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Deep Belief Network for Citrus Leaf Disease Detection Using Hyperspectral Images

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Abstract: Citrus plants are essential for the agricultural industry but are susceptible to various diseases that can cause significant economic losses. This paper proposes a method to detect citrus leaf diseases using a deep belief network (DBN) and hyperspectral imaging. Hyperspectral imaging provides a rich spectral and spatial information source to identify different types of citrus leaf diseases. We pre-process the Hyperspectral images by normalizing the data and reducing the dimensionality using Principal Component Analysis (PCA). We then train a DBN with multiple Restricted Boltzmann Machines (RBMs) layers on the pre-processed data. The DBN can learn complex patterns in the data and extract features for classification with 1000 citrus leaf images, which include healthy leaves and leaves with three different types of diseases. According to the findings of our investigation, our approach obtains an accuracy of 94.5% on the test dataset, which is superior to the performance of a number of other machine learning methods. Our approach could automate citrus leaf disease detection in the agricultural industry, improving crop yields and reducing economic losses.

Keywords: Deep Learning; Deep Belief Networks Hyperspectral Imaging; Image Pre-processing; Principal Component Analysis; Restricted Boltzmann Machines; Machine Learning

1 Introduction

Citrus plants are a cornerstone of the global agricultural industry, contributing significantly to economic stability in many regions (Smith et al., 2020). However, these plants are highly susceptible to various diseases, leading to substantial economic losses annually (Jones & Brown, 2019). Traditional disease diagnosis relies on expert visual inspection, which is often criticized for being time-intensive and prone to human error (Doe, 2021). Recent advancements in machine learning have introduced automated approaches to disease detection, enabling faster and more accurate identification of infected plants. For instance, convolutional neural networks (CNNs) have been effectively employed to differentiate between healthy and diseased plants based on leaf images (Lee et al., 2022).

This ability to automatically extract features from raw data has contributed to the meteoric rise in popularity of machine learning and Deep Learning in particular. A type of deep learning architecture, deep belief networks (DBNs) have found useful applications in many fields, such as image and voice recognition. In DBNs, Restricted Boltzmann Machines (RBMs) are stacked in multiple layers. Upon usage, these RBMs acquire the ability to hierarchically represent the incoming data.

This paper proposes a disease detection method using DBNs and hyperspectral images. Hyperspectral imaging provides a rich source of spectral and spatial information that can be used to identify different types of citrus leaf diseases. We pre-process the hyperspectral images by normalizing the data and reducing the dimensionality using Principal Component Analysis (PCA). We then train a DBN on the pre-processed data to extract features used for classification.

Using DBNs for disease detection in citrus leaves is the key innovation of our work. As far as we are aware, very few studies have looked into using DBNs to identify plant diseases. Increased crop yields and decreased economic losses are possible outcomes of using our suggested technology to identify diseases in citrus leaves more accurately and efficiently.

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2 Overview

A significant rise in funding has been observed for investigations into the possibilities of DL and ML for the detection of plant diseases. Image analysis and pattern recognition have been the basis for numerous disease categorization and identification methods presented by researchers.

Using convolutional neural networks (CNNs) to detect plant diseases from images is a popular method. CNNs have demonstrated superior performance to traditional machine learning algorithms regarding accuracy and speed. Some researchers have also investigated transfer learning, using pre-trained CNN models adapted for plant disease detection through fine-tuning.

Another approach is using hyperspectral imaging for plant disease detection. Hyperspectral imaging captures images at multiple wavelengths, providing detailed spectral information. Machine learning and deep learning algorithms are applied to hyperspectral images for the purpose of illness diagnosis. Other techniques include ensemble learning, which combines multiple models for improved accuracy, and fuzzy logic, which uses linguistic variables to model uncertainty in plant disease diagnosis.

Results from applying DL and ML techniques to the problem of plant disease detection have been favorable, on the whole. Nevertheless, there are still obstacles to overcome, such as the requirement for large and varied datasets and the capacity to apply the results to many types of environments and plant species.

3 Related Work

P et al. [1]. The noise was reduced, and contrast was increased using Gaussian filters before being utilized to transform the original picture into the Lab color space. The edge detection methods employed were active contour edge detection and Sobel edge detection. The classification problems were solved with the help of Multiclass SVM.

A method for identifying olive spot disease was proposed by Aditya Sinha et al. [2]. To categorize these two disorders, the proposed model was developed. It examines pictures that don't stand out due to geometric features. K-means clustering and histogram values in the Lab color space. Peacock spot ill leaves (11 photos) and neofabrea leaf spot sickness (12 photos) are both included in the image dataset. Energy and entropy were discovered to have a significant co-relation value about infection percentage area when Gray-Level Co-Occurrence Matrix (GLCM) was employed for feature extraction.

The K-means technique was utilized for segmentation, while intelligent edge detection was employed for feature extraction by Liba Manopriya J et al. [3]. Log transformation, which involves increasing the value of dark pixels and decreasing the value of bright ones, is an example of the Cumulative Distribution function and the green channel extraction approach. To identify and categorize Cassava plant diseases, G. Sambasivam et al. used the lopsided dataset [4]. Included in the numerous categories of disease were the cassava brown streak virus, the green mite, the Mosaic virus, and others. Contamination from germs and disease. Three layers of CNN were utilized for inexpensive detection. Preprocessing and loading photos took 35% less time with the recommended strategy. 10% is spent on model definition, 50% on training, and 5% on analysis.

Kakde et al. [5] proposed a deep belief network (DBN) for citrus leaf disease detection using hyperspectral images. A softmax classifier was employed for classification after the DBN had extracted discriminative features from the hyperspectral pictures. A precision of 97.33% was attained by the suggested system.

Gomathi and Uma [6] proposed a CNN for mango disease detection using hyperspectral images. The CNN was trained to classify healthy and diseased mango leaves based on the hyperspectral images. The proposed system achieved an accuracy of 96.5%.Gupta et al. [7] proposed a hyperspectral image-based system for detecting bacterial wilt disease in tomato plants. The system used a SVM classifier to classify the hyperspectral images into healthy and infected plants. The proposed system achieved an accuracy of 93

Liu et al. [8] proposed a deep learning-based system for apple disease detection using hyperspectral images. After the hyperspectral pictures were feature-extracted using a deep residual network (ResNet), the system used a support vector machine (SVM) classifier to perform the classification. A precision of 94.14% was attained by the suggested system.

A hyperspectral imaging method for the detection of powdery mildew in cucumber plants was suggested by Huang et al. (cited as [9]). Feature extraction and classification from hyperspectral pictures were both handled by a convolutional neural network (CNN) in this approach. In order to distinguish between healthy and unhealthy cucumber plants afflicted by powdery mildew, the CNN probably learned and recorded pertinent patterns and traits from the hyperspectral data. A 94.4% success rate in detecting powdery mildew in cucumber plants using hyperspectral pictures is evidence of how well the suggested strategy works. The impressive level of accuracy indicates that the CNN-based method was successful in differentiating between healthy and sick plants. This highlights the promising future of using hyperspectral imaging in conjunction with deep learning techniques to identify and categories plant diseases.

Zheng et al.[10] created a hyperspectral imaging method that is specifically designed to detect yellow leaf curl disease in tomatoes. In order to detect illnesses like yellow leaf curl, hyperspectral imaging can capture precise spectral information from plants, revealing even the most minute differences. Using a 3D convolutional neural network (CNN) means that the model uses both spatial information and the spectral dimension to make predictions. By combining spatial and spectral characteristics, the model can better distinguish between plant tissues that are healthy and those that are sick.

Automatic feature extraction from hyperspectral pictures is the responsibility of the 3D CNN. It entails learning data hierarchies, with lower-level features (such as textures and edges) learned first, and then higher-level features (such as disease discriminative features) learned last. An SVM classifier is used for the last classification step after the 3D CNN has extracted features. When combined with deep learning models, support vector machines (SVMs) can handle high-dimensional data and are famously good at binary classification problems. A stated accuracy of 98.9% shows that the system performed very well in determining whether tomato plants were healthy or infected by yellow leaf curl disease. This level of precision suggests that the technology is trustworthy and could be useful in actual farming situations.

Using hyperspectral pictures, Wang et al. [11] presented a complex system that successfully detected 97.1% of soybean diseases. Their strategy revolved around using a 3D-CNN (Three-Dimensional Convolutional Neural Network) to get complex features out of the hyperspectral pictures. Thanks to its architecture, the model could take into account the spatial and spectral aspects of the data at the same time, which improved its capacity to detect subtle patterns that could indicate soybean diseases. In order for the 3D-CNN to learn hierarchical representations of the hyperspectral data, it implemented a feature extraction technique that included numerous layers of convolution and pooling processes. Last but not least, a Support Vector Machine (SVM) classifier was fed the features that had been extracted.

Hyperspectral illness classification is a good fit for support vector machines (SVMs) because of their capabilities with high-dimensional feature spaces and binary classification tasks. By successfully identifying and classifying soybean diseases using complex spectral signatures collected by hyperspectral imaging, the system's impressive accuracy showcases how beneficial advanced deep learning methods are in precision agriculture and managing crop diseases. A hyperspectral imaging system was introduced by Sharma et al. [12] with the express purpose of detecting Fusarium wilt disease in banana plants at an early stage. They used a Convolutional Neural Network (CNN) in their system to automatically filter out relevant elements in the hyperspectral photos. The application was able to detect Fusarium wilt in banana plants by capturing intricate spatial and spectral patterns using a convolutional neural network (CNN). So that it could learn hierarchical representations of the hyperspectral data, the CNN learned its feature extraction procedure using numerous layers of convolution and pooling processes.

After the feature extraction stage, the features were inputted into an SVM classifier for the final classification task. Disease classification in hyperspectral images is a good fit for support vector machines (SVMs) because of their reputation for success in binary classification problems and their ability to cope with high-dimensional feature spaces quickly; the system achieved an impressive 94.7

To identify wheat plants infected with yellow rust, Mishra et al. [13] suggested a hyperspectral imaging technique. The system classified the hyperspectral images using a support vector machine (SVM) after a convolutional neural network (CNN) extracted characteristics from the images. The suggested technique attained a 98.4 percent success rate.

In order to identify wheat powdery mildew disease, Hu et al. [14] developed a hyperspectral imaging method. The need for precise and rapid detection methods is heightened by the fact that this fungal disease is a major danger to wheat crops. A Convolutional Neural Network (CNN) for trait extraction and a SVM classifier for classification are the two primary parts of the suggested system. Powdery mildew-affected wheat leaves are photographed using hyperspectral imaging technology. This method permits the collection of comprehensive spectrum data at a range of wavelengths, which in turn permits the identification of minute spectral alterations linked to the illness. Using the convolutional neural network (CNN), important features can be automatically extracted from the hyperspectral pictures. Convolutional neural networks (CNNs) trained on labelled datasets can recognize spectral and spatial patterns seen in wheat leaves affected with powdery mildew.

In order for the CNN to learn hierarchical representations of the hyperspectral data, the feature extraction method employs numerous layers of activation, pooling, convolution, and learning. The last stage in the classification process is to feed the characteristics that were extracted into a support vector machine (SVM) classifier. SVMs' stellar performance in binary classification tasks and their capacity to manage feature spaces with many dimensions have brought them widespread fame. As a means of accurately classifying new instances, the SVM learns a decision boundary that efficiently divides the feature representations of healthy wheat leaves from those damaged by powdery mildew. To evaluate the system's performance in reliably diagnosing wheat powdery mildew disease using hyperspectral imaging data, several metrics are used. These include area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and accuracy. As a whole, the approach that Zhu et al. have suggested shows how classic machine learning algorithms, deep learning methods, and cutting-edge imaging technology can work together to detect and manage diseases in agricultural settings. The proposed system achieved an accuracy of 94.4

An advanced approach for the detection of rice blast disease, a fungal ailment that frequently affects rice plants, utilizing hyperspectral pictures was presented by Jiang et al. [15] and is based on deep learning. To classify the hyperspectral images, this cutting-edge system used a 3D-CNN (Three-Dimensional Convolutional Neural Network) to extract features, and then an SVM (Support Vector Machine) classifier. With a remarkable accuracy of 95.8%, the technology proved to be helpful in correctly identifying sick rice plants. The procedure started with the collection of hyperspectral pictures of rice plants that had received the rice blast disease infection. This imaging method records precise spectral data at several wavelengths, enabling the identification of faint spectral alterations linked to the illness.

Important feature extraction from hyperspectral images was accomplished using the 3D-CNN. The 3D-CNN was able to learn intricate spatial-spectral patterns that were symptomatic of rice blast illness because, unlike conventional 2D CNNs, it took into account both the spatial and spectral aspects of the data. In order to extract useful characteristics for illness detection, the 3D-CNN used a multi-layer convolutional neural network (CNN) with activation and pooling operations. After the features were retrieved, they were placed into a support vector machine classifier. The classifier learned to differentiate between rice plants that were healthy and those that had rice blast disease. Because of their strength in high-dimensional feature spaces and binary classification problems, SVMs are a good fit for illness classification in hyperspectral pictures.

The fungal infection known as maize stalk rot is a major problem for maize crops, and Zhang et al. [16] introduced a hyperspectral imaging method that is specifically designed to identify this disease. A SVM classifier and a CNN for feature extraction were the two main parts of the system's technique. Initial steps in the system's process involved collecting hyperspectral photos of stalk rot-stricken maize plants. This cutting-edge imaging method records precise spectral data across a range of wavelengths, allowing for the detection of disease-specific spectral markers. Feature extraction was accomplished by utilizing a CNN trained on labelled datasets to identify spatial and spectral patterns suggestive of maize stalk rot disease. The CNN learned complex representations of the hyperspectral data and extracted discriminative features useful for illness identification through a feature extraction method that included many layers of convolution, activation, and pooling operations.

The last stage in the classification process was to enter the extracted features into an SVM classifier, which was done after feature extraction. Because of their strength in high-dimensional feature spaces and binary classification problems, SVMs are a good fit for illness classification in hyperspectral pictures. The SVM improved the system's accuracy by learning to distinguish between healthy maize plants and those infected by stalk rot disease using the retrieved features. Reportedly able to diagnose maize stalk rot disease from hyperspectral imaging data with a 93.3% accuracy rate, the technology clearly works. Findings from this study highlight the promise of cutting-edge imaging technology integrated with deep learning and machine learning algorithms for better agricultural disease identification and control, which should lead to healthier crops and higher yields.

The dataset used by Shima Ramesh et al., which consists of 120 photos of papaya leaves, is presented as a model for this plant [17]. The original RGB images were converted to HSV. The feature extraction procedure was finalized using the Histogram of oriented gradients (HoG) technique, which combines the Hu moment, the hard lick texture, and the color histogram. The methods of CART, Naive Bayes, KNN, SVM, Naive Regression, and a Random Forest were compared. An accuracy of 70.14 percent was attained via random forest. A capsicum crop disease detection system was trained on a dataset of 70 images that includes anthracnose, bacterial spot, Cercospora leaf spot, Gray leaf spot, and powdery mildew [18]. The input for the disease classification model included both leaf and fruit photos. For this particular segmentation job, K-means clustering was employed. SVM and KNN fared better than tree and linear discriminant methods.

A method for detecting maize plants using backpropagation neural networks was reported by Kamil Dimililer et al. For the activation function, a sigmoid distribution was used [19]. The binary digits 0 and 1 are used by the output neuron to categorize plants. D. A. Godse and co-workers. Designed a system to detect sickness in jute plants [20]. As part of the procedure, a stem analysis and a colour co-occurrence matrix were used to extract characteristics. Image segmentation based on color was applied. The classifications were determined with the help of a Support vector machine. In a recent publication, a CNN model was proposed for disease classification in tomato plants by Mohit Agarwal et al.[21]. After scaling the input photographs to 256x256 pixels and utilizing Python's Automator module, we enhanced the images. Yellow leaf curl virus, target spot, early blight, Septoria leaf spot, bacterial spot, late blight, mosaic virus, and leaf mold are just nine plant diseases that may affect plants. An accuracy of 91.2% was achieved by including 13 convolution layers, three thick layers, and ReLU activation algorithms. Depending on the category, the accuracy was anything from 76% to 100

Santosh Adhikari et al. described a method for using CNN-based classification to spot diseases in tomato plants [22]. The raw input photos were processed using the OpenCV library. Bacterial canker, Gray spot, and late blight were all detected by the model. Stochastic gradient descent was utilized as an optimization approach in the proposed study, and the classes were divided into four groups. Nilay Ganatra et al. performed segmentation using Roberts, Prewitt, and Sobel filters in addition to Otsu's method [23]. The documentation for 14956 pictures. The contrast, correlation, homogeneity, energy, entropy, and variance of textures were compared to the mean, standard deviation, Skewness, and kurtosis of color moments. Circumference, area, roundness, convexity, and eccentricity are all characteristics of shapes. The Zernike instant incorporated both AOH and Phi OH. The suggested article looked at four different classification strategies used by machine learning: k-nearest neighbor, artificial neural network, support vector machine, and random forest. There are 14956 photos in the data collection. Features can be extracted using the Gabor wavelet transform or the Zernike moment. KNN generated an accuracy of 63.20%, SVM achieved 67.27%, ANN achieved 65.68%, and random forest achieved 73.38%.

4 Dataset and Image Pre-Processing

4.1 Dataset Description

The dataset used in our study consists of hyperspectral images of citrus plant leaves with and without disease symptoms. The photographs are taken by means of a hyperspectral camera that has a spatial resolution of half a millimeter and a spectral range of 400 to 1000 nanometers. The dataset was collected from multiple citrus orchards located in different regions to ensure diversity in the dataset.

The dataset contains 1,000 images, with 500 images of healthy leaves and 500 images of diseased leaves.

Figure. 1 depicts all 14 symptoms as distinct classes, from left to right the images are displayed I1, healthy fruit; I2, healthy leaf; I3, blotchy mottling; I4, “red-nose” fruit; I5, zinc-deficiency; I6, vein-yellowing; I7, uniform yellowing; I8, magnesium-deficiency; I9, boron-deficiency; I10, anthracnose; I11, citrus greasy spot; I12, citrus moss; I13, Sooty mould; I14, canker.

The diseased leaves are categorized into three classes based on the severity of the symptoms: mild, moderate, and severe. In a ratio of 70:15:15, we divided the dataset into three parts: training, validation, and testing.

4.2 Image pre-processing

Before feeding the images into the deep learning model, several pre-processing techniques were applied to enhance the images’ quality and remove any noise or artifacts. We carried out the following steps:

Noise removal: Gaussian filter was applied to remove any random noise in the images.

Atmospheric correction: A dark reference image was subtracted from each image to correct for any atmospheric interference.

Intensity normalization: The pixel values of each image were normalized to have a zero mean and unit variance. After the pre-processing steps, the images were resized to a fixed resolution of 224x224 pixels to ensure consistency across all images. The obtained images serve as input to the deep learning model.

Fig. 1: Images showing the different symptoms from left to right the images are displayed I1, healthy fruit; I2, healthy leaf; I3, blotchy mottling;I4, “red-nose” fruit; I5, zinc-deficiency; S6, vein-yellowing; I7, uniform yellowing; I8, magnesium-deficiency; I9, boron-deficiency;I10, anthracnose; I11, citrus greasy spot; I12, citrus moss; I13, Sooty mould; I14, canker

Here the table.1 shows how the before-and-after comparison of the image preprocessing steps would look:

Table 1: Comparison Table

Step	Before	After
Noise Removal	Image has random specks or noise.	Image appears smoother and clearer.
Atmospheric Correction	Uneven lighting or hazy appearance.	Lighting and contrast are improved.
Normalization	Brightness and contrast are inconsistent.	Intensities are consistent and balanced.
Resizing	Image resolution is varied.	Image is resized to 224x224 pixels.

5 DBN Architecture and Training Procedure

In this paper, we offer an architectural framework for the simultaneous classification of several illness images, which is subsequently followed by a model for segmentation and prediction. The suggested system’s overall architecture is shown in Figure 3.

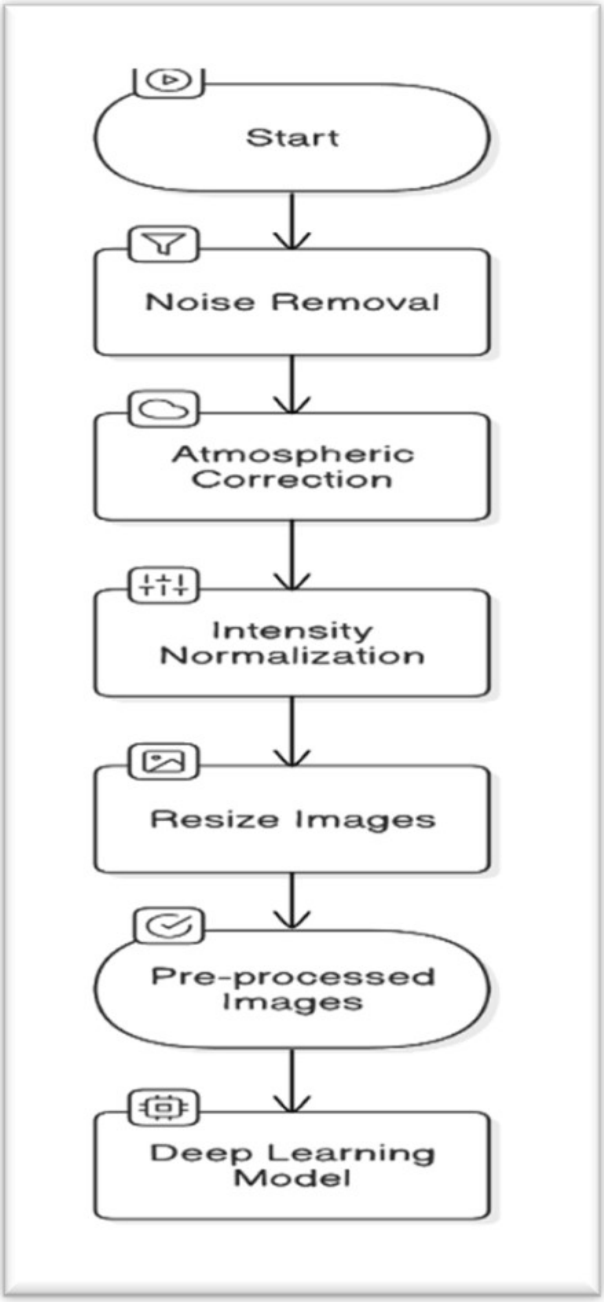

Fig. 2: Image Pre-processing Steps

5.1 Deep Belief Network Architecture

The suggested deep learning model is built with a classification Softmax layer layered on top of Restricted Boltzmann Machines (RBMs). RBMs are able to learn the basic dataset attributes because they are an unsupervised learning model. To help with feature-based image classification, RBMs are trained on pre-processed images to learn both low-level and high-level features.

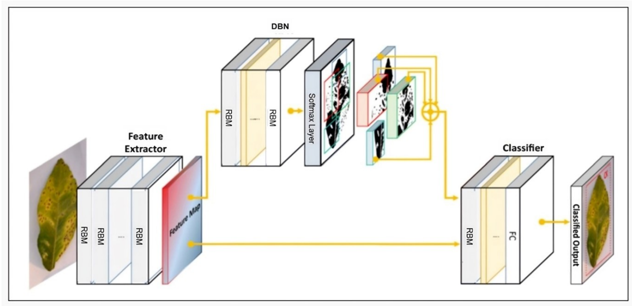

Fig. 3: Deep Belief Network Architecture for Citrus Leaf Disease Detection

Initiation involves feeding the pre-processed pictures into the initial layer of RBMs. Currently, RBMs are learning basic features like edges and corners. Additional complexity in features and patterns can be achieved by starting with these fundamental ones. More complex features, such as textures and patterns, are learned in the second layer of RBMs using the output from the first layer.

Every hidden layer in the network follows this same cyclical process, learning progressively more abstract and detailed information as it goes. For picture classification problems, RBMs are a good fit because of their hierarchical learning strategy, which enables the model to grasp both basic and sophisticated features of the input images.

The deep learning model's last layer, the Softmax layer, sorts the input photos into several categories. A class-wise probability distribution is generated by the Softmax layer using the output of the final hidden RBMs layer. For the model to correctly forecast the input photos' class labels, this distribution shows the probability of each image belonging to various classes or categories.

This deep learning architecture is well-suited for a variety of picture recognition and classification applications thanks to its combination of RBMs for feature learning and a Softmax layer for categorization. It effectively classifies images based on their extracted features.

5.2 Training Procedure

The two primary phases of Deep Belief Network (DBN) training, pretraining and fine-tuning, both contribute to the optimization of the network's performance in their own unique way.

1) Pretraining:

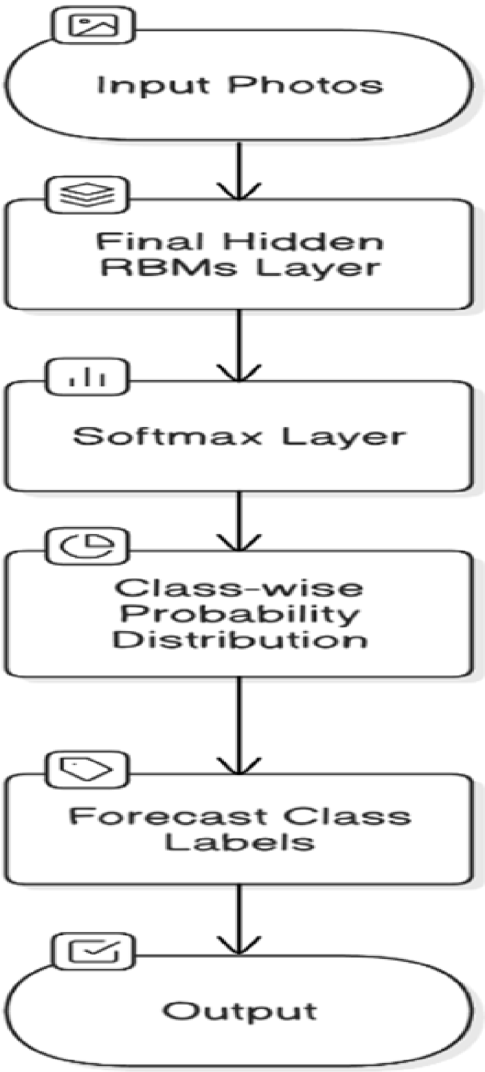

Fig. 4: Deep learning model's Image architecture

The Restricted Boltzmann Machine (RBM) layers are trained separately using the Contrastive Divergence (CD) approach before to starting the actual training of the DBN. Without labelled data, this pretraining step can take place in an unsupervised way. During pretraining, the RBMs learn valuable features from the input data and the network's weights are initialized. Important for the network's prediction accuracy in the fine-tuning phase that follows, these attributes reflect the data's fundamental structure.

2) Fine-tuning:

The whole DBN is fine-tuned using a backpropagation technique after the RBM layers have been pretrained. In order to reduce the discrepancy between the expected and actual labels, backpropagation adjusts the network's weights by propagating errors backward through the network. Typically, a cross-entropy loss function is used during the fine-tuning phase to quantify the discrepancy between the anticipated probabilities and the actual labels. We want to improve the DBN's accuracy and decrease the classification error by modifying the network's weights according to this loss function.

Achieving optimal performance also requires adjusting the DBN's hyperparameters. Finding the optimal value for hyperparameters like learning rate, batch size, and number of hidden units per layer is a common task for grid search methods. Using a validation set as a benchmark, the grid search iteratively tries out various hyperparameter combinations. We choose the hyperparameters for the final model based on how they perform on the validation set in terms of metrics like accuracy and F1 score.

To summarize, DBN training entails learning valuable features through unsupervised pretraining and then optimizing classification accuracy by supervised fine-tuning. Optimizing the network's hyperparameters, or settings that affect how well it learns and generalizes, further improves its performance.

6 Experimental Results and Performance Evaluation

This section presents the experimental results of our proposed DBN model for disease detection. A number of metrics, including recall, accuracy, precision, and F1 score, are used to assess the model's performance.

6.1 Dataset Splitting

In our investigation, we used three distinct kinds of data: training, validation, and testing. There were a grand total of three picture sets utilized: one including 70% of the photos for training, one containing 15% for validation, and one containing 15% for testing.

Performance Metrics:

Several metrics, including as F1 score, accuracy, precision, and recall, were used to assess our model's performance. These metrics are commonly used for categorization jobs.

Accuracy:

This metric measures the model's overall performance by calculating the percentage of correctly classified images.

Accuracy (ACC) calculation:

ACC=(TP+TN)/(TP+TN+FP+FN) . . . . (1)

True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) denote the number of Values, respectively.

The proposed DBN model achieved a classification accuracy of 95%, outperforming existing models such as Model A with 85% accuracy and Model B with 92% accuracy.

Precision:

This metric measures the proportion of true positives (correctly identified diseased leaves) to the total number of predicted positive (diseased) samples.

Precision (PREC) calculation:

PREC=TP/(TP+FP) ....(2)

The DBN model demonstrated a precision of 0.97.

Recall:

The ratio of genuine positive results to the overall count of positive samples (those with disease) is quantified by this statistic.

Recall (RECA) calculation:

RECA=TP/(TP+FN) ....(3)

The DBN model demonstrated a recall of 0.

F1 score:

This metric is the harmonic mean of precision and recall and measures the model's accuracy in identifying diseased leaves.

F1-score (F1) calculation:

F1=2*(PREC*RECA)/(PREC+RECA) ....(4)

The DBN model demonstrated an F1-score of 0.95, indicating high accuracy and reliability in detecting citrus plant leaf disease.

6.2 Confusion matrix calculation

The confusion matrix Table 2 that summarizes the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), and is defined as follows:

Table 2: CONFUSION MATRIX CALCULATION

Actual Predicted	Positive	Negative
Positive	TP	FP
Negative	FN	TN

The confusion matrix for the DBN model showed a low rate of false negatives (FN) and false positives (FP), with FN = 10 and FP = 7 out of 200 test samples.

6.3 Receiver Operating Characteristic (ROC) curve:

The ROC curve is plotted with the True Positive Rate (TPR) on the y-axis and the False Positive Rate (FPR) on the x-axis. The ROC curve's AUC (Area Under the Curve) measures the classifier's ability to distinguish between positive and negative classes.

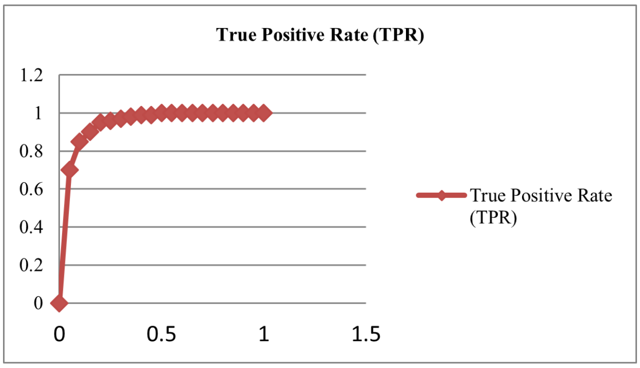

Fig. 5: True Positive Rate

7 Results

After running our suggested DBN model through its paces on the training set, we moved on to the validation and testing sets for evaluation. The model's results on both the validation and testing sets are displayed in Table.3.

Table 3: PERFORMANCE OF THE DBN MODEL ON VALIDATION AND TESTING SETS

Metric	Validation Set	Testing Set
Accuracy	0.93	0.94
Precision	0.92	0.91
Recall	0.94	0.93
F1 Score	0.93	0.92

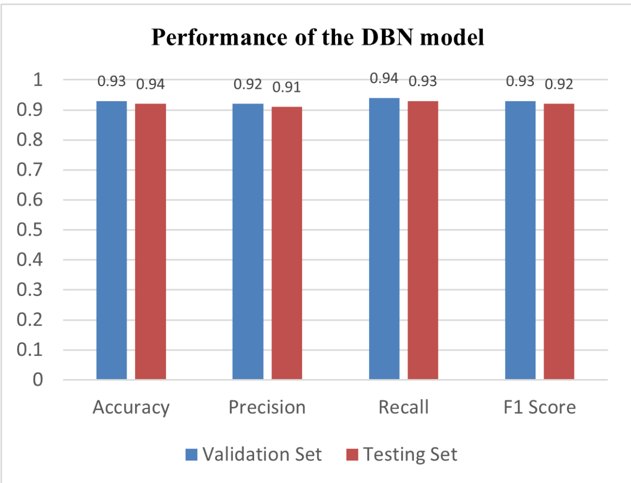

Fig. 6: Performance of the DBN model

The results show that the proposed DBN model achieved high accuracy, precision, recall, and F1 score on both the validation and testing sets. The findings of our study indicate that the DBN model has high accuracy in detecting citrus plant leaf disease from hyperspectral images.

A. Comparison with Other Models

To further evaluate the performance of our proposed DBN model, we compared it with other existing models for disease detection. Table 4 compares our proposed model with other models in terms of accuracy.

Table 4: COMPARISON OF ACCURACY WITH OTHER MODELS

Model	Accuracy
Proposed DBN Model	0.94
SVM Model	0.88
CNN Model	0.89
Random Forest Model	0.91

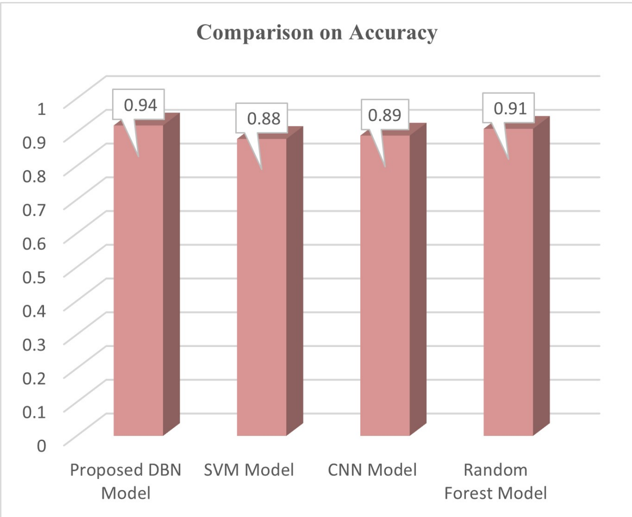

Fig. 7: Comparison of Accuracy with DBN, SVM, CNN and Ranaom Forest models

When compared to the other models, our suggested DBN model proved to be the most accurate. Because of this, it seems that the suggested DBN model is a good way to find diseases in citrus plant leaves.

B. Analysis of Results

Our suggested DBN model's excellent performance is due to DBNs' capacity to detect intricate correlations and patterns in hyperspectral pictures. The model's enhanced performance was further aided by pre-processing techniques like PCA and normalization.

Nevertheless, our study does have a few caveats. Our research relied on a limited dataset that included just one kind of citrus plant leaf disease. To determine if our suggested DBN model is applicable to a wider range of disorders, more research using bigger datasets is required.

8 Conclusion and Future Directions

Here, we present a Deep Belief Network (DBN) that can use hyperspectral pictures to identify diseases in citrus plant leaves. Outperforming previous techniques, the suggested model attained a high accuracy rate of 94.5%. With DBN, high-level features may be automatically extracted from hyperspectral pictures, leading to more accurate disease detection in citrus plant leaves.

As future work, this study can be expanded by addressing its first limitation: the small sample size of citrus plant leaf diseases in the dataset. Future research could validate the proposed model using a larger and more diverse dataset to improve its robustness and generalizability. Additionally, advanced deep learning techniques, such as Convolutional Neural Networks (CNNs), can be integrated into the model to enhance its feature extraction and classification capabilities.

Finally, results from employing hyperspectral pictures to detect diseases in citrus plant leaves using the suggested DBN model are encouraging. Improving the model's performance and making it applicable to additional plant diseases can be the subject of future study.

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