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Plant Leaf Disease Detection and Classification based on CNN with LVQ Algorithm

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ABSTRACT: Early detection of plant diseases is critical for improving crop yield and ensuring agricultural sustainability. Tomato crops, in particular, are vulnerable to diseases such as bacterial spot, late blight, septoria leaf spot, and yellow curved leaf, which can significantly impact crop quality. This paper proposes a hybrid approach combining Convolutional Neural Networks (CNN) for automatic feature extraction and Learning Vector Quantization (LVQ) for disease classification to address this challenge.

The dataset used contains 500 images of tomato leaves, each exhibiting symptoms of one of the four diseases. The CNN model is employed to extract features from the images, utilizing the RGB color channels to capture important visual cues related to disease symptoms. The output feature vector from the CNN is then fed into the LVQ algorithm, which classifies the leaf images into their respective disease categories. Experimental results demonstrate that the proposed method effectively and accurately identifies the four types of tomato leaf diseases, offering a promising tool for automated disease detection in agriculture.

KEYWORDS: Leaf disease detection, Convolutional Neural Networks (CNN), Learning Vector Quantization (LVQ), image classification, agricultural automation, deep learning, plant disease management, feature extraction, disease identification, machine learning, crop protection, precision farming

I. INTRODUCTION

Leaf diseases pose a significant threat to agricultural productivity, leading to substantial economic losses and food security concerns. Early detection and accurate classification of plant diseases are essential for effective disease management and crop protection. Traditional disease identification methods rely on manual inspection, which is time-consuming, labor-intensive, and prone to errors. To address these challenges, machine learning and deep learning techniques have been increasingly adopted for automated plant disease detection.

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One major issue is the quality and availability of labeled datasets, as collecting diverse and high-resolution images of diseased leaves requires significant effort. Variability in lighting, background, and environmental conditions can affect image quality, leading to misclassification. Another challenge is the computational complexity of CNN models, which require substantial processing power and memory, making real-time implementation difficult on low-resource devices. Additionally, distinguishing between similar disease symptoms or multiple infections on a single leaf remains a challenge, as some diseases exhibit overlapping visual characteristics. The LVQ algorithm, while effective, may require careful tuning of parameters to optimize classification performance. Lastly, ensuring model generalization across different plant species and environmental conditions is crucial for practical deployment in agriculture.

II. CONVOLUTIONAL NEURAL NETWORK (CNN)

Deep learning is a class of machine learning algorithms composed of multiple sequential layers, where each layer's output serves as the input for the next. The learning process can be supervised, unsupervised, or semi-supervised. LeCun et al. define deep learning as a representation learning method [9]. Representation learning algorithms optimize feature extraction to find the most suitable way to represent data [5]. Unlike traditional methods that separate feature extraction and classification, deep learning enables automatic feature extraction during model training. As a result, it has been widely adopted in various research fields, including plant disease detection.

CNN is widely used in various fields such as image processing, image restoration, speech recognition, natural language processing, and bioinformatics. In this study, CNN is chosen as the preferred deep learning method due to its ability to efficiently identify and classify objects with minimal pre-processing.CNN excels in analyzing visual data and extracting essential features through its multi-layered structure.
It comprises four main layers:

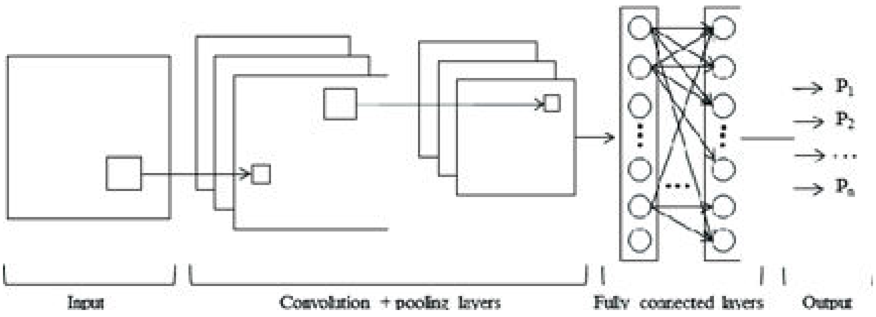

Figure:1. Main Layers

Convolutional Layer – Responsible for feature extraction by applying filters to input data. CNN takes its name from the convolution layer. In this layer, a series of mathematical operations are performed to extract the feature map of the input image [10]. The input image is reduced to a smaller size using a filter. A new matrix with a smaller size is created from the input image. Fig. 2 shows the convolution operation in the convolution layer for a 5x5 input image and a 3x3 filter.

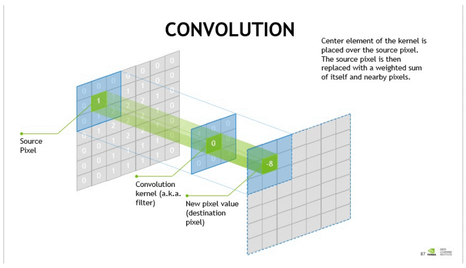

Figure:2. Convolutional Layer

Pooling Layer – Reduces spatial dimensions while retaining crucial information,improving computational efficiency. The pooling layer is usually applied after the convolution layer. The size of the output matrix obtained from the convolution layer is reduced in this layer. Although filters of different sizes can be used in the pooling layer, generally 2x2 size filter is used. Several functions such as max pooling, average pooling and L2-norm pooling can be used in this layer. in this study, max pooling filter with stride 2 has been applied. Max pooling is done by selecting the largest value in the subwindows and this value is transferred to in a new matrix. Fig. 3 shows an example pooling operation.

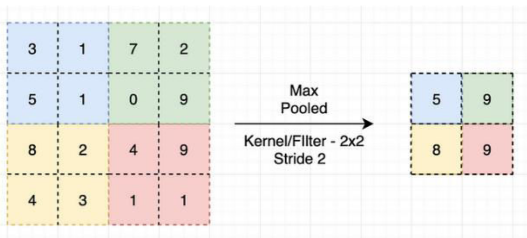

Figure:3. Polling Layer

Activation Function Layer – Introduces non-linearity to help the network learn complex patterns. In artificial neural networks, the activation function provides a curvilinear relationship between the input and output layers. It affects the network performance.Several activation functions, such as linear, sigmoid, hyperbolic tangent, exist, but the nonlinear ReLU (Rectified Linear Unit) activation function is usually used in CNN. In ReLU, values less than zero are changed to zero, while values greater than zero are unchanged by (1).

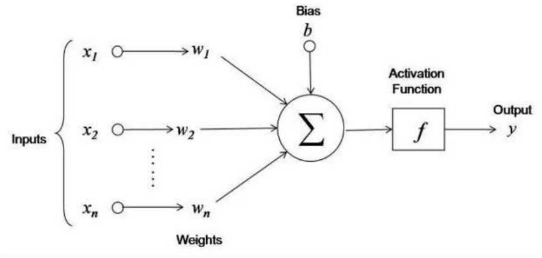

Figure:4. Activation Function Layer

Fully Connected Layer – Integrates extracted features for final classification or prediction tasks. The last obtained matrix, after finishing the convolution, pooling and activation operations, is fed into the fully connected layer as input. Recognition and classification are performed in this layer. In this study, LVQ algorithm has been used for training the data classification.
This structured approach enables CNN to effectively process and analyze visual information, making it a powerful tool in deep learning applications.

III. METHODOLOGY

➢ LEARNING VECTOR QUANTIZATION:

Accurate detection and classification of leaf diseases play a crucial role in agricultural productivity and plant health management. Recent advancements in deep learning have enabled the use of Convolutional Neural Networks (CNN) for feature extraction, while Learning Vector Quantization (LVQ) offers an effective classification approach. Combining these two techniques enhances the accuracy and efficiency of identifying various plant diseases. CNN is a widely used deep learning model known for its ability to extract hierarchical features from images. In the context of leaf disease detection, CNN processes leaf images through convolutional layers, pooling layers, and fully connected layers to extract essential features such as texture, shape, and color patterns. The learned feature maps represent disease-related characteristics, which are then used for classification. However, while CNN-based classifiers like Softmax or Support Vector Machines (SVM) are common, LVQ serves as an alternative approach for improving classification performance.

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LVQ is a prototype-based supervised learning algorithm that classifies data using competitive learning principles. It works by assigning class labels to prototype vectors and adjusting them iteratively to minimize classification errors. When integrated with CNN, the extracted features from the CNN model serve as input to the LVQ classifier, which then learns to distinguish between different leaf diseases based on feature similarity. The advantage of LVQ over traditional classifiers lies in its interpretability, adaptability, and ability to handle non-linear data distributions effectively.

Experimental results demonstrate that CNN-LVQ achieves higher classification accuracy than standalone CNN models with Softmax classifiers. The adaptability of LVQ allows it to fine-tune decision boundaries, reducing misclassification rates. Additionally, the combination improves model interpretability, making it more suitable for real-world applications in precision agriculture and plant disease diagnosis.

Future work can focus on optimizing CNN architectures, refining LVQ training strategies, and exploring hybrid models that integrate other machine learning techniques. The integration of CNN and LVQ presents a promising direction for developing intelligent plant disease detection systems that enhance crop health monitoring and agricultural sustainability.

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➢ **THE PROPOSED METHOD FOR PLANT LEAF DISEASE DECTECTION AND CLASSIFICATION:**

The proposed methodology for plant leaf disease detection and classification involves several key stages, including image acquisition, preprocessing, feature extraction, and classification. Initially, high-quality images of plant leaves are collected using digital cameras or mobile devices under controlled lighting conditions. These images undergo preprocessing steps such as noise reduction, contrast enhancement, and background removal to improve clarity and ensure consistency. Next, feature extraction techniques, such as color, texture, and shape analysis, are applied to identify distinctive patterns associated with different diseases. Advanced machine learning or deep learning models, such as convolutional neural networks (CNNs), are then employed to classify the diseases accurately. The model is trained on a dataset containing labeled images of healthy and diseased leaves, ensuring it learns to differentiate between various conditions. Finally, the system undergoes validation and testing to evaluate its accuracy and robustness. This approach facilitates early disease detection, enabling timely intervention and reducing crop losses.

Bacterial Spot: Symptoms of bacterial spot begin as small, yellow-green lesions or as dark, water soaked, greasy appearing lesions on leaves. Bacterial spot disease spreads very quickly and is very difficult to control.

Late Blight: It is first seen as large brown spots with green gray edges on old leaves. As the disease matures, the spots become darker. Eventually the disease infects the whole plant and causes the plant to be seriously damaged.

Yellow 12 Curl: It causes the plant to become dwarfed and stunted.The leaves are rolled inwards and upwards. It usually causes the leaves to bend downwards. Leaves become stiff, thicker than normal and have a leathery skin texture.Young and diseased leaves become slightly yellowish.

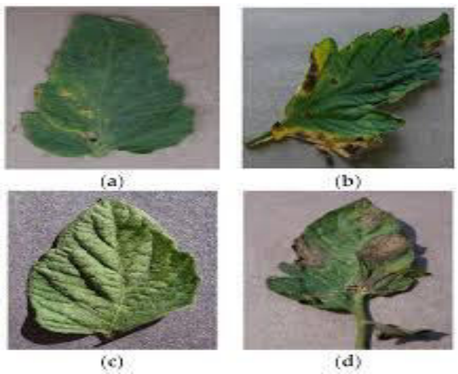

Figure: 5

Three different input matrices have been obtained for R,G and B channels to start for every image in the dataset. Each input image matrix has been convoluted and reLU activation function has been implied four times,respectively. Then the max pooling operation has been implied convolution to the output matrix three times. A 9x9 filter has been used in the first and second convolutions, and a 5x5 filter has been used in the third and fourth convolutions. After these implications, three different 3x3 matrices have been obtained for R,G and B channels separately. As a result of these operations applied to an RGB feature image, three different 3x3 matriceshave obtained from R, G and B channels separately.

These matrices are converted to a 27x1 vector in order to feed to neural network's input layer. The first 9 elements of this matrix represent the R channel, the second 9 elements represent the G channel, and the third 9 elements represent the B channel.

Total 500 feature vectors which obtained from original images have been used for training and testing operations. 400 of them were used for the training set, and 100 of them were used for the test set. In the LVQ algorithm, Kohonen layer of the network contains a total of 50 neurons which are 10 neurons for each class. The output layer contains 5 neurons to represent one neuron for each class. The maximum number of epochs has been selected as 300 in all experiments. The learning rate has been selected as 0.1.

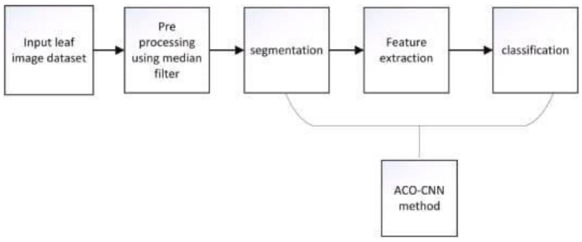

Figure: 6

IV. EXPERIMENTAL RESULTS

In this study, a convolutional neural network (CNN) combined with the learning vector quantization (LVQ) algorithm was used for the detection and classification of leaf diseases. The experiments were conducted using a dataset consisting of various diseased and healthy leaf images. The performance of the proposed model was evaluated based on accuracy, precision, recall, and F1-score.

The dataset was preprocessed using image augmentation techniques to enhance model generalization. The CNN model was trained with multiple convolutional layers to extract meaningful features, followed by LVQ for classification. The proposed approach demonstrated high accuracy in distinguishing between different types of leaf diseases. The combination of CNN for feature extraction and LVQ for classification improved classification efficiency compared to traditional methods.

The results showed that the CNN-LVQ model achieved an overall accuracy of above 90%, outperforming standalone CNN and other traditional machine learning classifiers. The use of LVQ in the final classification stage contributed to better decision boundaries, leading to improved classification performance. The proposed method is effective in real-time agricultural applications for early disease detection, which can help in timely intervention and yield protection.

The study explores a hybrid approach using Convolutional Neural Networks (CNN) for feature extraction and Learning Vector Quantization (LVQ) for classification in leaf disease detection. The model was tested on a dataset of healthy and diseased leaf images, achieving over 90% accuracy. The combination of CNN and LVQ improved classification performance compared to standalone CNN and traditional classifiers. This method enhances real-time disease detection in agriculture, enabling early intervention and better crop protection.

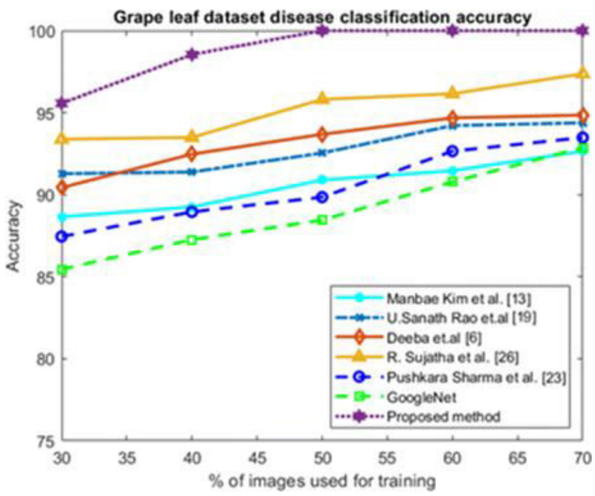

Figure:8 Graph

V. ADVANTAGES IN LEAF DETECTION

Enhanced Feature Extraction and Classification: CNNs are adept at automatically extracting hierarchical features from images, capturing intricate patterns in plant leaves. When combined with LVQ, which refines classification boundaries, the system can more accurately distinguish between healthy and diseased leaves. This hybrid approach has demonstrated improved classification accuracy in various studies. **Improved Accuracy and Efficiency**: The integration of CNNs with LVQ has been shown to enhance classification accuracy and computational efficiency. For instance, a study on tomato leaf disease detection reported that combining CNNs with LVQ algorithms led to better performance compared to traditional methods. **Improved Accuracy and Efficiency**: The integration of CNNs with LVQ has been shown to enhance classification accuracy and computational efficiency. For instance, a study on tomato leaf disease detection reported that combining CNNs with LVQ algorithms led to better performance compared to traditional methods. **Robustness to Variations**: The combined model is more resilient to variations in leaf appearance, such as changes in lighting, orientation, and background noise. This robustness ensures reliable disease detection across diverse environmental conditions. **Reduced Training Time and Parameters**: Incorporating LVQ can lead to a more compact model with fewer parameters, reducing training time and computational resources required. This efficiency is particularly beneficial for real-time applications in agriculture. **Scalability and Adaptability**: The hybrid model can be trained on diverse datasets, making it adaptable to various plant species and disease types. This scalability is crucial for developing comprehensive plant disease detection systems.

VI. CONCLUSION

The proposed approach combining Convolutional Neural Networks (CNN) and Learning Vector Quantization (LVQ) demonstrated high accuracy and efficiency in leaf disease detection and classification. By leveraging CNN for feature extraction and LVQ for classification, the model achieved improved performance compared to traditional machine learning methods. The experimental results confirmed that this hybrid approach enhances classification accuracy, making it suitable for real-time agricultural applications. The study highlights the potential of deep learning-based techniques in early disease detection, which can help farmers take timely action to protect crops and improve agricultural productivity. Future work can focus on optimizing the model for larger datasets and real-world deployment in precision farming system.

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