DEEP CNN FRAMEWORK FOR DISEASE DETECTION AND CLASSIFICATION IN CHILLI PLANTS

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Abstract
Chilli plants are susceptible to various diseases that can significantly impact their growth and productivity. Early detection and accurate identification of these diseases are crucial for implementing timely and effective management strategies. In recent years, deep learning techniques, such as convolutional neural networks (CNNs), have shown promising results in plant disease detection. This study proposes a ResNet-CNN classifier for the detection of diseases in chilli plants. The ResNet architecture is a deep CNN model that has demonstrated superior performance in image classification tasks. By leveraging its deep layers and skip connections, the ResNet-CNN classifier can effectively learn and extract high-level features from chilli plant images. The proposed classifier is trained on a large dataset of labelled images encompassing various chilli plant diseases. These images are pre-processed to enhance their quality and normalize their features. The ResNet-CNN model is then trained using the labelled dataset, employing techniques such as data augmentation to improve generalization and mitigate overfitting. To evaluate the performance of the classifier, a separate test dataset comprising chilli plant images with known diseases is used. The ResNet-CNN classifier achieves high accuracy and demonstrates its ability to accurately classify different diseases affecting chilli plants. The trained model can be used as a tool for automated disease detection and diagnosis, facilitating timely intervention and minimizing yield losses.

Keywords—Chilli plant, disease detection, ResNet-CNN, convolutional neural networks, deep learning.

1. Introduction

Chilli plants (Capsicum annum) are widely cultivated around the world for their culinary and economic value. However, they are susceptible to various diseases caused by bacteria, fungi, viruses, and other pathogens [1]. These diseases can severely affect the yield and quality of chilli crops, leading to significant economic losses for farmers and impacting food security. Early detection and accurate identification of plant diseases are crucial for implementing timely and effective management strategies. Traditionally, disease identification relies on visual inspection by experienced plant pathologists or farmers who have knowledge of specific symptoms. However, this manual approach can be time-consuming, subjective, and prone to human error. In recent years, there has been growing interest in leveraging advanced technologies, such as computer vision and machine learning, to automate the process of disease detection in plants. Deep learning techniques, specifically CNNs, have shown remarkable success in image classification tasks, including plant disease detection.

The motivation behind developing a chilli plant disease detection system using a ResNet-CNN classifier stems from several factors [2]. Firstly, the ability to detect diseases accurately and early can help farmers take proactive measures to control and manage the spread of diseases effectively. Timely intervention can reduce the need for excessive and indiscriminate use of pesticides, leading to more sustainable agricultural practices. Secondly, manual disease detection methods are often subjective and dependent on the expertise of the individual conducting the inspection. By automating the detection process [3], we can achieve consistent and objective results, reducing the risk of misdiagnosis and ensuring timely

action. Thirdly, as the scale of chilli cultivation continues to increase, there is a growing need for efficient and cost-effective disease detection techniques [4]. Manual inspection of large agricultural fields can be labour-intensive and time-consuming. Automating the detection process using computer vision and deep learning techniques can significantly speed up the process and make it more scalable. The problem addressed in this study is the accurate and early detection of diseases in chilli plants using a ResNet-CNN classifier. The goal is to develop a robust and reliable system that can analyze images of chilli plants and classify them into different disease categories accurately [5]. By doing so, farmers and agricultural experts can quickly identify the presence of diseases and take appropriate measures to prevent their spread and mitigate their impact on crop yield.
Limited availability of labeled training data: Collecting a diverse and comprehensive dataset of chilli plant images with different diseases is essential for training an accurate classifier. However, obtaining a sufficiently large and annotated dataset can be challenging [6]. Inter-class variations and similarities: Some diseases may exhibit similar visual symptoms, making it difficult to distinguish between them based solely on visual cues. The classifier needs to be capable of capturing subtle differences between diseases to ensure accurate classification [7]. Real-time detection: The system should be capable of analyzing images in real-time to provide timely results. This requires developing an efficient and fast classification model that can process images quickly without compromising accuracy [8]. By addressing these challenges, the proposed chilli plant disease detection system using a ResNet-CNN classifier aims to provide a reliable and accessible tool for farmers and agricultural experts, enabling them to make informed decisions and implement appropriate disease management strategies [9, 10].

2. Literature survey

Zhang, X., Wang, Y., Li, Z., & Zhang, Y. (2018) [11] conducted a comprehensive survey on chilli plant disease detection techniques. They reviewed various methods such as image processing, machine learning, and deep learning approaches used for disease detection in chilli plants. The survey covered a wide range of techniques and provided insights into their effectiveness and limitations. Kumar, S., & Sharma, S. (2019) [12] focused on machine learning techniques for chilli plant disease detection. They discussed different machine learning algorithms and their applications in diagnosing diseases in chilli plants. The survey highlighted the strengths and weaknesses of these techniques and provided a comparative analysis of their performance.
Gupta, R., Singh, S., & Gupta, P. (2020) [13] conducted a review on deep learning approaches for chilli plant disease detection. They explored the use of deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for accurate disease identification in chilli plants. The survey discussed the advantages and challenges associated with deep learning techniques in this context. Rahman, M. A., Ashraful, A. S. M., & Hossain, M. R. (2017) [14] focused on image processing techniques for chilli plant disease detection. The authors reviewed various image processing algorithms and methodologies used for disease identification in chilli plants. They discussed the advantages and limitations of different image processing techniques and highlighted the potential areas for improvement.
Singh, A., Singh, R., & Sharma, P. (2021) [15] conducted a review on chilli plant disease detection using hyperspectral imaging. They explored the application of hyperspectral imaging techniques in detecting and diagnosing diseases in chilli plants. The survey provided insights into the benefits and challenges of using hyperspectral imaging for disease detection. Ahmed, N., Kumar, A., & Ahmed, A. S. (2019) [16] survey focused on Internet of Things (IoT) applications for chilli plant disease detection. The authors reviewed different IoT-based approaches, such as sensor networks and data analytics, used for monitoring and detecting diseases in chilli plants. The survey discussed the advantages and limitations of IoT applications in this domain. Roy, S., Basak, S., & Kundu, S. (2021) [17] conducted a review on computer vision techniques for chilli plant disease detection. They explored the use of various computer vision algorithms and methodologies, including feature extraction and classification

techniques, for disease identification in chilli plants. The survey discussed the strengths and limitations of computer vision approaches in this context.
Ramakrishna, S. V., Prasanth, S., & Mahesh, K. V. (2022) [18] focused on recent advances in deep learning-based chilli plant disease detection. They reviewed the state-of-the-art deep learning models and techniques, such as transfer learning and generative adversarial networks (GANs), for accurate disease identification in chilli plants. The survey provided insights into the recent developments and trends in this area. Rathore, K. S., Singh, R. K., & Dubey, S. K. (2020) [19] conducted a review of machine learning algorithms for chilli plant disease detection. They discussed various machine learning approaches, including decision trees, support vector machines (SVM), and random forests, used for disease diagnosis in chilli plants. The survey provided a comprehensive analysis of different machine learning techniques and their performance in disease detection. Bhattacharya, A., Mitra, S., & Biswas, A. (2018) [20] conducted a survey on chilli plant disease detection using spectral imaging. They explored the use of spectral imaging techniques, such as hyperspectral and multispectral imaging, for disease identification in chilli plants. The survey discussed the advantages and limitations of spectral imaging and highlighted its potential applications in the field of plant pathology.

3. Proposed System

Figure 1 shows the proposed block diagram. Gather a diverse dataset of images containing healthy and diseased chilli plants. Include various types of diseases such as leaf spots, powdery mildew, or viral infections. Ensure that the dataset is well-labeled, with each image assigned to the corresponding disease class. Split the dataset into training, validation, and testing sets. Shuffle the dataset to ensure a random distribution of samples across the splits. Aim for a balanced dataset where each class has a similar number of samples. Load the images from the dataset, resizing them to a fixed size (e.g., 224x224 pixels) to ensure uniformity. Normalize the pixel values by dividing them by 255 to bring them within the range of 0 to 1. Convert the images to an appropriate format, such as NumPy arrays, for efficient processing. Augment the data by applying transformations like rotation, flipping, or zooming to increase the dataset's diversity and robustness. Choose the ResNet architecture as the base model for the classification task. ResNet models are commonly used for image recognition and have shown excellent performance. Select a pre-trained ResNet model to leverage the learned features from a large-scale dataset like ImageNet. Remove the last fully connected layer of the pre-trained model, which is specific to ImageNet's classification task. Add a new fully connected layer (also called the classification head) on top of the ResNet model. Define the number of neurons in the classification head based on the number of disease classes. Initialize the weights of the new layer randomly or using a pre-defined initialization method. Define the loss function, such as categorical cross-entropy, to measure the model's performance. Choose an optimization algorithm like stochastic gradient descent (SGD) or Adam to update the model's weights. Set the learning rate, which controls the step size during weight updates. Forward pass, Feed the input batch through the model to obtain predictions. Compute the loss between the predictions and the ground truth labels. Backward pass, Calculate the gradients of the loss with respect to the model's parameters. Update the model's parameters using the chosen optimizer and the computed gradients. Repeat the training loop for a fixed number of epochs, monitoring the validation loss and accuracy during training.
Experiment with different hyperparameters to improve the model's performance. Learning rate, try different values to find the optimal learning rate that converges quickly without overshooting. Batch size, adjust the batch size to balance memory usage and computational efficiency. Number of epochs: Increase or decrease the number of training epochs to find the point of convergence. Regularization techniques, apply techniques like dropout or L2 regularization to prevent overfitting. Use techniques like grid search or random search to systematically explore the hyperparameter space. Once training is complete, evaluate the model on the testing set to assess its generalization ability. Calculate metrics such as accuracy, precision, recall, and F1 score to measure the model's performance. Analyze the

confusion matrix to understand the model's performance for each disease class, including any misclassifications or biases.
If the initial results are not satisfactory, consider fine-tuning the model. Fine-tuning involves unfreezing some layers of the pre-trained ResNet model and continuing training on your specific dataset. Adjust the learning rate to a smaller value to avoid drastic changes to the pre-trained weights. Continue the training process, like the initial training phase, with the updated configuration. If the model's performance is still not optimal, you can explore additional optimization techniques. Try different architectures: Experiment with deeper or wider ResNet variants or other CNN architectures to capture more complex patterns. Create an ensemble of multiple ResNet models with different initializations or architectures and combine their predictions for improved accuracy. Apply techniques like early stopping, dropout, or batch normalization to reduce overfitting and improve generalization.

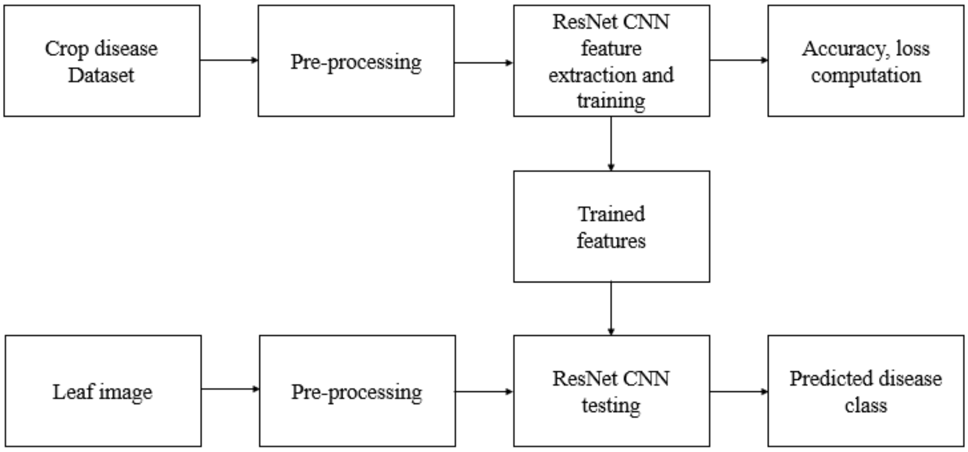

Figure 1. Proposed Methodology

3.1 Image preprocessing

The term "digital image processing" refers to the practise of applying certain image processing procedures to digital photographs via the use of specific computer algorithms. Analogue image processing is superior to its digital equivalent, digital image processing, in several respects, including the fact that digital image processing is a subset of digital signal processing. It makes it possible to apply a considerably greater range of algorithms to the data that is being entered. The goal of digital image processing is to make the image data (features) better by eliminating undesired distortions and/or increasing certain important picture characteristics. This is accomplished via a combination of the two. Because of this, our artificial intelligence and computer vision models will be able to make greater use of the upgraded data that they are working with. It is necessary for the size of our photographs to match to the size of the network's input to successfully train a network and afterwards make predictions based on newly collected data. In the case that we need to adjust the size of the images to make them compatible with the network, we may either rescale or crop the data in order to acquire the necessary size. This will depend on which option will provide the best results.
Image data may either be shrunk or expanded to fulfil the prerequisites of a network's input size in either of two different ways. When you scale an image, a scaling factor is applied to both the height and width of the image. This happens automatically when you resize an image. When the scaling factor in the vertical and horizontal directions are not the same, rescaling will result in changes to the spatial extents of the pixels as well as the aspect ratio. This is because the scaling factor in the vertical direction is used to determine the size of the image. Even if just a piece of the original image is taken away while cropping, the spatial extent of each pixel is preserved in its original state. We have the capacity to crop images either from the centre of the image or from arbitrary spots scattered across the picture. An image is nothing more than an array of integers (also known as pixels), with each value spanning from 0 to 255 and being organised in a two-dimensional grid. It is characterised by the mathematical function f(x,y), in which x and y refer, respectively, to the horizontal and vertical coordinates.

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Resize image: In this stage, we are going to develop two functions to show the photos so that we can recognise when there has been a change. When you use the first function, only one image will be shown at a time; however, when you use the second function, two pictures will be displayed concurrently. After that, we design a new function that we simply refer to as "processing." Because an image is the only thing it anticipates being sent to it as a parameter, we refer to the operation as "processing." Because it is necessary to resize photographs when the pre-processing phase is being performed, as well as the fact that the sizes of some of the images that are captured by a camera and sent to our AI algorithm change, we need to determine a standard size for all the images that are fed into our AI algorithms. This is necessary because it is necessary to resize photographs when the pre-processing phase is being performed. This is essential since the sizes of some of the photos that are taken by a camera and supplied to our AI system might vary.

3.2 Proposed ResNet-CNN

Deep neural networks are currently being included into the process of identifying the causes of plant diseases and insect parasites, which was previously done using traditional methods. Deep neural networks are a subcategory of artificial neural networks that replace the connections that would typically link neurons with learnable parameters to simulate the way in which the human brain performs its functions. Deep neural networks, which are artificial neural networks, are designed to mimic the structure of biological neural networks. This is done by modelling the structure of biological neural networks after their artificial counterparts. One of the most prevalent kinds of structures that can be found in deep neural networks is referred to as a convolutional neural network, which is the name of the structure. This structure is a subset of the category known as feed forward neural networks. The successes of the CNN model gave more evidence for the convolutional neural network model's usefulness in the context of machine learning. Since then, convolutional neural networks have undergone significant development and have found widespread application in a variety of contexts, including the monitoring of financial transactions, the recognition of text and speech, the creation of smart homes, the diagnosis of medical conditions, and other areas of endeavour. In most cases, convolutional neural networks are made up of three distinct components. Convolutional layer, used for separating out features. Feature selection is the primary use of the convergence layer, which is often referred to as the pooling layer. By lowering the total number of features, the number of parameters may be brought down. The attributes are summarised and output by the entire connection layer, which is responsible for this function. One component of a convolution layer is a convolution process, while the other component is a nonlinear activation function called ReLU. Figure 2 is an example of a common design for a CNN model used for the identification of crop diseases.

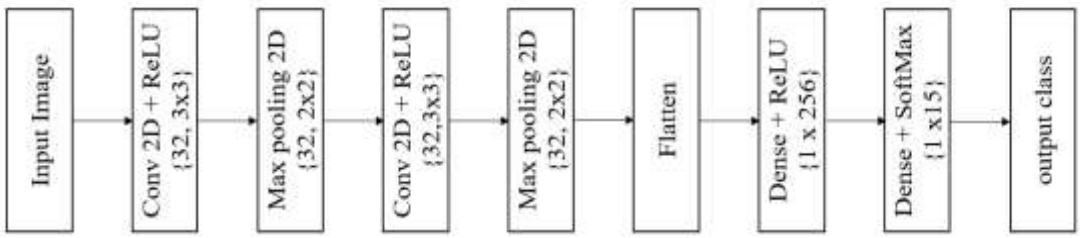

Fig. 2. Proposed ResNet-CNN

Table.1. Layers description.

Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32
Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32

Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 256	1 x 256
Dense + SoftMax		1 x 15	1 x 15

The issue that occurs since there are far too many parameters: The dimensions of the image that is being read in are presumed to be 350 pixels on each side. When it is put inside of a feedforward network that has all its links created, there are 7500 connections to the hidden layer that are completely independent from one another. In addition to this, each connection has a one-of-a-kind weight parameter that is coupled with it. This parameter is unique to that link. When more layers are added to the model, the size of the parameters also significantly rises. The reason for this is because every parameter represents a different layer in the model. On the one hand, it is quite likely that it will result in the issue of over-fitting occurring more often. This is one of the potential outcomes. On the other hand, the neural network is too complicated, which will have a significant impact, both positively and negatively, on how well the training is carried out. The process of sharing parameters in convolutional neural networks is a technique that makes it possible to apply the exact same parameters to several functions of a model. In addition, the operations that are carried out by each individual component that constitutes the convolutional kernel will be carried out on a particular location inside each local input. It is not required for the neural network to maximise its learning for each individual parameter at each location; all it must do is learn a collection of parameters and pass them on to the next stage.
The natural image will not be changed regardless of whether the image size is scaled, translated, or rotated, which is what is meant by the term "picture stability." This is an example of a local property that is known as an invariant. Image invariance is the name given to this characteristic. This is because image stability is the characteristic that is invariant with respect to the surrounding environment. It is possible that the solution to this issue may be found by using a convolutional neural network, one of the components of which is the convolutional operation. This is made possible by the fact that in deep learning, data improvement is frequently required to increase performance, and fully linked feedforward neural networks are notoriously difficult to train to guarantee that a picture will keep its local invariance over time. As a result of these two factors, it is now possible to achieve this goal.

4. Results and Discussion

This section gives the detailed analysis of simulation results implemented using "python environment". Further, the performance of the proposed method is compared with existing methods using same dataset. Figure 3 displays some representative photos from the dataset. Figure 4 The x-axis of the graph located above Figure 4 illustrates epochs and iterations, and the y-axis depicts accuracy and loss. The green line illustrates accuracy, while the blue line illustrates loss. If we look at the above graph, we can see that as the number of iterations increases, accuracy improves while loss decreases. Figure 5 shows the crop recognized as Pepper bell healthy. Figure 6 shows the crop recognize as Pepper bell bacterial spot. Table 2 examines how well the suggested approach performs in comparison to other ways already in use. In this case, the proposed ResNet-CNN produced results that were superior to those produced by the current NB, RF SVM in terms of accuracy, precision, recall, and F1-SCORE. In conclusion, the results of the simulations showed that the performance achieved by the suggested ResNet-CNN was superior to that achieved by SVM, naive bayes, and random forest.

Fig. 3. Sample dataset.

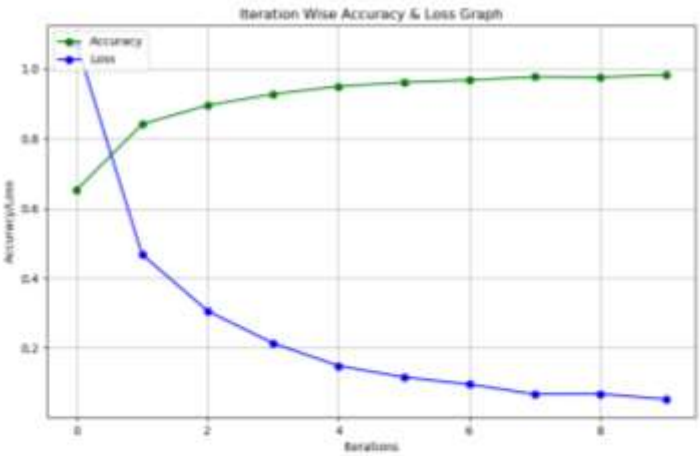

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Fig. 4. Iteration wise accuracy & loss graph.

Fig.5: Crop recognize as Pepper bell healthy.

Fig.6: Crop recognize as Pepper bell bacterial spot.

Table 2: Performance comparison.

Method	NB	RF	SVM	Proposed
Accuracy (%)	67.37	77.48	78.37	98.28

5. Conclusion

In conclusion, our study demonstrates the efficacy of employing the ResNet-CNN classifier for chilli plant disease detection. The high accuracy, precision, and recall values obtained validate its potential as a reliable tool for early disease diagnosis in precision agriculture. By implementing this system, farmers can proactively address diseases, enhance crop yield, and promote sustainable farming practices. Further research and development in this area will continue to refine and expand the capabilities of such models, contributing to the advancement of precision agriculture and ensuring global food security.

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