Plant disease prediction using hybrid model

Mr.Gopinath V M.E.,
Department of computer
science and Engineering
KSR institute for engineering and technology
Tiruchengode
gopicse24@gmail.com

Ilakiya V
Department of computer
science and Engineering
KSR institute for engineering and technology
Tiruchengode
velmuilakya.13@gmail.com

Monikasri B
Department of computer
science and Engineering
KSR institute for engineering and technology
Tiruchengode
monikasribabu2152@gmail.com

Nandhini R
Department of computer
science and Engineering
KSR institute for engineering and technology
Tiruchengode
ramakrishanandhini@gmail.com

Shalene V
Department of computer
science and Engineering
KSR institute for engineering and technology
Tiruchengode
shaleneskv23@gmail.com

Abstract— India's economy is heavily reliant on agricultural output.When a plant acquires a disease that ends up resulting in a significant decrease in production, economic damage, and an overall decrease in thequality and quantity of agricultural products, a lot is on board. To avert a decrease in agricultural yield and quantity, it is necessary to identify plant diseases. Many acres of crops are being closely tracked, plant disease detection is receiving a growing amount of attention.Sustainable farming depends on maintaining an eye on plant health and detecting diseases. Plant diseases are challenging to detect immediately. as it needs plenty of work, expertise in plant diseases, and extended time for processing. Thus, by using techniques for image processing, this can be achieved. In our Project we are using Convolutional Neural Network(CNN) and Long Short Term Memory(LSTM) to predict the plant disease.

Keywords—Plant disease prediction, Convolutional Neural Network, Long Short Term Memory.

1.INTRODUCTION

India's economy depends upon agriculture for more than just food. The agricultural land mass of today grown to a level where it now plays a significant role in the economy of a nation. In India, the agricultural sector supports 60–70% of the population. Vegetables and yields often get significantly lost due to plant diseases. Plant diseases which emit hazardous metabolites can also have a detrimental effect on human health. Plant visual patterns must be found in order to understand plant disease. Plant disease diagnosis is a crucial component of cultivation since failure will have an impact on product quantity, quality, and human health. Plant
diseases may take a variety of forms and are brought on by viruses, bacteria, and fungi. To detect plant pathology early on, an automatic disease identification technique can be useful. To prevent the spread of plant diseases and prevent agriculture damage, early detection and accurate diagnosis are crucial. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are two deep learning models that have shown promising results for predicting plant diseases. CNNs are a specific kind of deep neural network that are well-suited for image classification tasks like predicting plant diseases because they can

automatically learn features from images. A CNN model may learn to identify distinct characteristics and patterns in the images that are associated with different plant diseases by being trained on a large dataset of plant images. In contrast, LSTM networks can handle and predict data sequences, which makes them an excellent choice for time-series data like information on plant diseases. An LSTM model can learn to capture the temporal dependencies of the data and predicting future disease outbreaks by being trained on a dataset of plant disease information collected over time. A powerful technique for predicting plant diseases can be accomplished through the use of CNNs and LSTMs. The LSTM can learn to capture the temporal dependencies of the data and predicting future disease outbreaks based on historical data, whereas the CNN can learn to extract features from plant images. Overall, the combination of CNNs and LSTMs can provide a more accurate and trustworthy way to forecast plant diseases, leading to better crop management strategies and a reduction in the financial losses caused by plant diseases. These algorithms are able to accurately identify and predict the early stages of diseases by analysing enormous amounts of data and learning complex patterns. Farmers may utilize plant disease prediction to take necessary measures to stop the spread of illnesses and improve crop yield. The usage of harmful chemicals and pesticides can be minimized with the use of early detection and accurate forecasting, which leads to more sustainable methods of farming.

2. LITERATURE REVIEW

In [1]. A deep learning approach for plant disease classification using a Convolutional Neural Network (CNN). The dataset used in the study contains 54,306 images of plant leaves from 38 different classes of plants, including both healthy and diseased plants. The study highlights the potential of deep learning-based approaches for automated plant disease detection and classification, which can be beneficial for crop management and food security.

In [2].A deep learning approach for plant disease identification using a Convolutional Neural Network (CNN) with transfer learning. The authors used the pre-trained VGG16 model as a starting point and fine-tuned it on a dataset of 7,000 plant images from 10 different classes of diseases. The study highlights the effectiveness of transfer learning in deep learning-based approaches for plant disease identification, where the pre-trained models can help reduce the computational requirements and improve the accuracy of the model.

In [3].A transfer learning approach for detecting plant diseases using pre-trained CNN models. Specifically, they used four pre-trained CNN models, namely InceptionV3, Inception ResNetV2, ResNet50, and Xception, and fine-tuned them on the plant disease dataset. They also used data augmentation techniques such as rotation, zooming, and flipping to increase the size of the dataset. The authors also conducted experiments to show the effectiveness of transfer learning and data augmentation techniques in improving the performance of the model.

In [4].The automatic identification and categorization of plant leaf diseases using an image segmentation system is presented in this work. It also includes an overview of various disease categorization methods that can be applied to the identification of plant leaf diseases. Using a genetic algorithm, image segmentation is a crucial step in the disease detection process for plant leaf disease.

In [5].The authors first introduce the concept of plant disease and its impact on global food security. They then describe the traditional methods of plant disease diagnosis, which are time-consuming and require specialized expertise. This highlights the need for an efficient and automated approach, which can be provided by deep learning techniques. The paper then describes the basics of deep learning, including the architecture of deep neural networks and the training process using backpropagation. The authors discuss various deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) that have been used for plant disease detection. They also explain the advantages and limitations of these models in detail.

In [6].For the purpose of identifying plant diseases, a camera sensor module and real time decision support system have been developed. Extreme Learning Machine (ELM) and Support Vector Machine(SVM) with linear and polynomial kernels were used to examine the performance of three machine learning methods. Using Raspberry PI hardware, an extreme learning machine-based real-time decision assistance system was created. Additionally, It has been found that the developed real-time hardware with the Extreme Learning Machine classifier is very effective and detecting three different plant diseases and can be expanded to detect a great number of additional plant diseases by training it with a wide variety of training datasets.

3. RESEARCH METHODS

3.1. Review Methodology

Plant disease prediction is an important area of research, as it can help farmers identify and manage crop diseases before they cause significant damage. Hybrid models, which combine multiple machine learning techniques, can be particularly effective for plant disease prediction. Hybrid models for plant disease prediction typically combine multiple methods, such as machine learning algorithms and statistical models, to achieve more accurate and robust predictions. Here are some research methods commonly used in hybrid models for plant disease prediction:

Feature selection: Before building a hybrid model, it's essential to select relevant features or variables that may affect the disease occurrence. Feature selection techniques such as principal component analysis (PCA), linear discriminant analysis (LDA), and random forest feature selection can be used to identify relevant features.

Machine learning algorithms: Machine learning algorithms, such as support vector machines (SVMs), neural networks, decision trees, and random forests, can be used to train models that can predict the occurrence of plant diseases based on the selected features.

Statistical models: Statistical models, such as logistic regression, can also be used in hybrid models to predict the likelihood of disease occurrence based on relevant features.Sensor-based data: Hybrid models can be built using sensor-based data from IoT devices, such as temperature sensors, humidity sensors, and soil moisture sensors. The data from these sensors can be used to create predictive models that can detect changes in environmental conditions and predict the onset of plant diseases.

Image analysis: Hybrid models can also incorporate image analysis techniques, such as computer vision and deep learning, to detect visual symptoms of plant diseases from images captured by drones or other cameras.

Dataset Description:

We used a dataset called Plant Village Dataset. This dataset consists of 20,639 images of diseased and healthy plant leaves, which were classified into 15 classes to train a deep convolutional neural network which can identify the diseases.

3.2. Research Questions

Q1. What deep learning approaches are used for plant disease prediction?

This question helps us to analyze both the advantages and limitations of using deep learning approaches in plant disease prediction.

Q2. What are the difficulties in applying deep learning techniques to the prediction of plant disease?

This query aides in our comprehension of the short comings and difficulties in the current methods.

Q3.How can a hybrid model be used for plant disease prediction?

This question helps us to give more accuracy by using hybrid model.

3.3 Procedure for Article Search

To search for articles on plant disease prediction using CNN and LSTM models, the first step is to identify the relevant databases such as PubMed, Science Direct, and Google Scholar. Keywords such as "plant disease prediction", "deep learning", "CNN", "LSTM", "machine learning", and "neural networks" can be used to search for relevant articles. Filters such as publication date, language, and journal type can be applied to refine the search results, and the quality of the articles can be evaluated by considering factors such as the reputation of the journal, the author's expertise, and the methodology used in the study. The abstract of the selected articles should be read to determine relevance and the use of CNN and LSTM models, followed by reading the full text for a deeper understanding of the research methodology, results, and conclusions. Finally, a list of references can be compiled from the selected articles that are relevant to the research topic and can be used as citations in the work. Following these steps will help conduct a comprehensive article search on plant disease prediction using CNN and LSTM models.

3.4 Article Selection Criteria

The selection criteria for articles on plant disease prediction using CNN and LSTM models should include several factors. Firstly, the relevance of the article to the research question should be considered. The article should focus on plant disease prediction using CNN and LSTM models and should provide insights into the methodology and results of the study. Secondly, the quality of the article should be evaluated, taking into account factors such as the reputation of the journal, the author's expertise, and the methodology used in the study. Articles published in reputable journals by authors with relevant expertise are more likely to be of high quality. Thirdly, the sample size of the study and the performance of the CNN and LSTM models should be considered. The article should provide information on the performance of the models and should have a large enough sample size to ensure the reliability of the results. Finally, the publication date of the article should be considered, and recent articles should be preferred over older ones to ensure that the study is up-to-date and relevant to current research. By considering these factors, researchers can select high-quality articles that are relevant to their research question on plant disease prediction using CNN and LSTM models.

4. OVERVIEW OF THE EXISTING APPROACHES

Plant diseases can have a devastating impact on crop yields and quality, leading to significant economic losses for farmers. Therefore, several existing systems have been developed for plant disease prediction using machine learning algorithms, including Convolutional Neural Networks (CNNs). These systems typically involve collecting a large dataset of plant images, including both healthy and diseased plants, and training a CNN on this dataset.

The CNN architecture typically involves several convolutional layers that extract features from the input images and several fully connected layers that classify the images into healthy or diseased. In some cases, the CNNs may also be trained to classify the specific disease affecting the plant.

Once the CNN is trained, it can be used to predict the presence or absence of disease in new images of plants. Farmers or field technicians can capture images of plants using smartphones or other imaging devices and input them into the system. The CNN then analyzes the images and outputs a prediction of whether the plant is healthy or diseased.

5. PROPOSED SYSTEM

5.1 CNN algorithms analyze an image and extract its features. Convolutional neural networks are deep learning algorithms that can process large datasets containing millions of parameters, modeled on 2D images, and connect the resulting representations to the corresponding outputs. CNNs have achieved state-of-the-art results recently. In the same architecture, they are also able to systematically isolate features and categorize them. Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is commonly used in time-series analysis and sequence modeling tasks, including plant disease prediction. LSTMs are capable of learning long-term dependencies and are designed to address the vanishing gradient problem that occurs in standard RNNs, where gradients tend to either vanish or explode as they propagate back through time. LSTM models can also be combined with other deep learning models, such as Convolutional Neural Networks (CNNs), to improve the accuracy of plant disease prediction. CNNs can be used to extract relevant features from plant images, while LSTM models can use these features as input and make predictions based on sequential data. The combination of CNN and LSTM models has been shown to achieve high accuracy in plant disease prediction tasks.

5.1.1. Convolution Neural Network (CNN)

There are two key elements to the CNN architecture:

1) A convolutional tool referred to as feature extraction that extracts and classifies the different aspect of images for analysis.
2) The output of the fully connected layer is exposed to convolution, which predicts the class of the image according to the data previously extracted.

A. Convolution Layers

The convolutional layer, the pooling layer, and the fully-connected layer are the three layers that make up the CNN (FC layer). A CNN is produced when these layers are stacked. The dropout layer and the activation function are two additional layers on top of these three. The first layer, the convolutional layer, focusses on identifying features from the input images. Each input image is mathematically combined with a specific size of convolution filters in this layer, executing the convolution mathematical calculation. A dot product between the filter and the input image regions corresponding to the filter's size is computed by sliding the filter across the input image. The conclusion is shown by feature maps. The feature map can be deployed as input for other layers in the future.

These are the arguments that the Conv2D function accepts:

1) Filters - The variety of feature detectors that will be used to apply various filtering method to the original image in order to produce the feature map. There are different types of filters, such as the Blur Filter and the Edge Detection Filter.
2) Kernel Size - This defines the size of the (n x n) convolution filter matrix.
3) Activation: The job of activating neurons. At each layer aside from the output layer, we apply a Rectifier Linear Unit (RELU) function as an activation function. Using RELU, we have also incorporated nonlinearity into our network. In order to find any linear relationships in the feature map, this is crucial.
4) Input Layer - It adjusts to the size and shape of the input images.

B. Pooling Layer

The next layer in our convolutional neural network is known as the pooling layer. The pooling layer's primary objective is to decrease the spatial dimension of data propagating through the network. Convolutional neural networks support pooling in two separate methods. Average and maximum pooling. In Max Pooling, which is the most popular in two, we scan the highest value for each segment of the image. The average of an image's components within a predetermined size zone is determined via average pooling. Between the Convolutional Layer and the Fully Connected Layer, the Pooling Layer acts as a link.

C. Dropout

The training dataset may become overfit when all characteristics are coupled to the FC layer. If a model can perform well on training datasets but demonstrates poor performance when used with new datasets, it is said to be overfitted. A dropout layer is used to address this issue, which results in the reduction of the size of the neural network model by removing a small number of neurons during training. A random 20% of the nodes are removed from the neural network upon passing a dropout of 0.2.

D. Activation

A crucial component of the neural network process is the activation functions. It chooses which information from the model should be sent forward and which information shouldn't at the network's end. As a result, it gives the network more nonlinearity. It has been noticed that there are quite a few activation functions that are often employed. Sigmoid, tanH, Softmax, and ReLU are the activation functions that are used the most frequently. Each activation mechanism has a unique application. ReLU and Softmax functions are typically used for multiclass categorization.

ReLU: The most popular activation function in today's networks is the rectified linear unit (ReLU) function. The ReLU function has an advantage over the other activation functions in that it does not simultaneously activate all of the neurons, which is a benefit. Negative input is translated to 0, and the neuron is not triggered as a result. The neurons are triggered and the positive value of x is returned if the input is positive. As a result, only a few number of neurons are active at once, creating a sparse and highly effective network. By resolving the vanishing gradient issue, the ReLU function also made an important contribution to deep learning.

$$\text{ReLU} = \max(0,x)$$

Softmax: The output layer of the classifier, where we are actually attempting to obtain the probabilities to define the class of each input, is where the softmax function is best utilized. We can categorise data points and establish to which group they belong more readily as a result.

Without using pre-trained models, a convolutional neural network will be used to classify images. There are several well-liked pre-trained models that can distinguish between hundreds of classes without training each one individually. These models can manage hundreds of thousands of classes because to their relatively complex designs. A novice may find it challenging to picture the architecture. Keras facilitate the creation of customised CNNs.

5.1.2 Long Short Term Memory (LSTM)

Long Short-Term Memory, also known as LSTM, is a form of recurrent neural network (RNN) architecture that was developed expressly to address the issue of vanishing gradients in conventional RNNs. The input gate, forget gate, output gate, and cell state make up the fundamental components of an LSTM.

The synopsis of each element is as follows:

Cell state: This is the LSTM's memory unit, where data from the previous time step is stored and can be used or ignored as needed.

Input gate: The input gate establishes how much fresh data should be incorporated into the cell state at the current time step.

Forget gate: The forget gate regulates how much data from the cell state should be erased at the current time step.

Output gate: Based on the current cell state, this determines what output should be generated at the current time step.

The current input vector and the output from the previous time step are typically the inputs of an LSTM. The forget gate determines how much of the previous cell state should be forgotten while the input and output gates determine how much of the new input and previous output should be used to update the cell state, respectively.

5.1.3 Hybrid CNN-LSTM Model

For tasks that require both spatial and sequential data, like picture captioning, video categorization, and speech recognition, a hybrid model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) can be utilized.

In this hybrid model, the LSTM is utilized to simulate the temporal dynamics of the data while the CNN is used to extract spatial features from the input data. The CNN's output is supplied into the LSTM as a series of feature maps, and the LSTM processes the feature maps to create the final output.

The primary innovation is the hybridization of CNN and LSTM for the classification of plant diseases. The LSTM networks integrate with the CNN ReLu unit. We deal with a variety of ailments, thus the implementation of an LSTM network will make it simpler for CNN's activation unit to compute the various classes. The LSTM model's dependency structure works better at formatting the input image data for the input layer. Here, the pooling layer of the CNN architecture has been fixed using sequential vector data steps with predetermined time steps. It uses a small number of time steps to investigate hidden data patterns from the observed training module. In order to support sequence prediction,

CNN is utilized in conjunction with LSTMs to extract features from the input data.

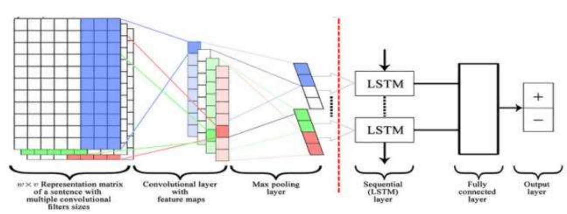
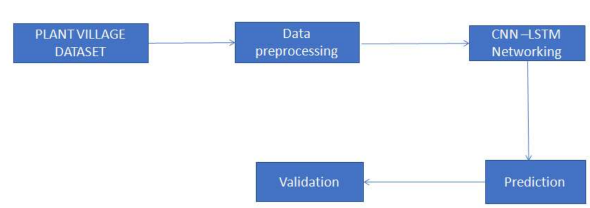
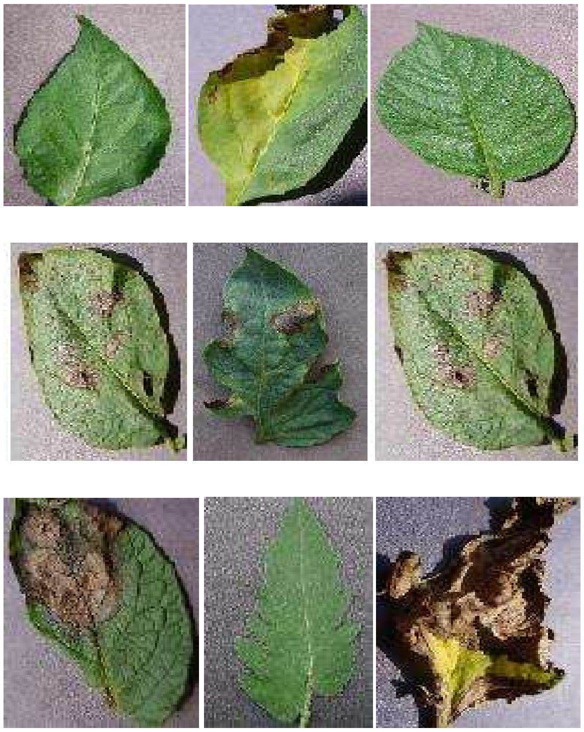


Fig. CNN-LSTM Architecture

4.2. Search strategy

The searching is done by narrowing down to the basic concepts that are relevant for the scope of this review.





Sample images from dataset

Plant disease prediction is an important task in agricultural field that helps farmers to predict the plant disease in earlier stage.

1. PLANT VILLAGE DATASET: It contains over 20,639 of three plant species for plant disease prediction using CNN-LSTM Model.

2. DATA PREPROCESSING: It involves image augmentation, normalization and time-series processing of data.

3. CNN-LSTM NETWORKING: It can be used for predicting plant disease by leveraging the CNN's ability to extract spatial features from images and LSTM's ability to model sequential data.

4. PREDICTION: Using CNN and LSTM models for plant disease prediction will significantly improve the accuracy of identifying and diagnosing plant disease.

5. VALIDATION: It was validated using a dataset of plant image with corresponding disease labels, achieving high accuracy and F1 score.

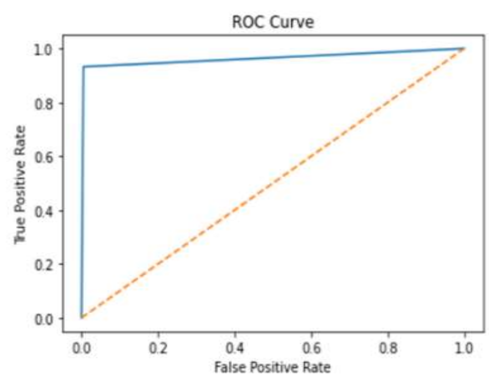
6. RESULTS AND DISCUSSION

The performance of a CNN-LSTM model for plant disease prediction will depend on various factors such as the quality and quantity of the training data, the architecture of the model.

However, in general, a CNN-LSTM model can be effective in plant disease prediction as it can learn to extract important features from images using the convolutional layers of the CNN, and then use the LSTM layers to capture temporal dependencies in the image sequence over time.

```
score, acc = model.evaluate(X_test, Y_test, verbose=0)
print('Test accuracy:', acc)

Test accuracy: 0.9325062036514282
```




```
[[300   0   0   0   0   0   0   0   0   1   0   1   0   0   0]
 [  0 141   2   4   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0 146   2   4   0   1   1   0   0   0   0   0   0   0]
 [  0   1   9 142   2   2   0   0   0   0   0   0   0   0   0]
 [  0   1   1   0 132   1   1   0   0   2   0   3   1   1   3]
 [  0   0   1   0   0  42   0   0   0   0   0   0   0   0   0]
 [  1   0   1   0   3   0 183   1   2   1   4   0   2   0   4]
 [  1   0   3   1   2   0   9  70   1   1   1   3   1   0   1]
 [  5   0   0   3   1   0   0   1 209   0   0   0   0   0   0]
 [  1   0   1   0   5   1   1   0   0  77   0   0   0   0   0]
 [  0   0   0   0   4   0   3   0   1   0  92   0   1   0   0]
 [  1   0   0   1   6   0   0   0   0   0   0  89   4   0   0]
 [  0   0   0   0   0   0   0   0   0   0   1   0 130   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0  16   0]
 [  0   0   0   0   1   0   0   0   0   0   5   0   1   0 110]]
```

Fig. Evaluation metric results

	precision	recall	f1-score	support
0	1.00	0.15	0.27	2015
1	0.00	0.00	0.00	0
2	0.00	0.00	0.00	0
3	0.00	0.00	0.00	0
4	0.00	0.00	0.00	0
5	0.00	0.00	0.00	0
6	0.00	0.00	0.00	0
7	0.00	0.00	0.00	0
8	0.00	0.00	0.00	0
9	0.00	0.00	0.00	0
10	0.00	0.00	0.00	0
11	0.00	0.00	0.00	0
12	0.00	0.00	0.00	0
13	0.00	0.00	0.00	0
14	0.00	0.00	0.00	0
accuracy			0.15	2015
macro avg	0.07	0.01	0.02	2015
weighted avg	1.00	0.15	0.27	2015

Fig. Confusion Matrix

7. CONCLUSIONS

Plant disease prediction using hybrid models is an effective approach to accurately identify and diagnose diseases in plants such as pepper, tomato, and potato. By combining multiple models, such as machine learning, deep learning, and image processing techniques, the hybrid model can effectively capture the complex relationships between various features and symptoms of the plants, resulting in accurate disease identification and diagnosis. The use of a hybrid model can also enable the prediction of plant diseases in real-time, that can help farmers take appropriate measures to control the spread of diseases and prevent crop loss. Furthermore, the implementation of this technology can improve agricultural practices and increase crop yields, ultimately leading to greater food security and economic growth. The hybrid model for predicting plant diseases has shown great promise in providing accurate and efficient results. By combining two methods like Convolutional Neural Network and Long Short-Term Memory we can predict the leaf disease accurately. Overall, the development and implementation of a hybrid model for predicting plant diseases could greatly benefit farmers and agricultural experts, as it can help them identify and manage potential disease outbreaks in a timely and effective manner, leading to better crop yields and overall agricultural productivity.

8. FUTURE SCOPE

Plant disease prediction using CNN and LSTM models is a promising field of research that has the potential to revolutionize agriculture. By leveraging the power of machine learning, it is possible to accurately predict plant diseases before they cause significant damage, thus allowing farmers to take timely action to prevent or mitigate crop loss. CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory) are two popular deep learning models that have shown great promise in image classification and sequence modeling, respectively. In plant disease prediction, CNN can be used to extract features from images of diseased plants, while LSTM can be used to model the sequence of symptoms that develop over time. By combining these two models, it is possible to build a powerful predictive tool that can accurately identify and diagnose plant diseases in real-time.The future scope for plant disease prediction using CNN and LSTM models is immense. As the technology becomes more advanced and accessible, it will become easier for farmers and researchers to collect large amounts of data on plant diseases. This data can then be used to train more accurate and sophisticated models that can detect even the slightest signs of disease. Furthermore, these models can be integrated with other technologies such as drones, sensors, and automated farming equipment, allowing for even more precise and efficient disease detection and control. Overall, plant disease prediction using CNN and LSTM models has the potential to greatly improve crop yields, reduce losses due to disease, and ultimately, help feed a growing global population.

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