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Plant disease classification using novel integration of deep learning CNN and graph convolutional networks

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ABSTRACT

Plant diseases present substantial challenges to global agriculture, significantly affecting crop yields and jeopardizing food security. Accurate and timely detection of these diseases is paramount for mitigating their adverse effects. This paper proposes a novel approach for plant disease classification by integrating convolutional neural networks (CNNs) and graph convolutional networks (GCNs). The model aims to enhance classification accuracy by leveraging both visual features extracted by CNNs and relational information captured by GCNs. Using a Kaggle dataset containing images of diseased and healthy plant leaves from 31 classes, including apple, corn, grape, peach, pepper bell, potato, strawberry, and tomato. Standalone CNN models were trained on image data from each plant type, while standalone GCN models utilized graph-structured data representing plant relationships within each subset. The proposed integrated CNN-GCN model capitalizes on the complementary strengths of CNNs and GCNs to achieve improved classification performance. Through rigorous experimentation and comparative analysis, the effectiveness of the integrated CNN-GCN approach was evaluated alongside standalone CNN and GCN models across all plant types. Results demonstrated the superiority of the integrated model, highlighting its potential for enhancing plant disease classification accuracy.

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1. INTRODUCTION

Plant diseases represent a formidable challenge to global agriculture, exerting immense economic pressures and jeopardizing food security on a global scale. The timely and precise identification of these diseases plays an indispensable role in implementing proactive mitigation measures and upholding sustainable crop production practices. However, traditional disease diagnosis methods predominantly rely on manual visual inspections conducted by agricultural experts. While these methods have served as the cornerstone of disease management for decades, they are inherently prone to limitations such as being time-consuming, labor-intensive, and susceptible to human error. In recent years, the landscape of disease detection and classification has undergone a paradigm shift with the advent of deep learning (DL) technologies. DL techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools capable of revolutionizing various domains, including medical imaging and object recognition. CNNs excel in learning hierarchical representations of image features, enabling them to discern subtle patterns and nuances in visual data. In the context of plant disease detection, CNNs hold immense promise for automating the process of identifying diseased plant tissues from their healthy counterparts with unprecedented accuracy and efficiency. Moreover, the integration of graph convolutional networks (GCNs) into the realm of plant disease classification presents an exciting frontier in agricultural research. GCNs offer a unique framework for modeling relational data and capturing intricate dependencies among interconnected entities, making them particularly well-suited for analyzing complex agricultural ecosystems. The convergence of CNNs and GCNs heralds a new era of innovation in plant disease detection, offering a synergistic blend of visual feature extraction and relational modeling capabilities.

Demilie [1] research addressed DL and machine learning (ML) methods, notably CNNs, for image identification and classification. CNNs were preferred for image classification because they automatically extracted key visual characteristics and captured spatial hierarchies. Problem type, data availability, and computing resources determined the decision between traditional ML and DL. When data and computing resources were abundant, DL, particularly CNNs, performed better in image identification and classification. Ullah *et al.* [2] suggested an innovative, efficient, and lightweight DL architecture for plant leaf disease prediction and categorization. DeepPlantNet has 28 learnt layers, including 25 ConV layers. A new plant disease classification framework was developed using Leaky rectified linear unit (LReLU), batch normalization (BN), fire modules, and a combination of 3×3 and 1×1 filters.

Saad and Salman [3] proposed Siamese neural network (SNN) one-shot learning (OSL) methods for plant disease classification with minimal datasets. To expand the dataset, it used data augmentation and used region-based picture segmentation. Generalization enhanced using support vector machine (SVM)-based classifiers for primary diagnoses. OSL with Siamese networks had far higher classification accuracy and fewer mistakes than normal transfer learning, with a processing time of 5 ms for real-time applications. The authors identified 182 plant disease detection and classification studies using keywords from peer-reviewed publications between 2010 and 2022 in [4]. After title, abstract, conclusion, and full text exclusion, 75 articles were reviewed. Data-driven methods improved plant disease diagnosis system performance and accuracy, making this study useful for researchers. Anandhi and Sathiamoorthy [5] used DL-based automated rice plant disease recognition and classification (DL-ARPDRC) to improve accuracy and diagnostics. Pre-processing began with picture scaling and gaussian filter (GF) to increase image quality. Otsu's threshold-based segmentation isolated lesions from the background, concentrating on the area of interest. To distinguish illnesses, visual geometry group (VGG)-19 architectural feature extraction and extreme gradient boosting (XGBoost) classification were used. Experimental findings indicated that DL-ARPDRC outperformed other contemporary methods. Degadwala *et al.* [6] accurately diagnosed hop plant diseases, indicating early detection and exact management. By CNN architectures, hops plant disease classification performance is compared. Their method might automate and enhance hops plant disease control, maintain hop crop sustainability and quality for brewing, and provide the groundwork for similar agricultural issues.

A deep CNN model for plant disease identification that overcomes field issues was proposed [7]. It performed well on the PlantVillage dataset, which included pictures of 14 healthy and sick crop leaves in 31 varieties. The CNN model has 98% training and 94% test accuracy in experiments. The program identified leaf diseases early, indicating it may be used for agricultural health monitoring. Using optimization and DL, [8] built a you only live once (YOLO)-based leaf disease detection and classification system. Pre-processing, PCFAN feature map generation, and ShuffleNet/ERSO classification optimization comprised the framework. FCN-RFO identified disease-prone locations. On a custom plant leaf picture dataset, the model surpassed earlier methods with high accuracy. These studies showed that DL classifiers might identify leaf diseases. Rice, wheat, and maize databases were created in [9] to address the stated problems. The datasets examined two bacterial and two fungal illnesses for rice, four fungal diseases for maize, and four fungal diseases for wheat, which destroy the whole plant. With constant training hyperparameters, eight fine-tuned DL models were used. Pre-trained deep CNN models were tested using EfficientNetB3-adaptive augmented DL (AADL) for exact illness diagnosis [10]. It is shown that the proposed model can provide accurate, real-time agricultural disease diagnosis.

The 'Zero-shot transfer learning' approach was proposed in [11] to improve classifier performance in tomato and potato datasets when the source domain has different classes than the destination domain. CNN models, data augmentation, synthetic data creation, and strong discriminative losses improved classifier performance in zero-shot conditions. Rashid *et al.* [12] proposed CNN-based precision agricultural disease classification architecture MMF-Net. MMF-Net improved accuracy with RL-block and PL-block 1 and 2 multi-contextual features. Fusion adaptively created the final judgment probability score, classifying maize leaf diseases with 99.23% accuracy. Overall, MMF-Net seemed promising for PA plant leaf disease detection. Ahmad *et al.* [13] evaluated plant disease detection DL models across datasets and settings. Five maize foliar disease datasets were used to test DL-based image classification algorithms. The best pre-trained DNN architecture for transfer learning was DenseNet169. Generalization accuracy was highest in CD&S RGBA photographs without backgrounds. New field and lab data improved model performance, suggesting field-deployable disease management methods.

A deep CNN model for plant disease categorization was developed in [14] to solve these issues. The model used PlantVillage photos of 14 healthy and sick crop leaves divided into 38 classifications. The CNN model has 98.01% training accuracy and 94% test accuracy in experiments. These data showed that the model was efficient for early leaf disease detection. A SVM and image processing method for grape leaf disease detection and classification was suggested [15]. Imaging, denoising, enhancement, segmentation, principal component analysis (PCA) feature extraction, and classification utilizing particle swarm optimizartion (PSO) SVM, back propagation neural network (BPNN), and random forest algorithms were performed. In grape leaf disease classification and detection, PSO SVM performed better. Sameera *et al.* [16] applied various DL models and achived reported good results for plant disease detection. Padma *et al.* [17] focused on Downey and Powdery Mildew, which produce significant grape fruit production losses, to effectively detect and classify illnesses in folio descriptions. For classifier-based identification, the research recommended deleting leaf traits like the major and small axes. Early illness detection and categorization benefit from image processing. Elfatimi *et al.* [18] introduced a method for classifying bean leaf diseases, optimizing network architecture, hyperparameters, and evaluating on a public dataset. MobileNetV2 architecture demonstrated high accuracy on the training set and test set for unhealthy (angular leaf spot disease and bean rust disease) and healthy classes.

Depth-wise, point-wise convolutions were added to the Inception module version in [19]. The Inception module and pre-trained MobileNet were the support extractors for high-quality picture features. For crop disease classification and detection, a fully connected Softmax layer and single shot detector (SSD) block were included. The model was trained using two-stage transfer learning. Wu *et al.* [20] introduced a fine-grained disease categorization method using an attention network. The "Classification model" incorporated attention mechanisms for enhanced identification. During training, a "Reconstruction-generation model" directed focus on differentiating areas, and adversarial loss reduced noise from the "Discrimination model". These were used exclusively during training, avoiding complexity in the inference phase. The method improved generalization ability, increasing identification accuracy with lower memory requirements. [21] extracted deep corn plant characteristics using two pre-trained CNNs, EfficientNetB0, and DenseNet121. Deep features from each CNN were concatenated to create a more complicated feature set to improve model learning. Data augmentation diversified the training dataset to help the model handle more complicated instances.

Ahmad *et al.* [22] used memory-efficient CNNs to identify plant disease symptoms. The suggested training setup reduced training time and handled class imbalance using statistics. Stepwise transfer learning was suggested to address negative transfer learning concerns during knowledge transfer between domains. Chen *et al.* [23] improved YOLOv5 for real-time strawberry disease detection. To decrease parameters and FLOPs, it included GhostConv. An involution operator broadened the receptive field, while a CBAM increased feature extraction. Content-Aware ReAssembly of Features replaced upsampling. A modified lightweight CNN may enhance fine-grained crop disease categorization [24]. The upgraded SqueezeNext model with a multi-scale convolution kernel and coordinate attention mechanism outperformed the original model in recognition accuracy. The lower model size and somewhat greater accuracy of ResNet50 and MobileNetV2 compared to Xception. A reconstructed residual dense network for tomato leaf disease detection [25] combined deep residual and dense network benefits. The model, originally built for picture super-resolution, scored 95% on the Tomato test dataset.

2. METHOD

The proposed method for plant disease prediction was shown in Figure 1. The research methodology involved several sequential steps to ensure robustness and effectiveness in plant disease classification. Initially, a diverse dataset was compiled, consisting of images portraying both diseased and healthy states across various plant types. Rigorous efforts were made to ensure sufficient coverage of plant diseases and authenticity of the dataset to minimize biases. Following data collection, the dataset was meticulously prepared by dividing it into distinct subsets corresponding to different plant types such as Apple, Cherry, Corn, Grape, Peach, Pepper bell, Potato, Strawberry, and Tomato. The next phase involved partitioning each plant-specific dataset subset into training, and testing subsets using appropriate ratios. Special attention was given to maintaining proportional representation of diseased and healthy samples in each subset to avoid bias and ensure model generalization. Subsequently, standalone CNN models were developed, tailored specifically for plant disease classification.

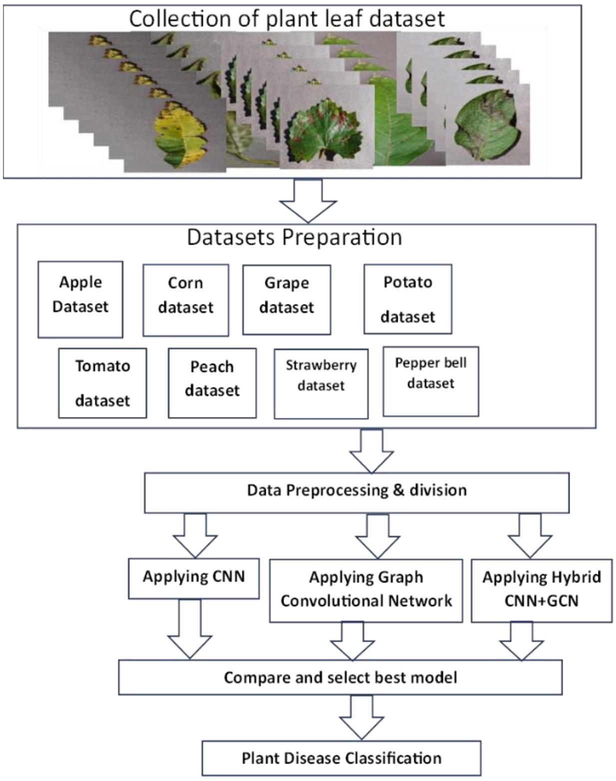


Figure 1. Proposed methodology

The CNN models were fine-tuned on the training set of each plant-specific dataset subset, with adjustments made to hyperparameters and regularization techniques. Model validation was conducted on corresponding validation subsets, with performance metrics monitored and architecture refined based on results. In parallel, standalone GCN models were constructed to exploit relational information encoded in graph structures of the dataset subsets. Graph representations were constructed where nodes represented plants and edges represented relationships such as co-occurrence or spatial proximity.

As a last phase of methodology, an integrated architecture combining CNNs and GCNs was developed to fuse visual and relational information for enhanced classification. This involved establishing connections between CNN and GCN components to facilitate seamless information flow and feature integration. The integrated model was trained on the training sets of each plant-specific dataset subset, with parameters fine-tuned and fusion strategies optimized to maximize performance. Model validation was performed on corresponding validation subsets, with performance compared against standalone CNN and GCN models. After applying GCN+CNN hybrd integraion, it is observed that the results with integrated model was better than the individual models.

2.1. Plant leaf image dataset gathering and preparation

A plant leaf image dataset was gathered from Kaggle [26]. The dataset contains 31 classes of images with Apple, Corn, Grape, Peach, Pepper bell, Potato, Strawberry, and Tomato types. This dataset is further divided as serrate datasets. The details of separated datasets are shown in Table 1. From Table 1, it is observed that the number samples available from Apple, Corn, Grape, Peach, Pepperbell, Potato, Tomato and Strawberry datasets are 3171, 3852, 4062, 2657, 2475, 2152, 18160, and 1565 respectively.

2.2. Convolutional neural networks

CNNs are DL models for image identification and classification. Convolutional, pooling, and fully linked CNN layers capture hierarchical and spatial picture characteristics well. CNNs excel at plant disease categorization. CNNs can assess detailed plant leaf patterns and textures to identify healthy from unhealthy plants by automatically learning key information from photos. CNNs classify plant diseases accurately and efficiently using feature extraction and hierarchical representation learning. CNNs have improved plant disease categorization accuracy and speed, enabling more prompt and effective agricultural treatments.

Table 1. Dataset preparation details

Dataset	Type of images	Number of images
Apple_dataset	Apple___Apple_scab	630
	Apple___Black_rot	621
	Apple___Cedar_apple_rust	275
	Apple___healthy	1645
Corn_dataset	Corn_Cercospora_leaf_spot	513
	Corn_Common_rust_	1192
	Corn_healthy	1162
	Corn_Northern_Leaf_Blight	985
Grape_dataset	Grape_Black_rot	1180
	Grape_Esca_(Black_Measles)	1383
	Grape_healthy	423
	Grape_Leaf_blight	1076
Peach_dataset	Peach___Bacterial_spot	2297
	Peach___healthy	360
Pepperbell_dataset	Peppebell_Bacterial_spot	997
	Pepperbell_healthy	1478
	Potato___Early_blight	1000
Potato_dataset	Potato___healthy	152
	Potato___Late_blight	1000
	Tomato___Bacterial_spot	2127
	Tomato___Early_blight	1000
	Tomato___Late_blight	1909
	Tomato___Leaf_Mold	952
	Tomato_Septoria_leaf_spot	1771
	Tomato_Spider_mites Two-spotted_spider_mite	1676
	Tomato___Target_Spot	1404
Tomato_dataset	Tomato__mosaic_virus	373
	Tomato_Yellow_Leaf_Curl_Virus	5357
	Tomato___healthy	1591
Strawberry_dataset	Strawberry___Leaf_scorch	1109
	Strawberry___healthy	456

2.3. Graph convolutional networks

GCNs are good at capturing linkages and dependencies in non-Euclidean domains including social, citation, and biological networks, unlike grid-like neural networks. GCNs can be used to classify plant diseases by evaluating correlations between plant species, weather, and geography. by propagating information across the network via graph convolutional layers, GCNs let the model to learn from data point interconnectivity. In plant disease categorization, GCNs may capture intricate connections between plants, illnesses, and external variables, helping to comprehend the agricultural environment. Incorporating relational information into plant disease classification using GCNs offers a possible path for more comprehensive and context-aware disease detection in agriculture.

2.4. Integration of CNN and GCN

The combination of GCNs with CNNs for plant disease categorization is innovative and synergistic. This hybrid model combines CNNs' visual pattern recognition with GCNs' capacity to represent agricultural network interactions. The combined GCN+CNN model provides a more complete and context-aware plant disease diagnosis solution by combining spatial image characteristics with graph-based information such plant species relationships and environmental parameters. This novel method improves accuracy and interpretability, offering a comprehensive foundation for agricultural disease control.

3. RESULTS AND DISCUSSION

During the data preparation stage, eight datasets were created, each tailored for experimentation. All experiments were carried out in Google Colab using PyTorch. Initially, a CNN served as the base model. Subsequently, GCN was implemented individually with each of the eight datasets. Finally, a novel integrated approach, combining both CNN and GCN (CNN+GCN), was applied for a comprehensive evaluation.

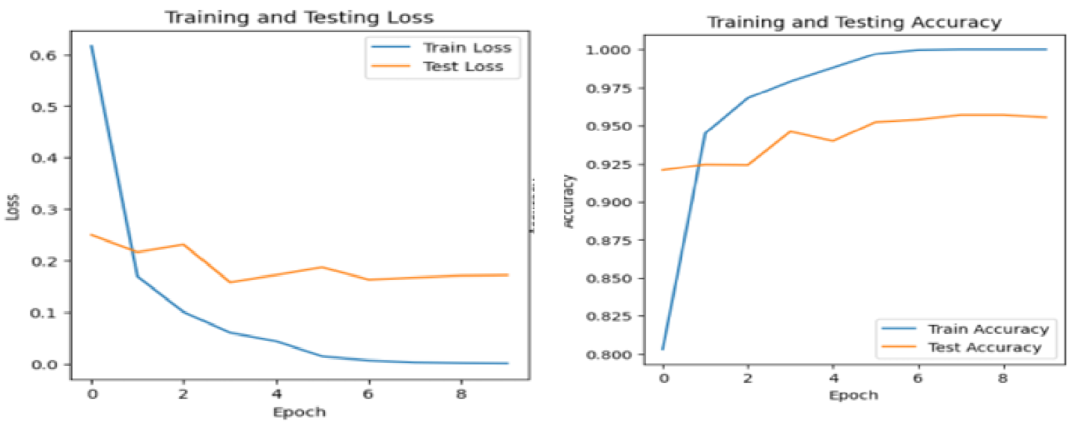
3.1. Applying convolutional neural networks

In the experimentation phase, we employed a CNN as the foundational model for plant disease classification. All the eight datasets underwent preprocessing and organization, utilizing the PyTorch framework within Google Colab for flexibility and scalability. Image resizing to a consistent dimension of 224×224 pixels and conversion to tensors were achieved through PyTorch's torchvision library. The dataset was then split into training and testing sets to ensure robust model evaluation. The CNN model architecture, designed to capture spatial features within the images, comprised convolutional layers for hierarchical pattern extraction, followed by max-pooling layers for down sampling. The fully connected layer facilitated the classification process for four disease categories. The model underwent ten epochs of training using the Adam optimizer and cross-entropy loss function. The performance was evaluated on a separate test set to assess generalization capabilities. The results of CNN experiment were shown in Table 2. Table 2 shows accuracy and loss values obtained with eight types of plants. The epoch wise accuracy and loss also shown for two datasets namely Apple and Tomato.

Figure 2 shows epoch wise performance of model with apple dataset. Figure 2(a) shows epoch wise training and testing loss for Apple dataset. Figure 2(b) shows epoch wise training and testing accuracy. The accuracy obtained for Apple dataset is 88%. Figure 3 shows epoch wise performance of model with Tomato dataset. Figure 3(a) shows epoch wise training and testing loss. Figure 3(b) shows training gand testing accuracy for Tomato dataset. The accuracy obtained for Apple dataset is 88%.

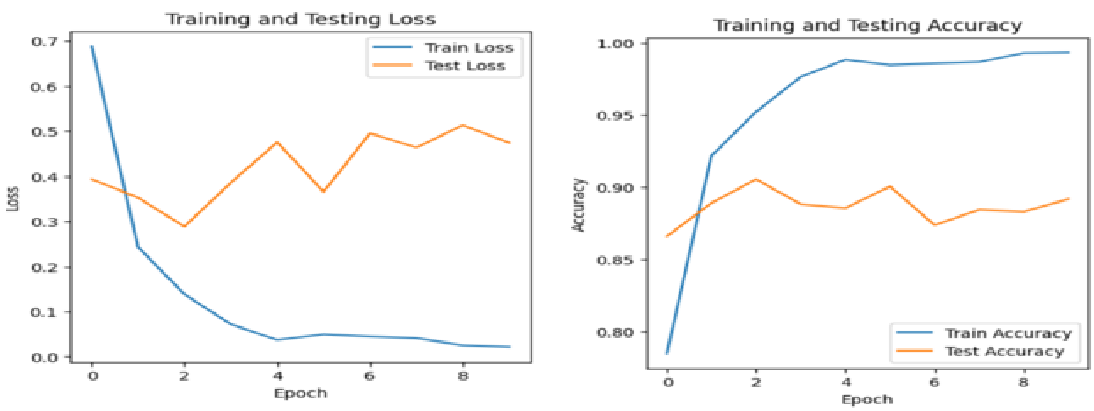
Table 2. Results with CNN

Dataset name	Accuracy	Loss
Apple_dataset	0.93	0.18
Corn_dataset	0.93	0.15
Grape_dataset	0.92	0.20
Peach_dataset	0.97	0.05
Pepperbell_dataset	0.95	0.11
Potato_dataset	0.97	0.07
Tomato_dataset	0.88	0.416
Strawberry_dataset	0.97	0.09



(a) (b)

Figure 2. Epcohwise (a) loss for apple dataset and (b) accuracy for apple dataset



(a) (b)

Figure 3. Epcohwise (a) loss and (b) accuracy for tomato dataset

3.2. Applying graph convolutional network

The GCN model architecture defines the structure of the GCN, consisting of two fully connected layers with ReLU. These layers enable the model to capture non-linear relationships between nodes in the graph. During the training procedure, the loss function (criterion) is specified as cross-entropy loss, and the optimizer (optimizer) is defined as Adam. The calculate_accuracy() function computes the accuracy of model predictions, and the train_model() function trains the GCN model iteratively across epochs, executing forward and backward passes and updating model parameters based on gradients. Following training, evaluation, and performance analysis are conducted. The model's performance is assessed using the test dataset, computing metrics such as accuracy and loss. The results of GCN experiment were shown in Table 3. Table 3 shows accuracy and loss obtained with eight types plants.

Table 3. Results with GCN

Dataset name	Accuracy	Loss
Apple_dataset	0.94	0.24
Corn_dataset	0.93	0.34
Grape_dataset	0.93	0.17
Peach_dataset	0.97	0.09
Pepperbell_dataset	0.96	0.21
Potato_dataset	0.95	0.09
Tomato_dataset	0.89	0.52
Strawberry_dataset	0.98	0.12

3.3. Applying novel integration of CNN and GCN

In this phase, we integrated Convnets with GCNs for plant disease classification, aiming to enhance accuracy and efficacy in diagnosing diseases based on leaf images. Our approach centers on the robust ResNet18 architecture within the CNN component, renowned for its effectiveness in image classification tasks. By adapting the fully connected layer to our dataset's requirements, we ensure seamless integration with the subsequent stages of our hybrid model. Complementing this, the GCN component captures relational information among images through two carefully crafted GCN layers, leveraging graph-based representations. Graph convolutional operations and activation functions enhance the classification process with nuanced relational insights. During training, our hybrid model undergoes optimization facilitated by the Adam optimizer, evolving collaboratively to enhance classification accuracy. The model traverses epochs with a shared learning rate, refining parameters through iterative forward and backward passes. The cross-entropy loss function guides optimization, ensuring alignment with ground truth labels in plant disease classification. Post-training, rigorous evaluation on an independent test set illuminates real-world performance using metrics such as test loss and accuracy. The aggregation of average test metrics provides a comprehensive snapshot of the model's diagnostic capabilities. In essence, our fusion of CNN and GCN marks a new era in plant disease classification, promising unparalleled accuracy and robustness.

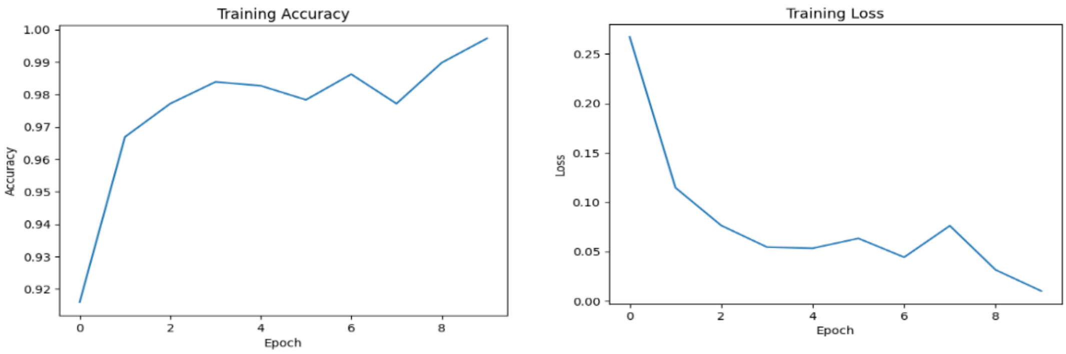
By combining image feature extraction and relational information modeling, our hybrid model stands poised to revolutionize agricultural technology, enhancing crop protection and sustainable practices. The results with integrated CNN and GCN is shown in Table 4. From Table 4, it is observed that, the integration of CNN anf GCN boost the accuracy and redice the loss values for all types of plants.

Table 4. Results with integration of CNN+GCN

Dataset Name	Accuracy	Loss
Apple_dataset	0.99	0.04
Corn_dataset	0.94	0.15
Grape_dataset	0.98	0.03
Peach_dataset	0.99	0.01
Pepperbell_dataset	0.99	0.05
Potato_dataset	0.99	0.008
Tomato_dataset	0.98	0.05
Strawberry_dataset	0.99	0.001

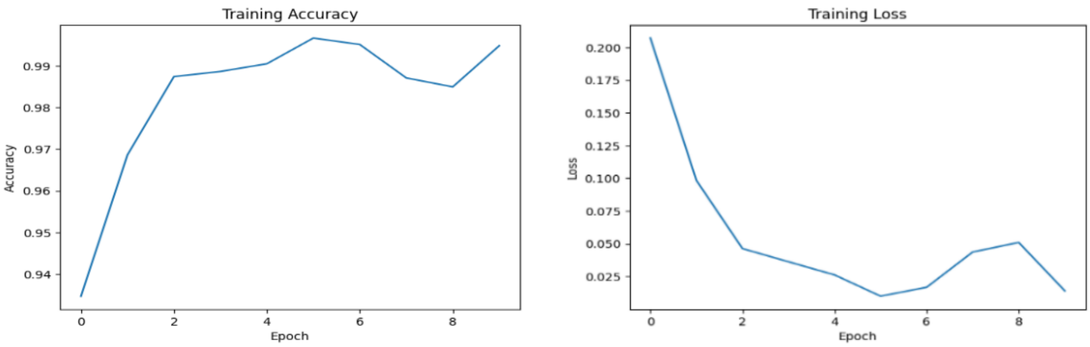
The epoch wise performance of the model for apple dataset is shown in Figure 4. Figure 4(a) shows epoch wise training accuracy and Figure 4(b) shows epoch wise training loss. It is observed that the accuracy increased gradually from epoch1 to epoch-10. The training loss value values gradually decreased from epoch-1 to epoch-10.

The epoch wise performance of the model for grape dataset was shown in Figure 5. The epoch wise training accuracy is shown in Figure 5(a). Figure 5(b) shows epoch wise training loss for grape dataset It is identified that the accuracy increased gradually from epoch1 to epoch-10. The training loss value values gradually decreased from epoch-1 to epoch-10. The similar type of trend achieved for all the eight datasets.



(a) (b)

Figure 4. Epochwise (a) accuracy and (b) loss values for apple dataset



(a) (b)

Figure 5. Epochwise (a) accuracy and (b) loss values for grape dataset

3.4. Comparison with existing work

Table 5 shows the comparison of proposed work with previous work. Ullah *et al.* [2], applied a novel DeepPlantNet and achieved an accuracy of 98%. Anandhi and Sathiamoorthy [5], the ensemble model of several DL techniques given highest accuracy of 91%. Lakshmanarao *et al.* [14], an accuracy of 95% achieved with transfer learning techniques. The proposed integration of CNN and GCN achived an accuracy of 99% and outperformed the conventional models.

Table 5. Comparison with existing work

Dataset Name	Accuracy
DeepPlantNet [2]	98%
Ensemble model [5]	91%
Transfer learning [14]	95%
Proposed method	99%

4. CONCLUSION

Plant diseases had posed significant challenges to global agriculture, profoundly impacting crop yields and threatening food security. Accurate and timely detection of these diseases had been paramount for mitigating their adverse effects. In this study, we proposed a novel approach for plant disease classification by integrating CNN and GCNs. Our model aimed to enhance classification accuracy by leveraging both visual features extracted by CNNs and relational information captured by GCNs. Using a Kaggle dataset containing images of diseased and healthy plant leaves from 31 classes, including Apple, Corn, Grape, Peach, Pepper bell, Potato, Strawberry, and Tomato, we partitioned the dataset into separate subsets for each plant type. Standalone CNN models were trained on image data from each plant type, while standalone GCN models utilized graph-structured data representing plant relationships within each subset. Our proposed integrated CNN-GCN model capitalized on the complementary strengths of CNNs and GCNs to achieve improved classification performance. Through rigorous experimentation and comparative analysis, we evaluated the effectiveness of our integrated CNN-GCN approach alongside standalone CNN and GCN models across all plant types.

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