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A graph neural network framework for vascular streak dieback recognition

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ABSTRACT

Vascular streak dieback (VSD) is one of the most destructive diseases affecting cocoa production in Southeast Asia, including Indonesia, where early visual symptoms are often subtle and spatially distributed across the leaf surface. Conventional image-based disease recognition approaches, particularly those relying solely on convolutional neural networks (CNNs), are effective in extracting local visual features but remain limited in modeling long-range structural relationships such as venation disruption and lesion spread. To address this limitation, this study investigates a hybrid CNN-graph neural network (CNN-GNN) framework for automated VSD recognition from cocoa leaf images. A primary dataset consisting of 1,000 RGB images collected directly from cocoa plantations in Jember Regency was used to reflect realistic field conditions. In the proposed approach, CNNs are employed for local feature extraction, while graph-based representations enable GNNs to capture global relational patterns through message passing. Experimental results demonstrate stable learning behavior and strong classification performance, achieving a maximum validation accuracy of 95.2% and an area under the curve (AUC) of approximately 0.94. Further analysis shows balanced precision and recall across classes, indicating reliable discrimination between Sehat and VSD-infected leaves. These findings suggest that hybrid CNN-GNN modeling provides an effective strategy for capturing both local and distributed structural characteristics of VSD symptoms and highlights the potential of graph-based reasoning to complement convolutional feature learning in plant disease diagnostics.

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1. INTRODUCTION

Cocoa is an essential product for farmers throughout Indonesia, including those in Jember. However, this does not mean that cocoa farming is without its challenges. Indonesia, on the other hand, is considered geographically suitable for cocoa cultivation, but geography alone does not determine the success of cocoa cultivation. One cause of cocoa crop failure is fungal disease, one of which is vascular streak dieback (VSD), caused by Ceratobasidium theobromae, and is considered a serious threat [1]. VSD in cocoa causes anatomical and physiological symptoms that, if left untreated, will lead to decreased yields and will affect the long-term results of cocoa plantations. When production decreases but demand remains constant or increases, this will cause cocoa prices to rise [2]. Several studies, such as those from [2], show that cases of VSD in cocoa show a pattern of increasing in Southeast Asia, including Indonesia. Based on [3], Indonesia itself is one of the countries that produces cocoa and exports cocoa in significant quantities, which is supported by the latest report from BPS [4]. Cocoa diseases can be visually recognized, one of which is from the color of the leaves. This is supported by research results from [1], [2], [5], which stated that there are color changes in the leaves of cocoa plants experiencing VSD disease symptoms.

Convolutional neural networks (CNNs) have been widely used in plant disease recognition due to their ability to extract local texture and color features from leaf imagery [6]. Previous researches such as Mohanty *et al.* [7] showed that deep CNNs could classify plant diseases from RGB images, meanwhile Too *et al.* [8] compared multiple transfer learning architectures for agricultural applications, achieving significant classification accuracy improvements. More recently, Kouassi *et al.* [9] applied CNNs detecting diseases of cocoa leaf, where CNN-based feature extraction combined with XGBoost classification yielded reliable results. However, CNNs persist limitation in modeling long-range spatial dependencies and structural relationships across different leaf regions. To overcome these constraints, researchers have explored graph neural networks (GNNs), which model explicitly relational structures and interactions among image regions [10]-[17]. For example, Zhao *et al.* [18] recommended a structural graph learning framework for image classification, Park *et al.* [19] were utilizing graph instruments to goal about visual relationships, and Wu *et al.* [20] established adaptive graph convolutional networks for fine-grained visual recognition. Although these GNN-based models effectively capture spatial dependencies, they often lack comprehensive visual context compared to CNNs. Accordingly, recent studies integrated both paradigms through CNN-GNN hybrid architectures [21]-[26], combination of CNN's strength in local feature extraction and GNN's capacity for relational reasoning to achieve better performance in complex image classification assignments such as detecting plant disease.

The motivation for this study is also rooted in our earlier work on agri-graph neural network (Agri-GNN), which leveraged graph-structured learning to capture spatial and relational dependencies in agricultural prediction tasks, outperforming conventional deep learning approaches for rice yield forecasting in Indonesia [27]-[30]. In this study, we collected primary data from 1,250 cocoa leaf photos collected in Jember Regency. Previous research related to cocoa disease diagnosis includes expert system–based approaches such as [31]; however, to the best of our understanding, there has been no study that specifically applies machine learning methods to VSD disease in cocoa.

Therefore, the research gap, most research on cocoa leaf disease detection is still limited to pure CNN approaches that only extract local spatial features without considering the relationships between leaf areas [32], [33]. Meanwhile, GNN-based models have shown the ability to understand relationships between nodes, but are unable to extract complex visual features in natural leaf images as far as we understand, there has been no research that combines these two approaches specifically for detecting VSD disease in cocoa leaves. Therefore, this study proposes a hybrid CNN-GNN model that utilizes CNN as a local feature extractor and GNN as a relationship modeler between leaf areas to be used as a model for classifying the dataset we have collected. This approach is expected to overcome the limitations of each model by producing a more comprehensive spatial-relational representation.

2. METHOD

2.1. Dataset and preprocessing

The 1,250 cocoa leaf images are divided into two classes, namely *Sehat* (healthy) and *Vascular Streak Dieback (VSD)*. The structure of the images is based on folders, enabling automatic label assignment with PyTorchs `ImageFolder` tool.

All images were resized to a fixed resolution of 224 × 224 pixels to ensure uniform input dimensions. Images were then transformed into tensor representations by normalizing the pixel values to the range $[0, 1]$. The dataset was divided into training validation and test sets at percentages of 70%, 10%, and 20% respectively. respectively ensuring balanced class distributions across all splits. A batch size of 32 was used for mini-batch data loading. Data shuffling was enabled for the training set to enhance generalization performance and decrease sampling bias. Our research flow is shown in Figure 1.

2.2. CNN backbone architecture

The core feature extractor was a lightweight CNN. Three convolutional blocks with progressively deeper channels 32, 64, and 128 make up the architecture. Accordingly, the rectified linear unit (ReLU) activation function comes after each convolutional layer spatial downsampling using max pooling. An adaptive average pooling layer was used at the end to create a fixed-length network, feature representation independent of the spatial dimensions of the input. An output with 128 dimensions is the end result, each feature vector acts as its visual embedding. The CNN backbone serves two purposes, both as a feature encoder in the CNN–GNN model and as a standalone classifier in the CNN-only baseline.

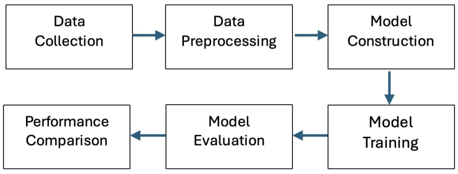

Figure 1. Overall research flow illustrating the main stages of the study

2.3. Graph construction

A graph structure was dynamically built to capture relational information between samples in every mini-batch. Pairwise cosine similarity was calculated between every sample batch of CNN feature embeddings. The top-K most similar samples were chosen as neighbors for each node, in this case study $K = 5$ is used.

An undirected graph was formed by creating edges in both directions, and the resulting structure was represented using the edge-index format needed for graph neural networks. During training, relational reasoning between visually comparable samples is made possible by this batch-wise graph building, which preserves computing efficiency.

2.4. Graph neural network module

A two-layer graph convolutional network (GCN) was used to create the graph-based reasoning component. A ReLU activation function comes after the first graph convolution layer, which converts the 128-dimensional CNN features into a 256-dimensional hidden representation. The hidden representation is projected into the output space that corresponds to the number of target classes by the second layer. The model may update feature representations based on inter-sample correlations and aggregate data from neighboring nodes by using graph convolution processes.

2.5. Training strategy

The CNN-only and CNN-GNN models were trained for 20 epochs at a learning rate of 1×10^{-3} using the Adam optimizer. The training target was the cross-entropy loss function. Backpropagation was used to tune the model's parameters, and generalization performance was evaluated by tracking validation accuracy.

Due to hardware limitations, every experiment was carried out in a CPU-based setting. The suggested training configuration is still appropriate for assessing the effectiveness of the suggested strategy even in the absence of GPU acceleration.

2.6. Evaluation metrics

Several metrics, including overall accuracy, precision, recall, and F1-score for each class, were used to evaluate the model's performance. Additionally, class-wise prediction errors were analyzed using confusion matrices. The models' ability to discriminate across various categorization thresholds was evaluated using receiver operating characteristic (ROC) curves and the associated area under the curve (AUC).

3. RESULTS AND DISCUSSION

3.1. Overall performance of the CNN-GNN model

The learning behavior remained stable throughout the training process, with both training accuracy and validation accuracy showing meaningful improvements when observed across each epoch as presented in the training versus validation curves. The maximum validation accuracy achieved by the model reached 95.2% as shown in Figure 2. This result can be used as a basis to state that the generalization capability is considered good, even though the training was conducted in a CPU-based environment.

It can be observed that the training accuracy and validation accuracy exhibit relatively similar rising and falling patterns. The results also show that the difference between the two values remains relatively small for each epoch, indicating that no significant overfitting occurs. This suggests that the combination of convolutional feature extraction and graph-based reasoning is able to learn meaningful representations from cocoa leaf images.

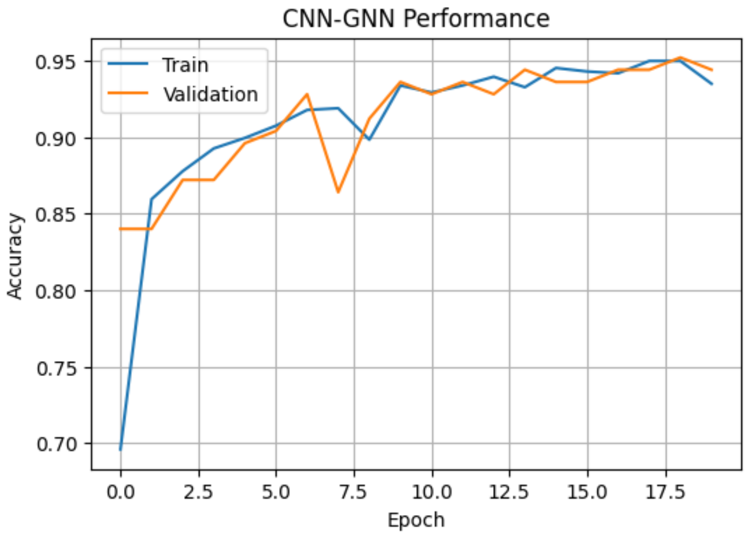

Figure 2. Training and validation accuracy curves of the CNN–GNN model over 20 epochs

3.2. Per-class evaluation and error analysis

Per-class metric evaluation was conducted to analyze the classification behavior of the CNN-GNN model in greater detail. The evaluation results show that the precision, recall, and F1-score values are relatively balanced for both classes. The complete results are presented as follows Table 1. These results indicate that the model is effective in detecting infected leaves while simultaneously maintaining a low false-positive error rate.

Table 1. Classification performance metrics

Class	Precision	Recall	F1-score	Support
Sebat	0.94	0.95	0.95	64
VSD	0.95	0.93	0.94	61
Accuracy		0.94		125
Macro Avg	0.94	0.94	0.94	125
Weighted Avg	0.94	0.94	0.94	125

The confusion matrix is shown in Figure 3. More detailed information is provided by the confusion matrix related to classification errors. From the confusion matrix, it can be stated that the classification is correct for most samples and only a small number of false negatives are observed. This context is important in cocoa leaf disease detection, because if an infection occurs but is not detected, it may result in significant agricultural production losses.

3.3. Discriminative capability analysis

In Figure 4, which represents the ROC curve of the CNN-GNN model, it is shown that approximately 0.94 is the AUC value of the model. Based on this, the discriminative capability is considered sufficiently strong in performing classification of cocoa leaves “Sehat” and those infected with VSD across various classification thresholds. The high AUC value indicates that the learned feature representations are effective in separating the two classes, even when the decision threshold is adjusted. This further confirms the robustness of the proposed approach.

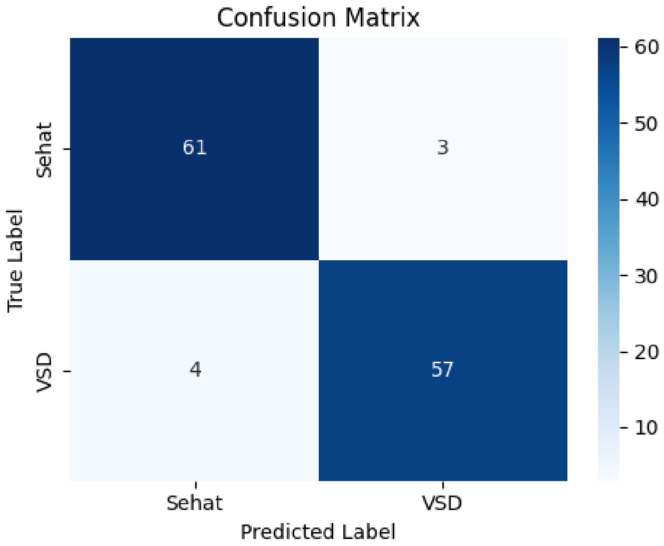

Figure 3. Confusion matrix of the CNN–GNN model on the validation dataset

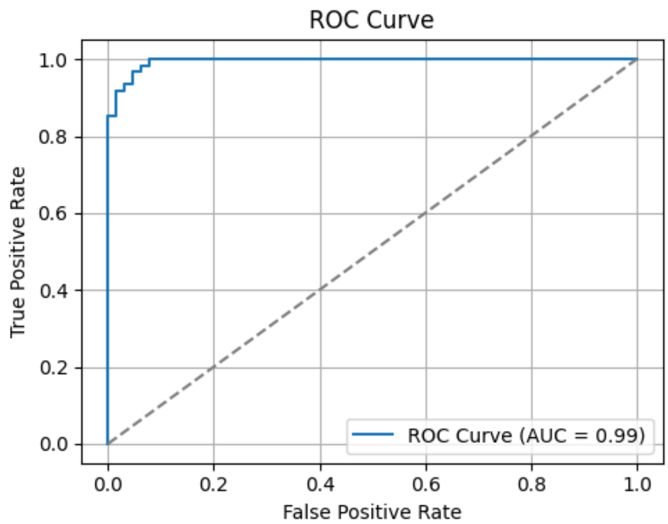

Figure 4. ROC curve of the CNN-GNN model with an AUC value of approximately 0.94

3.4. Ablation study: CNN vs. CNN-GNN

An ablation study was conducted to evaluate the contribution of the graph-based reasoning component. A comparison between the CNN-only model as a baseline and the CNN-GNN model is shown in Figure 5. In this section, it is interesting to observe that the CNN-only model achieved a maximum validation accuracy of 97.6%, which is higher than the 95.2% maximum validation accuracy obtained by the CNN-GNN model. This result suggests that, for the dataset used, visual features alone are already highly discriminative, such that additional relational modeling through graph structures does not always lead to performance improvement.

Such results may be influenced by several factors, including the possibility that convolutional features are sufficient to separate the visual characteristics of Sehat cocoa leaves and those infected with VSD. In addition, the ability of the GNN to model global relationships among samples may be constrained by the batch-wise graph construction strategy.

Interestingly, the CNN-only model achieved a slightly higher maximum validation accuracy (97.6%) compared to the CNN-GNN model (95.2%). These findings indicate that, for the dataset used, visual features alone are highly discriminative, and thus additional relational modeling via graph structures does not necessarily enhance performance. Another possible factor is that the relatively moderate dataset size may reduce the effectiveness of graph-based learning, as relational reasoning generally provides greater benefits for larger or more ambiguous datasets.

Nevertheless, these findings do not diminish the relevance of the CNN-GNN approach. Instead, the results emphasize that graph-based reasoning is most beneficial when inter-sample relationships provide complementary information beyond visual cues. Therefore, this ablation study offers important insights into the conditions under which graph-enhanced models can operate optimally.

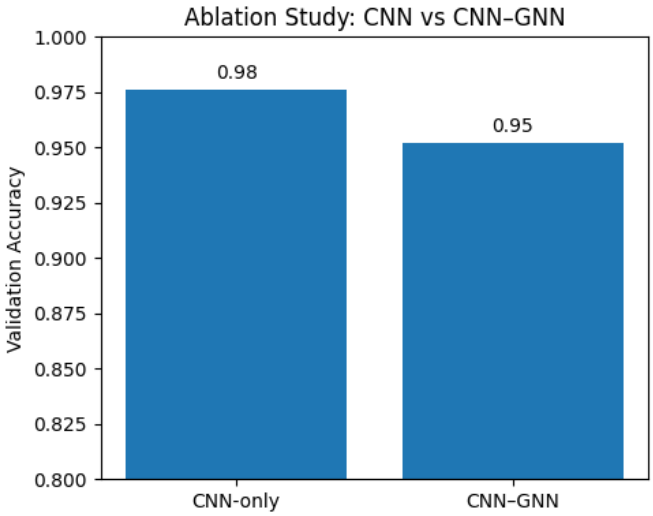

Figure 5. Ablation study comparing the validation accuracy of the CNN-only and CNN-GNN models

4. CONCLUSION

The study tests a hybrid framework using CNN and GNN to classify cocoa leaf diseases, focusing on distinguishing healthy leaves from VSD-affected ones. A CNN feature embedding-based k-nearest neighbor graph represents sample connections in the proposed approach, which combines feature extraction with graph-based relational reasoning. The experiments show that the CNN-GNN model performs reliably with validation accuracy over 95%, balanced precision and recall across classes, and high ROC-AUC, CNN had slightly higher maximum validation accuracy than the baseline CNN model in an ablation study. This indicates that visual features alone are highly effective at distinguishing categories in the dataset, making graph-based reasoning unnecessary for consistent performance improvements. These findings emphasize the importance of empirical assessment and ablation analysis in determining architectural element impact. This study illuminates graph-based deep learning model relevance in agricultural imagery. Graph-based reasoning uses sample relationships, but its effectiveness depends on the dataset's characteristics, graph construction methods, and data size. We will investigate global graph construction methods, alternative similarity metrics, and larger, more diverse datasets to better understand when CNN-GNN models outperform convolutional methods.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
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D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Each of the authors of this research declare no conflict of interest.

DATA AVAILABILITY

The data of this study has been collected directly by the authors in the cocoa plantations in Jember, Indonesia. The authors have recorded directly the visual appearance of cocoa leaves on a cocoa plant and replaced the background display with white by covering the background with perfect white paper and then saving it as image data of 1,250 cocoa leaf displays with white background image.

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