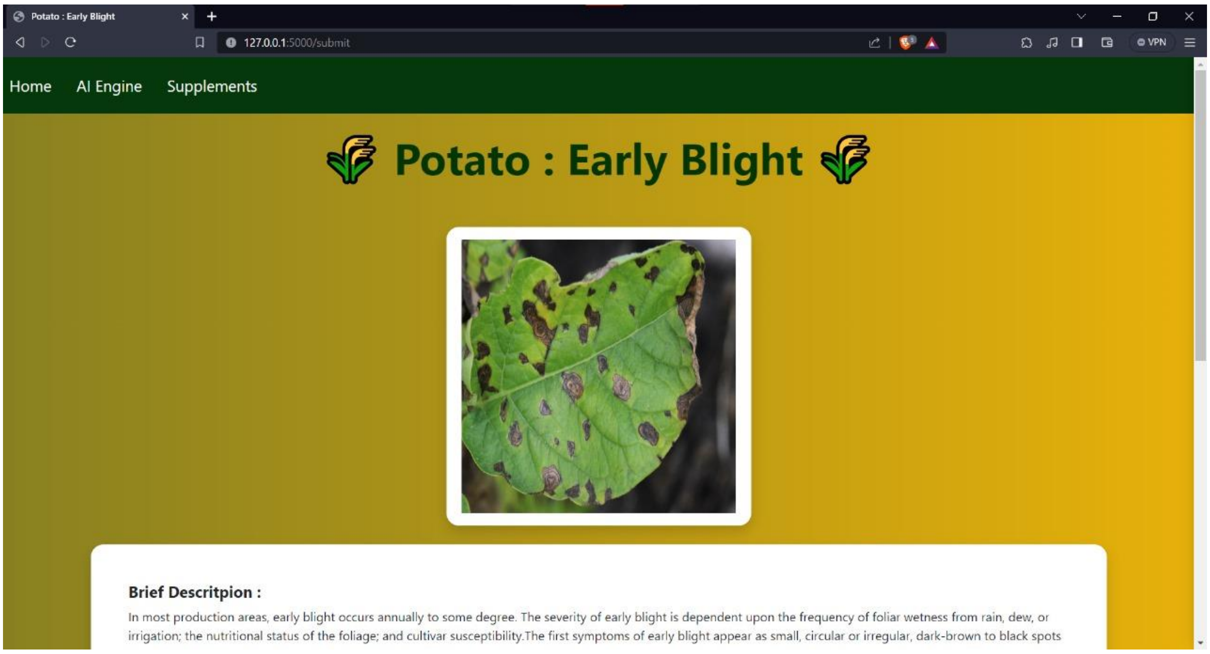


**Figure 9.1.** Disease Description page

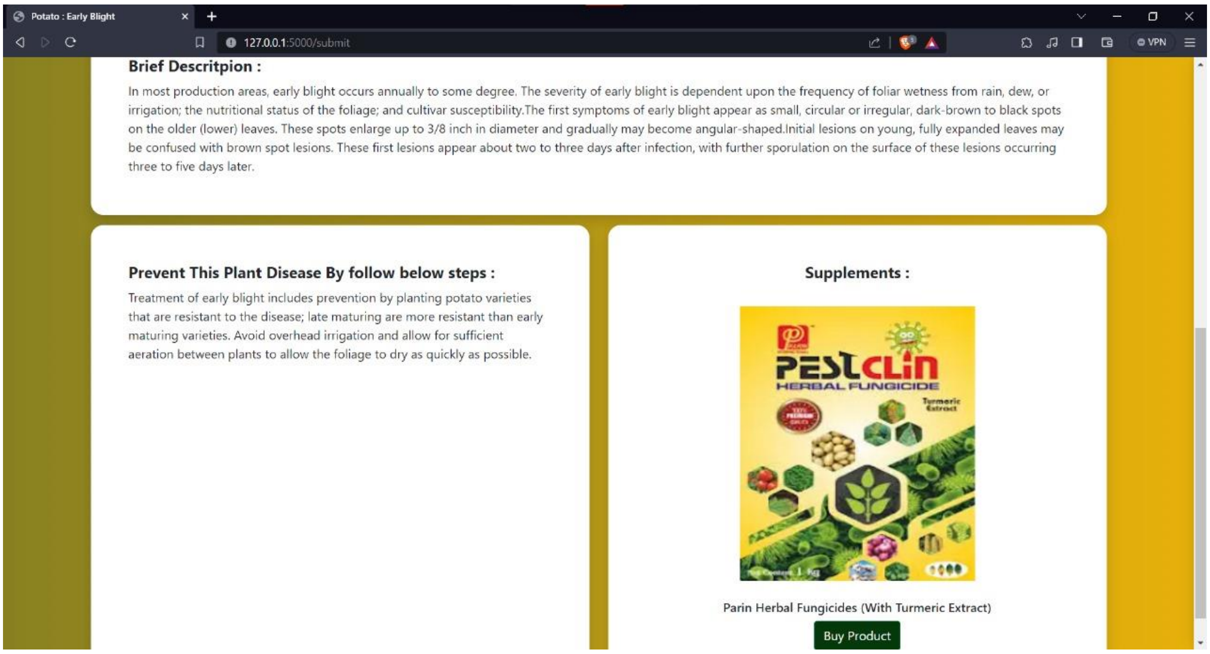


**Figure 9.2** Disease Description page

### Disease Prediction Based on User Input

The web page serves as the central point of interaction between the user and the leaf disease prediction system. It seamlessly integrates user input, image processing algorithms, and deep learning models to provide a comprehensive disease prediction solution. Users can easily upload images of plant leaves through an intuitive interface. The system then applies image preprocessing techniques to enhance the quality and consistency of the input images for optimal feature extraction. Subsequently, a trained convolutional neural network (CNN) model extracts relevant features from the preprocessed images. These features capture the essential characteristics of the leaf, such as shape, color, spots, and lesions. Finally, the extracted features are fed into the CNN model to classify the leaf image into one of two categories: healthy or diseased. The system provides users with the classification results along with recommendations for appropriate treatment measures. The web page also allows users to specify the type of plant, which further enhances the accuracy of disease prediction. This is because different plant species exhibit distinct leaf characteristics and are susceptible to different diseases. By considering the plant species, the deep learning model can provide more precise disease classification results.

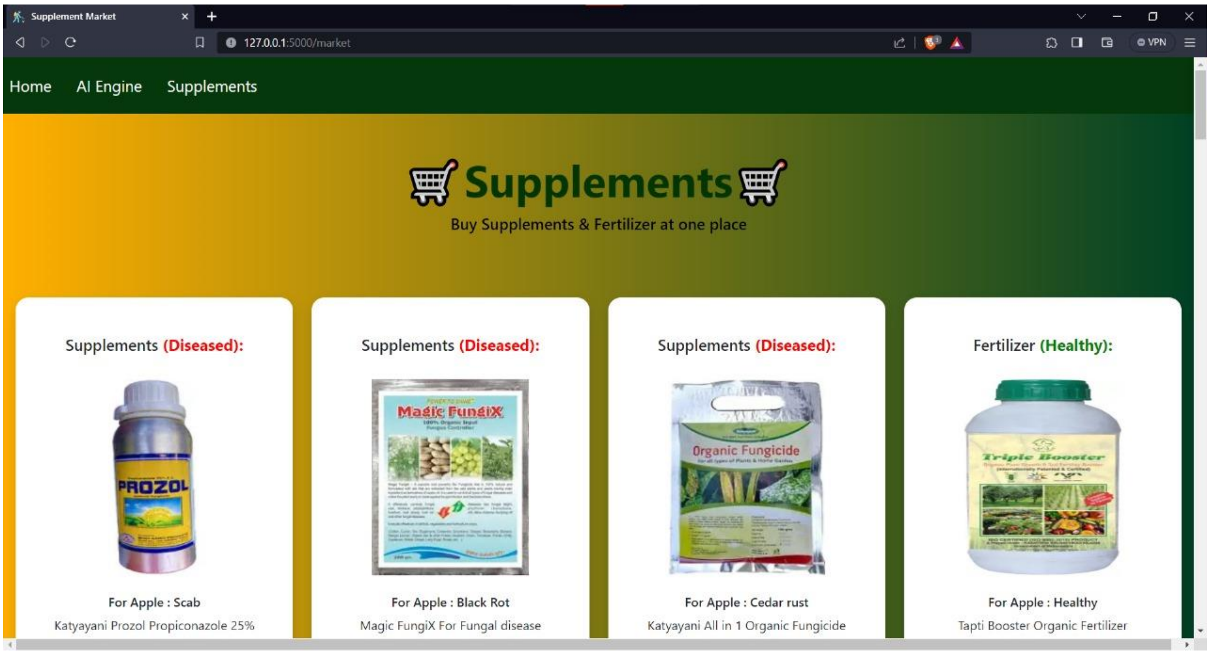


**Figure 10.** Supplements Recommendation page

**Personalized Pesticide Recommendations for Optimal Crop Health**

The web page goes beyond disease prediction to provide users with personalized pesticide recommendations tailored to the specific disease identified and the type of plant. This feature is crucial for effective and responsible pesticide use, ensuring that growers apply the appropriate pesticides at the right time and in the correct dosage to protect their crops while minimizing environmental impact.

## 9.CONCLUSION

Our groundbreaking automated splint complaint prediction system integrates state-of-the-art Convolutional Neural Network (CNN) and advanced image processing techniques, providing a robust solution to the pervasive challenge of leaf diseases that significantly impair agrarian productivity, resulting in substantial crop yield and quality losses. The timely identification of plant diseases is crucial for implementing effective management strategies, yet conventional manual identification methods often prove to be labour-intensive and time-consuming.

Leveraging the power of machine learning and computer vision advancements, our system adeptly extracts disease-specific features from splint images, employing a CNN classifier to discern between healthy and diseased leaves. Through an exhaustive training process on a diverse dataset of preprocessed splint images, the CNN model acquires the ability to recognize distinct features such as splint shape, color variations, as well as the presence of spots and lesions. Subsequently, the system becomes proficient in directly classifying new splint images into "healthy" or "diseased" categories, facilitating early disease detection for growers.

Notably, our system goes beyond mere classification by offering valuable recommendations for suitable fungicides and disease management strategies. This proactive approach enables visionary disease prevention, empowering growers to make informed decisions that mitigate the impact of diseases on their crops. By automating this pivotal aspect of agriculture, our proposed system not only ensures effectiveness and accuracy but also enhances accessibility, promising to significantly reduce crop losses and elevate overall agrarian yields.

In addition to its efficacy in disease prediction, our system accommodates grayscale leaf images, demonstrating adaptability and versatility in its application. This feature enhances its usability across a spectrum of scenarios, where grayscale images may be more readily available or preferred for specific analytical purposes.

In conclusion, our automated splint complaint prediction system, tailored to process grayscale leaf images, stands as an innovative and indispensable tool for modern agriculture. With its ability to streamline disease detection, provide timely recommendations, and accommodate diverse image inputs, our system is poised to revolutionize crop management practices, fostering a more sustainable and resilient agrarian ecosystem.

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