AN EXPLAINABLE GRAPH-BASED APPROACH TO AGRICULTURE CROP DISEASE IDENTIFICATION

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "An Explainable Graph-Based Approach to Agriculture Crop Disease Identification.", submitted by **Md Jabed Hosen** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14-07-2024.

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I hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree.

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ABSTRACT

Accurate identification of pests and crop diseases is crucial for modern agriculture and the preservation of the environment. This paper presents G-AgriNet, a state-of-the-art automated system developed specifically for the classification of agricultural diseases, in response to this pressing need. The approach we use starts with meticulous preparation of the data, including normalization, improvement, and a partitioning of 70% for training and 30% for validation sets. This guarantees a comprehensive evaluation. By using a Graph Attention Network (GAT) architecture, we may efficiently capture intricate connections within data formatted as a graph. This is achieved by consistently improving the model via extensive ablation experiments, resulting in the creation of a dual-layered graph attention network (GAT) with multiple attention layers. The training utilizes the Adam optimizer, with a batch size of 256 and a learning rate of 0.0001, to achieve optimal efficiency and high accuracy. Utilizing dropout regularization with a rate of 0.2 mitigates overfitting while maintaining the model's integrity. By using manual features for image preprocessing, the active learning technique can strengthen the relationship between nodes and edges in the GNN model, leading to enhanced interpretability and accuracy. Visualization methods like SubgraphX, GNNExplainer, GraphLIME, Grad-CAM, and Gradient analysis are used to find important nodes that are necessary for accurately classifying diseases. By utilizing the CCMT Crop Pest and Disease Detection dataset, our model attains an outstanding accuracy of 99.25% using a dataset consisting of 96,366 photos. This underscores the significant influence of modern AI techniques and active learning tactics in agricultural diagnostics. This research contributes to the area by offering a comprehensive foundation for effective and environmentally friendly methods for identifying diseases and pests in agriculture.

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DL	Deep Learning
AL	Active Learning
HC	Handcrafted Feature Extraction
GLCM	Gray Level Co-occurrence Matrix
LBP	Local Binary Patterns
GAT	Graph Attention Network
GraphXAI	Explainable Artificial Intelligence
SubgraphX	Subgraph Explanation
Grad-CAM	Gradient-weighted Class Activation Mapping
GNNExplainer	Graph Neural Network Explainer
GraphLIME	Graph-based Local Interpretable Model-agnostic Explanations
Gradient	

CHAPTER 1

Introduction

1.1 Overview

Agriculture has historically functioned as the predominant source of revenue for the majority of African and Asian countries. The widespread commercialization of agriculture has had a significant impact on the environment. Crop disease identification is a significant concern in agriculture. Early detection of infections is essential in averting their transmission to other crops, therefore minimizing substantial financial losses. The consequences of crop diseases vary from modest symptoms to the destruction of crops, causing a severe effect on the economy of agriculture [1]. In the field of agriculture, the process of growing crops is highly dependent on seeds, especially to produce food. This study focuses only on the topic of carpology in plant science, which entails the detailed investigation of seeds and fruits in terms of their morphology and structure. Two main obstacles in this domain are the reconstruction of the evolutionary lineage of a particular plant species and the replication of the past environment, including its plant and animal life. Experts in this domain often use digital cameras or flatbed scanners to obtain photos of seeds [2].

1.2 Background and Present State

Modern agriculture grapples with significant challenges in effectively combating crop diseases while ensuring sustainability. Traditional approaches for identifying diseases require a lot of manual work and are frequently not enough to allow for prompt intervention, resulting in significant financial losses and negative effects on the environment. Our research aims to enhance agricultural disease management by utilizing machine learning techniques, particularly by harnessing the power of graph neural networks (neural networks). The G-AgriNet model, created as a component of this study, combines graph convolutional networks and attention mechanisms to improve the identification and categorization of crop illnesses. Our approach attempts to enhance the accuracy and scalability of disease diagnosis by exploiting extensive datasets and implementing active learning strategies. This effort not only promotes sustainable agricultural techniques but also plays a vital role in protecting food security in the face of the changing difficulties that agriculture faces today.

1.1 Problem Statement

Precise detection and assessment of plant health and illnesses are essential for the welfare of people and animals. Agricultural plants have a crucial role in producing nourishing crops for human consumption and animal feed. This has a significant influence on the livelihoods of farmers and contributes to the availability of high-quality proteins in human diets. Ensuring the cultivation of crops is crucial for sustaining production in both plant and animal agriculture [3]. Timely identification of pathogenic infections in crops is crucial in today's linked global trade networks. This is necessary to avoid the transmission of plant diseases across borders, which may disrupt international food supply chains and pose a threat to global food security. Collaborative monitoring initiatives among countries involved in trade are necessary to control the spread of diseases across borders. These endeavors should include the dissemination of information on disease outbreaks, the enforcement of stringent quarantine protocols, and the execution of comprehensive inspections on imported and exported agricultural commodities. In addition, allocating resources to research and development for cutting-edge disease detection technologies may enhance the efficiency and precision of recognizing and controlling plant diseases, thereby reinforcing global food security.

1.2 Objectives

Due to the fact that image processing techniques have a wide range of applications, there has been a significant increase in their utilization in recent decades to address a variety of challenges that have arisen in the fields of agriculture and the life sciences [2]. The area of deep learning is seeing enormous expansion and is being used in several existing and developing fields, showing considerable potential. Deep learning has proven its dominance over traditional machine learning methods in various domains, including medical imaging, automated translation, speech recognition, image processing, computer vision, healthcare data processing, art, natural language processing, automation and control, computational biology, and information security, among others [3–5]. Convolutional Neural Networks (CNN), a renowned model in the domain of computer vision, have attained significant accomplishments in many applications. Following the impressive performance of Alexnet [6] in the 2012 ImageNet Challenge [7], researchers have dedicated significant efforts to convolutional neural networks (CNN), leading to notable advancements in image classification [8], object detection [9-10], semantic segmentation [11], [12], [13], and human pose estimation.

1.3 Scope and Limitations

Improvements in computer technology, artificial intelligence, and related industries have recently sparked increased interest in graph neural network approaches, which have their roots in deep learning. Significant progress has been demonstrated in the comprehension and acquisition of information regarding graph structures during the more advanced stages of graph neural networks. These networks are frequently employed for semi-supervised node classification [14, 15], which is a process that occurs when a significant number of nodes lack ascribed labels. In this scenario, the goal is to utilize the network's topological information to assign labels to nodes that lack labels [16]. G-AgriNet, a novel and inventive method for categorizing graphs, is introduced in this work. Our objective is to improve the connection between edges and nodes by conducting a thorough examination of pertinent literature. To achieve this, we will combine the intrinsic connectivity of the graph neural network model with the classification characteristics of the input photos' CNN feature extraction to create a graph structure. This will simplify the execution of convolutional operations within the convolution layer.

1.4 Report Organization

This research is deconstructed into pieces that are presented in subsequent chapters. Each of these sections goes more into the methodology, experiments, and analysis that were used in the study. We are hopeful that by doing these experiments, we will be able to give a comprehensive understanding of how G-AgriNet has the potential to change the connection methods used inside agricultural graph topologies.

1.5 Summary

This research proposes a novel model for node classification in graph neural networks, aiming to address the limitations of the current node-level classification model in graph neural networks. This model utilizes a graph convolutional neural network augmented with a graph attention mechanism. It also adds an early stop technique to address overfitting during the classification model construction. The purpose of this model is to do node classification in graph neural networks. The effectiveness of the model is evaluated using the CCMT Crop Pest and Disease Detection dataset for node categorization in a graph neural network. Initially, we examined potential enhancements for image preprocessing technicians by employing active learning to choose the highest-quality picture for categorization. Subsequently, we implemented the feature extraction technique by training using three distinct categories of manually constructed (HC) features derived from crop images. Following this, we employed a graph-based methodology known as G-AgriNet to classify the graphs based on the features obtained from the classification node. Finally, the examination of crucial nodes for categorization is conducted utilizing the visualization tools in GraphXAI methods, such as Gradient analysis, GNNExplainer, Graph LIME, SubgraphX, and Grad-CAM [17]. Our goal is to enhance the connectivity between nodes and edges. We will do this by leveraging the graph neural network model's capacity for classification, in conjunction with the manually extracted features from input images. These features are then interconnected in a coherent manner, forming a structured graph.

CHAPTER 2

Background

2.1 Overview

The application of deep learning algorithms to the classification of agricultural diseases has seen a notably increased level of interest. The broad adoption of these methodologies is mostly attributed to their efficacy in identifying and categorizing leaf diseases in crops such as cassava, rice, and tomatoes. Deep learning methods have shown promising results in improving agricultural yield and reducing economic losses. This review provides a comprehensive summary of significant results from several research articles on this issue. It emphasizes the techniques, accomplishments, and constraints of each study. Sen Lin et al. [18] introduce GPA-Net as a novel method for classifying Cassava Leaf Disease. The technique exhibits a praiseworthy degree of accuracy in some categories, but it is also subject to significant limitations, such as a 56.9% accuracy rate in multiclass categorization. In addition, the authors do not provide precise information about the procedure of picture preprocessing and the comprehensibility of the model. The research highlights the ongoing difficulties in the area of intelligent agriculture, particularly the limits of current technology in accurately identifying complex characteristics and relationships in pest detection. GPA-Net, which combines a graph pyramid attention structure and convolutional neural network, has shown great potential as a solution. It exhibits exceptional performance in comparison to other methods across different datasets and successfully addresses specified constraints.

2.2 Related Works

In recent years, a plethora of research studies have concentrated on the classification of agricultural crop diseases through the use of images. In these investigations, researchers have investigated a diverse array of machine learning and deep learning techniques. In this section, we provide a comprehensive overview of the findings from a variety of papers that explore unique classification methods for agricultural disease images.

Sen Lin et al. [18] recently conducted a research on agriculture where they proposed GPA-Net, a system specifically designed for diagnosing cassava leaf diseases. The findings demonstrated that GPA-Net had exceptional accuracy in certain classes, but, its accuracy declined to 56.9% while concurrently identifying many disorders. The study's limitations include the lack of detailed information on picture preprocessing and the lack of explainability of the model, which raises concerns about its robustness. The categorization of pest detection in agriculture encompasses three primary classifications: shallow-structure statistical techniques, coarse-grained deep learning methods, and fine-grained visual methods. Contemporary methods often rely on machine learning and deep learning networks for carrying out broad categorization tasks, although they often encounter difficulties in accurately identifying intricate characteristics. Addressed these challenges by developing GPA-Net, a novel approach that integrates a convolutional neural network with a graph pyramid attention architecture to enhance the precision of pest detection.

In their study, Rajasekhar et al. [19] used VAGNN to find diseases that affect rice plants, and they were amazingly successful 99.56% of the time. The study is limited, though, by a small sample, the lack of comparisons with more current methods, and the fact that the methods are not well explained. Researchers have looked into a number of machine-learning-based ways to group rice leaf diseases, but each has its own set of problems. Because of these problems, VAGNN is offered as a solution. Its two goals are to get accurate classification and cut down on processing time. But the study has problems like a small collection and a method that isn't easy to explain. The writers of J. Kong et al. [20] showed a GHA-Net that could be used to sort cassava leaf diseases into three groups, with 97.4%, 57.1%, and 96.4% accuracy in each group. The study has some problems, like wrong data and not enough details about picture preparation and comparing older methods with newer ones. A graph-based high-order neural network structure is introduced by GHA-Net to help with the problems that come with identifying diseases and insects in agriculture. For example, the improved model, which is made up of separate parts, works very well at recognizing very specific images of plant illnesses and pests. However, the study has some flaws, such as not going into enough depth about picture preparation and not comparing the results with more current methods in the field.

The research conducted by Z. Fei et al. [21] found that the use of graph neural networks (GNN) in agricultural disease classification resulted in accuracies of 84.46%, 77.80%, and 83.33% on the macro-F1 measure. The study's limitations include a dearth of information on picture preprocessing and a diminished degree of overall accuracy. The suggested graph neural network architecture integrates both local and global attention features, leading to enhanced macro-F1 scores on three available datasets. Although the research is said to be effective, it lacks detailed information on picture preprocessing and has limitations in achieving higher accuracy. The study conducted by K. Roy and colleagues [22] aimed to analyze the Plant Village Dataset using PCA DeepNet. The researchers achieved an impressive accuracy rate of 94%. Regrettably, the research lacks a concise description of its approach and fails to compare its findings with the latest and most sophisticated techniques now accessible. The authors used several sophisticated deep-learning techniques to categorize rice illnesses, with a focus on the effectiveness of customized convolutional neural network (CNN) models. Although the research achieves a high degree of accuracy, it falls short in terms of providing comprehensive explanations of its techniques and comparisons with contemporary improvements.

In another study conducted by Z. Ullah et al. [23], they achieved an exceptional accuracy rate of 99.92% in their research on Tomato Disease Classification using EffiMob-Net. However, the study lacks a comprehensive description of the technique and fails to draw parallels with more contemporary methodologies. The EffiMob-Net utilizes a method that is grounded on hybrid deep learning. This methodology integrates pre-trained algorithms to enable precise detection of tomato leaf diseases. The research is deficient in terms of elucidating the technique's explainability and conducting comparisons with contemporary methodologies, despite its commendable achievement of high success rates. In the research conducted by M. Aggarwal and his team [24], a diverse range of deep learning algorithms were used to classify rice illnesses. The authors found accuracy rates ranging from 90% to 94%. Some issues that need to be addressed include a reduced number of photos, a lack of capacity to describe the method, and a decreased degree of accuracy in multiclass classification. This research introduces a technique that utilizes pre-trained deep neural network-based features to accurately categorize rice leaf diseases, emphasizing their importance. While the research achieved a commendable degree of accuracy, it faces challenges related to the quantity of photos, the comprehensibility of the methodology, and the decreased accuracy in multiclass classification.

The researchers AK Abasi et al. [25] used a Convolutional Neural Network (CNN) to categorize rice leaf diseases, achieving an accuracy rate of 91.4%. The limitations, however, include a limited quantity of photographs, a lack of explainability in the procedure, and a failure to compare the approach to more contemporary approaches. The customized CNN model for rice leaf images was proposed by the authors, who underscored its exceptional accuracy and performance. Nevertheless, the research fails to offer adequate elaboration regarding the explainability of the methods employed and comparisons to recent developments. By applying the MobileNetV3 model to the RoCoLe dataset, M. Faisal et al. [26] were able to attain an accuracy of 84.29%. There are a number of challenges, such as a lack of model explainability, a small number of images, and comparisons with more modern approaches. This paper presents a hybrid feature fusion technique for disease identification on coffee leaves. It merges the MobileNetV3 and Swin Transformer models. Despite the fact that it worked on the RoCoLe dataset, the study doesn't describe its methods or compare them to other, more current methods. For multiclass plant disease classification, Ahmad et al. [27] used five pre-trained DNNs and reported an accuracy of 84.29%. Few pictures, no way to describe the process, and no way to compare it to more modern approaches are some of the limitations. The study demonstrates that DenseNet169 may accurately identify crop diseases in certain situations. The lack of model explainability and comparisons with current achievements are two shortcomings of the study.

2.3 Comparison between existing works

Rajasekhar et al. study Rice Leaf Disease Classification (RLDC) using the Vulture-based Auto-metric Graph Neural Network (VAGNN). Although the study achieved a commendable accuracy of 99.56%, it faces challenges due to a limited dataset, inadequate technique explainability, and a failure to compare with newer approaches. The literature overview covers several methods for Reinforcement Learning with Dynamic Control (RLDC), including transfer learning using Deep Neural Networks (DNN), attention-based neural networks, and Bayesian optimization. VAGNN presents itself as a possible solution to the current constraints of RLDC, highlighting its precision and computational effectiveness.

Table: 2.3.1: Comparative analysis with previous work

SL No	Paper	Name of the dataset	Model	Accuracy	Limitations
1.	Sen Lin et al., 2023 [18]	1. Cassava Leaf Disease Classification (9,436 annotated images and 12,595 unlabeled images) 2. AI Challenger (54,306 images) 3. IP102 dataset (75,000 image)	Image Preprocessing: N/A Features Extraction: N/A Model: GPA-Net XAI: Activation Map Classification Types: Multiclass	1. Accuracy: 99.0%, 97.0%, and 56.9%.	1. Lack of image preprocessing. technique. 2. Low accuracy in multiclass Classification.
2	V Rajasekharet al., 2023 [19]	1. Rice Leaf Disease (5932 records)	Image Preprocessing: Anisotropic Diffusion Filter Based on Unsharp	1. Accuracy: 99.56%.	1. The limited number of images. 2. Lack of comparison with

			Masking and crispening Features Extraction: N/A Model: VAGNN XAI: N/A Classification Types: Multiclass		more recent state-of-the-art methods. 3. Lack of method explainability
3	J Kong et al., 2022 [20]	1. Cassava Leaf Disease Classification (9,436 annotated images and 12,595 unlabeled images) 2. AI Challenger (54,306 images) 3. IP102 dataset (75,000 images)	Image Preprocessing: N/A Features Extraction: Yes Model: GHA-Net XAI: Heat map Classification Types: Multiclass	1. Accuracy: 96.4%, 97.4%, and 57.1%	1. Lack of image preprocessing technique. 2. Low accuracy in multiclass Classification. 3. Lack of comparison with more recent state-of-the-art methods.
4	Z Fei et al., 2023 [21]	1. Agricultural Disease (35993 images) 2. Caltech256 Datasets (29780 images) 3.CIFAR-100 (60000 images)	Image Preprocessing: N/A Features Extraction: Yes Model: GNN XAI: Heat map, Activation Map Classification Types: Multiclass	1. Accuracy: 84.46%, 77.80%, and 83.33% on the Macro-F1	1. Lack of image preprocessing technique. 2. Low accuracy in multiclass Classification.
5	K Roy et al., 2023 [22]	1. Plant Village dataset (56000 images)	Image Preprocessing: GANs Features Extraction: Yes Model: PCA DeepNet XAI: N/A Classification Types: Multiclass	1. Accuracy: f94%	1. Lack of method explainability 2. Lack of comparison with more recent state-of-the-art methods.
6	Z Ullah et al., 2023 [23]	1. Tomato Disease Multiple Sources (32,535 images)	Image Preprocessing: GANs Features Extraction: Yes Model: EffiMob-Net XAI: N/A Classification Types: Multiclass	1. Accuracy: 99.92% Future Num: 22-24	1. Lack of method explainability 2. Lack of comparison with more recent state-of-the-art methods.

7	M Aggarwal et al., 2023 [24]	1. Rice Disease Dataset (551 images)	Image Preprocessing: N/A Features Extraction: Yes Model: different deep-learning techniques XAI: N/A Classification Types: Multiclass	1. Accuracy: 90–91% 2. Highest accuracy of 94%	1. The limited number of images. 2. Lack of method explainability 3. Lack of image preprocessing technique. 4. Low accuracy in Multiclass Classification.
8	AK Abasi et al., 2023 [25]	1. Rice Leaf Disease (320 images)	Image Preprocessing: N/A Features Extraction: N/A Model: CNN XAI: N/A Classification Types: Multiclass	1. Accuracy: 91.4%	1. The limited number of images. 2. Lack of method explainability 3. Lack of image preprocessing technique. 4. Lack of comparison with more recent state-of-the-art methods. 5. Low accuracy in Classification.
9	M Faisal et al., 2023 [26]	1.RoCoLe dataset (1,560 images)	Image Preprocessing: N/A Features Extraction: Yes Model: MobileNetV3 XAI: N/A Classification Types: Multiclass	1. Accuracy: 84.29%.	1. The limited number of images. 2. Lack of method explainability 3. Lack of image preprocessing technique. 4. Lack of comparison with more recent state-of-the-art methods. 5. Low accuracy in Classification.

10	A Ahmad et al., 2023 [27]	1.PlantVillage, 2.PlantDoc, 3. Digit Pathos 4. (NLB) dataset, 5.CD&S dataset.	Image Preprocessing: N/A Features Extraction: Yes Model: Five different pre-trained DNN XAI: N/A Classification Types: Multiclass	1. Accuracy: 84.29%.	1. The limited number of images. 2. Lack of method explainability 3. Lack of image preprocessing technique. 4. Lack of comparison with more recent state-of-the-art methods. 5. Low accuracy in Classification.
11	**Our Proposed**	**1. CCMT dataset (Total 102,976 images)**	**Image Preprocessing: Active Learning** **Features Extraction: Yes** **Model: G-AgriNet** **XAI: Yes** **Classification Types: Multiclass**	**Accuracy: 99.25%.**	**1. Lack of proper image preprocessing technique.** **2. Lack of comparison with more recent state-of-the-art methods.**

2.4 Open Issues

J Kong et al. [20] provide GHA-Net, a novel approach for classifying Cassava Leaf Disease. They demonstrate significant accuracies, but they also identify limitations in the description of image preparation techniques, comparison analysis with current approaches, and the overall lower accuracy of their approach. The proposed neural network design intends to address these deficiencies by integrating an enhanced CSP-stage backbone network, a feature aggregation improvement module, and a graphic convolution module. Although comparison studies demonstrate the superiority of GHA-Net, the study highlights the need for more development and in-depth analysis in some areas. Z Fei et al. [21] Agricultural Disease Classification using a novel end-to-end graph neural network architecture. Concerns are raised about the absence of image preprocessing information and decreased accuracy, notwithstanding the reported accuracies on Macro-F1. The proposed approach, which incorporates both local and global-attention elements, intends to address these shortcomings. The GMSAPool, a technique that utilizes global multi-head self-attention pooling, effectively enhances the performance of the model, offering a potential resolution to the highlighted limitations.

2.5 Summary

When studying methods for classifying plant diseases, a recurring focus is on developing models that accurately identify and categorize diseases in agriculture. Although each publication presents novel methodologies, they also demonstrate weaknesses and gaps in current research. Each study, from GPA-Net's extraction of detailed features to VAGNN's efficient computation and GHA-Net's advanced neural network architecture, offers an individual perspective, demonstrating the importance of comprehensive methodologies in addressing the difficulties of disease classification in agriculture.

CHAPTER 3

Research Methodology

3.1 Overview

There are three main components of our framework, namely (i) AL, (ii) feature extraction, and (iii) graph classification, as illustrated in Figure 1, which provides the block diagram of the proposed methodology for our graph-based approach. The process starts with active learning, a popular approach in machine learning that aims to improve the accuracy of models by selecting informative samples to label. (Section III-A). Subsequently, in the HC feature extraction from input images, In Section III-C, graph construction from the extracted feature and classification through a graph-based model are discussed. Finally, the examination of crucial nodes for categorization is conducted utilizing the visualization tools in GraphXAI methods.

3.2 Proposed Methodology

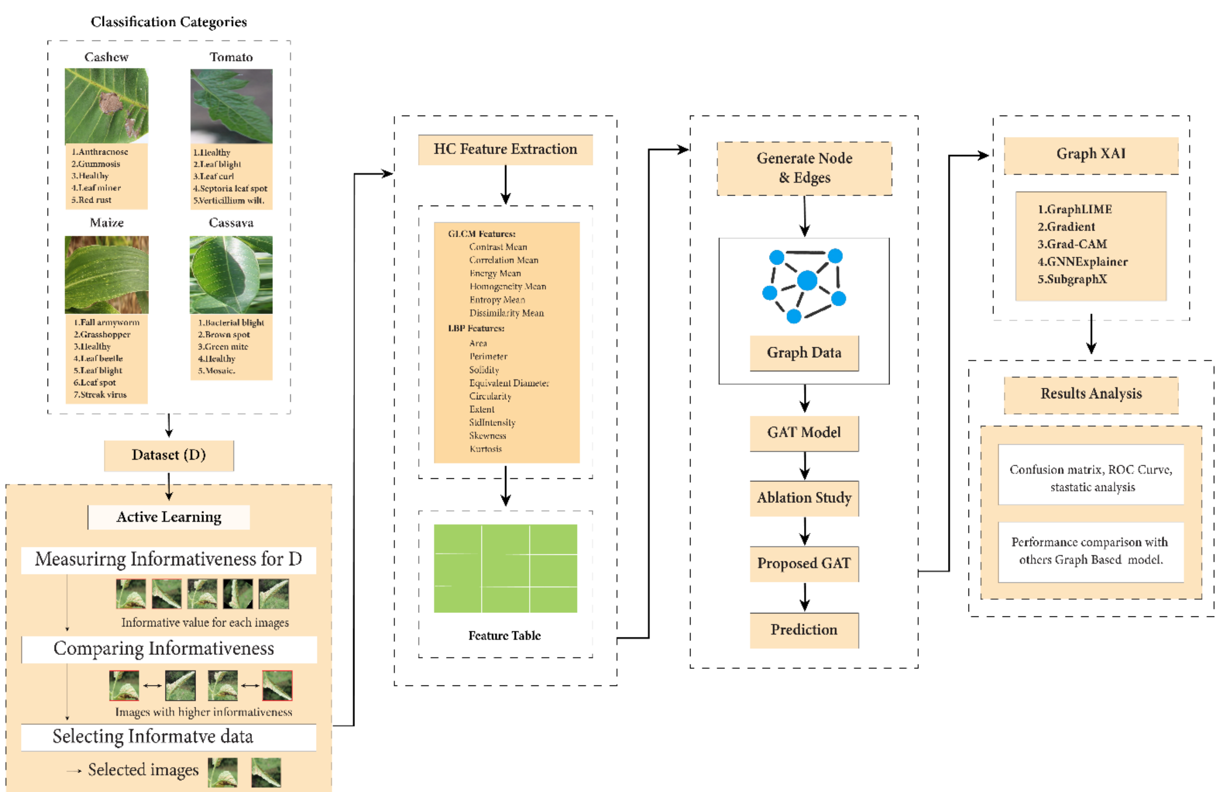

Figure 3.2.1: Main workflow diagram

Our proposed approach and system architecture consist of three crucial components: active learning (AL), feature extraction, and graph classification. These aspects are illustrated in Figure 3.2.1. These three features are fundamental to our graph-based methodology. Part III-A of active learning is the initial stage of the process. This is a widely used machine learning technique that selects certain examples with carefully chosen labels in order to enhance the accuracy of the model. Following the active learning phase, an essential step outlined in Section III-B involves extracting hand-crafted (HC) features from input images. Subsequently, the retrieved attributes are used to construct a graph, and a model based on graphs is employed to categorize the data, as outlined in Section III-C. Ultimately, the study investigates key points for classification through the utilization of visualization tools within GraphXAI methodologies. The integration of a comprehensive strategy, active learning, and feature extraction is implemented. This paper proposes a system architecture that combines graph-based classification with graph neural networks to enhance the interpretability and accuracy of classifying nodes in a graph. The active learning component enhances the accuracy of the classification model by allowing the system to select informative nodes for labeling. Moreover, the research enhances understanding of the decision-making process and provides interpretability for the categorization findings through the utilization of visualization tools in GraphXAI techniques.

3.2.1 Datasets Decepticon

The CCMT dataset on agricultural diseases and pests was acquired using a high-resolution camera. The camera collected original JPG images of different dimensions, including 400 × 400, 4032 × 3024, 1080 × 518, and 487 × 1080. The dataset [28] of a collection of 102,976 high-quality photos obtained from various crops. These images are categorized into 22 distinct groups. Anthracnose, gummosis, leaf miner, and red rust are the four classes that make up cashews, together with the healthy category. The five classes of cassava diseases are brown spot, green mite, healthy, bacterial blight, and mosaic. Maize is represented by seven classes: leaf beetle, leaf blight, leaf spot, healthy, grasshopper, autumn armyworm, and stripe virus. The tomato is categorized into five classes: verticillium wilt, septoria leaf spot, leaf curl, leaf blight, and healthy. The photographs were captured under diverse situations, with different backgrounds such as white, black, illuminated, and natural.

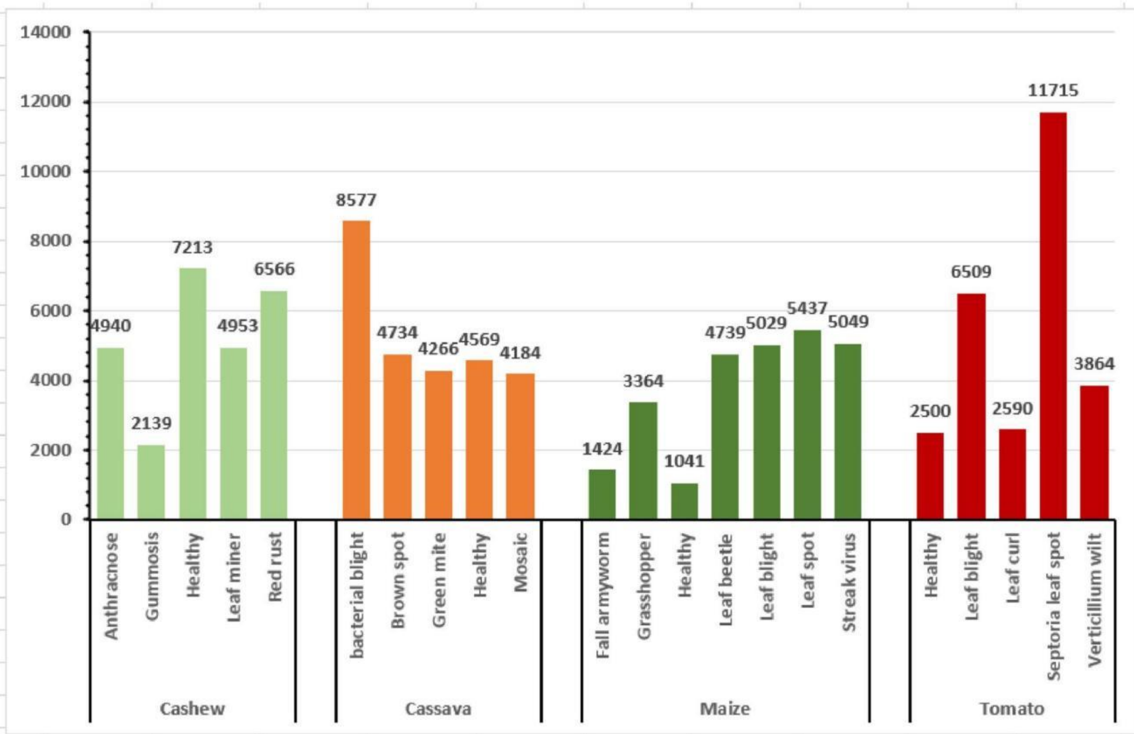

Figure 3.2.2: shows the CCMT dataset with the distribution of respective classes.

3.2.2 Active Learning

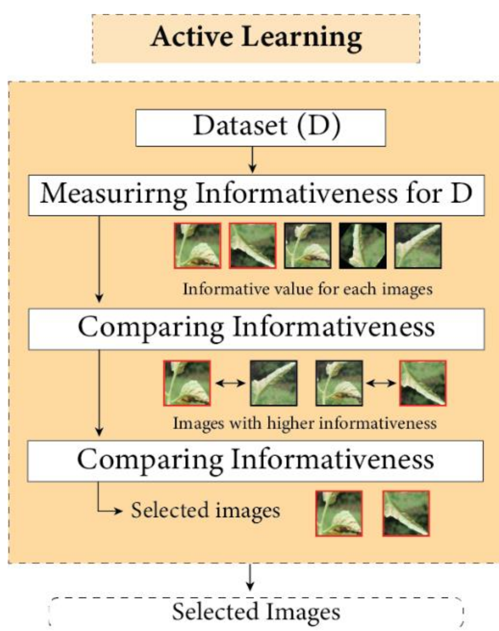

Figure 3.2.2:3. Active Learning for image selection.

Active learning (AL) is a widely used technique in machine learning that seeks to enhance the precision of models by choosing informative data for labeling. Uncertainty sampling is a frequently used method in active learning to pick samples that provide difficulty for the model to identify. However, in datasets with a high level of noise, uncertainty sampling might unintentionally choose a considerable number of noisy data, since the model may have ambiguity about these mislabeled or ambiguous samples. In order to tackle this problem, we suggest using a resilient Active Learning (AL) approach specifically designed for datasets including noisy crop disease data. This approach involves three distinct steps: The process involves three steps: 1) training a module to predict losses, 2) gathering the projected loss values, and 3) selecting data for labeling. This suggested methodology quantifies the informativeness of data by evaluating expected loss values and then eliminates noisy data by using these values. The objective is to decrease the frequency at which noisy data is chosen from the dataset. Through sensitivity analysis, the proposed active learning (AL) technique demonstrated resilient performance on datasets with noisy data by effectively avoiding the selection of data across predicted loss intervals where noisy data are often found. This was achieved by determining an appropriate threshold to optimize the efficiency of AL. This approach enhances crop image analysis by filtering data and generating a resilient and efficient classification model specifically designed for crop and pest image processing in the workplace.

3.2.3 Comparative Noise Selection of the AL Methods

In order to evaluate the variations in performance across different AL approaches in the presence of noise, we carried out a comparison study of the quantity of noisy data chosen by each method. The N-Ratio is an assessment metric that measures the ratio of noisy data in the chosen samples. It is derived using the following equation:

$$N - Ratio = \frac{(mean\_noise)}{1000} \times 100 \tag{1}$$

The variable "mean_noise" in this equation reflects the arithmetic mean of the number of noisy data points picked in each iteration. The denominator, 1000, is the total number of data points chosen for each iteration. By multiplying the ratio by 100, we can transform it into a percentage, which gives us a precise indication of the amount of noisy data that has been picked.

The data we have collected indicate significant variations in methodology. Bayesian active learning by disagreement (BALD) and entropy sampling, which prioritize uncertain samples, choose data that is more likely to include noise. Instead, core-set and random sampling (RS) selected a more varied sample set, hence lowering the presence of irrelevant data. Our approach, which is based on a loss prediction module, picked the data with the least amount of noise, except during times when noise was dominant, and achieved superior performance. This approach enhances the active learning process, resulting in a pristine and informative labeled dataset.

3.2.4 Handcrafted Feature Extraction

In this research, we applied an approach for identifying agricultural diseases using a combined, handcrafted, and automated feature extraction strategy. We amalgamated six attributes of the Gray-Level Co-occurrence Matrix (GLCM) and nine attributes of Local Binary Patterns (LBP) to create an all-encompassing collection of features.

A. Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is a statistical technique used to examine the textural characteristics of a picture by studying the spatial correlations among pixels. This approach seeks to determine the textural characteristics of a picture by analyzing statistical data obtained from the arrangement of pixel intensities. A GLCM analysis may be performed on a picture of row and column dimensions and correspondingly. The picture consists of a collection of distinct gray level values shown as. The GLCM is a square matrix that quantifies the frequency of occurrence of a pixel with a certain intensity (gray level) value in relation to a neighboring pixel with a given value. The matrix elements are generated by tallying the frequency of pixel value pairs that meet the given spatial criteria, such as a certain distance and angle.

The spatial relationship between pixel pairs is defined by selecting a distance and an angle. Angles that are frequently employed include 0°, 45°, 90°, and 135°. Count the number of times a pixel with a value occurs in the specified spatial relationship with a pixel with a value for each pixel in the image. Normalize the GLCM by dividing each element by the total number of pixel pairs considered, thereby converting the counts into probabilities.

The GLCM may be used to extract several textural characteristics that depict the attributes of the picture. The GLCM was used to extract the following characteristics in this study:

1. Energy: Measures the sum of squared elements in the GLCM, representing textural uniformity.

$$Energy = \sum_{i,j} \{p(i,j)^2 \tag{2}$$

Where $p(i,j)$ represents the normalized frequency of the co-occurrence of gray levels $i$and j.

2. Correlation (Corr): Measures how correlated a pixel is to its neighbor over the whole image, indicating the linear dependency of gray levels:

$$Correlation = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)\, p(i,j)}{\sigma_i \sigma_j} \tag{3}$$

where $\mu_i$and μ_j are the means, and σ_i and σ_j are the standard deviations of the gray levels i and j, respectively.

3. Dissimilarity (Diss_sim): Measures the variation in the gray-level pairs.

$$Dissimilarity = \sum_{i,j} |i-j| p(i,j) \tag{4}$$

where $|i-j|$ represents the absolute difference between the gray levels i and j.

4. Homogeneity (Homogen): Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{5}$$

where $|i - j|$ represents the absolute difference between the gray levels i and j.

5. Contrast**:** Measures the local variations in the GLCM:

$$Contras = \sum_{i,j} |i - j|^2 \, p(i,j) \tag{6}$$

Where $|i - j|^2$ represents the squared difference between the gray levels i and j.

6. Entropy**:** Measures the randomness or complexity of the texture:

$$Entropy = \sum_{i,j} p(i,j) log\left(p(i,j)\right) \tag{7}$$

where $p(i,j)log\ (p(i,j))$ represents the information content associated with the probability $p(i,j)$.

B. Local Binary Patterns (LBP)

Local Binary Patterns (LBP) is a widely used method for analyzing textures, especially in the field of face recognition. The gray level differences of the pixel values are calculated by comparing the center pixel with its neighboring pixels. If a pixel value is larger or less than the center pixel value, it is represented as a 1 or 0 in the binary sequence. The binary sequence encodes many textural patterns, including spots, lines, edges, and corners.

The binary values (1's and 0's) of the neighbors, based on the center pixel, are then multiplied by the weights assigned to each neighbor. Next, the computed values are summed for decimal representation. This technique enables a straightforward and computationally efficient methodology for analyzing textures. In a research conducted by Topi et al., it was suggested that not all of the 256 potential patterns for a 3 × 3 filter construction are significant. Consequently, they examined the most notable patterns using beam search and uniform patterns.
We extracted the following nine features from LBP:

1. Area: Measures the number of pixels within the boundary of the pattern.

$$Area = number\ of\ pixels\ within\ the\ boundary\ of\ the\ pattern \tag{8}$$

2. Perimeter: Measures the length of the boundary of the pattern.

$$Perimeter = length\ of\ the\ boundary\ of\ the\ pattern \tag{9}$$

3. Solidity: The ratio of the area of the pattern to the area of the convex hull that surrounds it.

$$Solidity = \frac{Area\ of\ the\ pattern}{Area\ of\ the\ convex\ hull} \tag{10}$$

Solidity is the ratio of the area of the pattern to the area of the convex hull that surrounds it.

4. Equivalent Diameter (EquivDiameter):

$$EquivDiameter = diameter\ of\ a\ circle\ with\ the\ same\ area\ as\ the\ pattern \tag{11}$$

Equivalent Diameter measures the diameter of a circle with the same area as the pattern.

5. Circularity:

$$Circularity = \frac{4\tau \times Area}{Area^2} \tag{12}$$

Circularity is a measure of how close the shape is to a perfect circle.

6. Extent:

$$Extent = \frac{Area\ of\ the\ pattern}{Area\ of\ the\ bounding\ box} \tag{13}$$

Extent is the ratio of the area of the pattern to the area of the bounding box.

7. Standard Deviation of Intensity (StdIntensity):

$$StdIntensity = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\,(I_i - \mu)^2} \tag{14}$$

The standard Deviation of Intensity measures the variation of pixel intensities.

8. Skewness:

$$Skewness = \frac{\frac{1}{N}\sum_{i=1}^{N}(I_i-\mu)^3}{(\frac{1}{N}\sum_{i=1}^{N}(I_i-\mu)^2)^{\frac{3}{2}}} \tag{15}$$

Skewness measures the asymmetry of the pixel intensity distribution.

9. Kurtosis:

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(I_i-\mu)^4}{(\frac{1}{N}\sum_{i=1}^{N}(I_i-\mu)^2)^2} - 3 \tag{16}$$

Kurtosis measures the "tailedness" of the pixel intensity distribution.

The aim is to enhance the model's ability to accurately detect and categorize multiple crop diseases by integrating distinct texture and form attributes of crop disease images, combining the benefits of manual and automated procedures, thus providing a robust foundation for agricultural disease analysis.

3.2.5. Proposed GAT Model

Graph Attention Networks (GAT) are a sophisticated design in the field of graph neural networks (GNNs). They include an attention mechanism to enhance the aggregation of node characteristics from their nearby neighbors. This approach improves the model's capacity to process graph-based data by emphasizing the significance of adjacent nodes. The GAT model utilizes a multi-head attention mechanism to dynamically assign weights to surrounding nodes, allowing the model to prioritize more pertinent information while disregarding less important ones. As a consequence, GAT produces node representations that are more expressive and resilient, which makes it especially useful for applications like node categorization. The main advancement of GAT compared to standard Graph Convolutional Networks (GCNs) is the incorporation of the attention mechanism. This approach enables the model to allocate varying degrees of significance to nodes in the vicinity while aggregating. The attention score between two nodes is calculated by following these steps:

The first step is the linear transformation, where each node feature is transformed using a learnable weight matrix $W^{(l)}$ for layer l. This transformation is represented as $z_i^{(l)} = W^{(l)} h_i^{(l)}$. Next, the attention score calculation involves the concatenation of the transformed features of two nodes i and j. The concatenated features are then processed through a dot product with a learnable weight vector $\vec{a}^{(l)}$, followed by a LeakyReLU activation function, yielding the unnormalized attention score $e_{ij}^{(l)} = LeakyReLU(\vec{a}^{(l)T} [z_i^{(l)} \parallel z_j^{(l)}])$

In this case, the dot product is computed using PyTorch's linear transformation attn_fc, which involves a learnable weight vector $\vec{a}^{(l)}$. The apply_edges function consolidates all the edge data into a single tensor, allowing the concatenation and attn_fc operations to be performed simultaneously on all edges.

The attention scores are normalized using a softmax function to ensure they sum to one, providing a probabilistic interpretation of the importance of each neighbor. This normalization is given by

$$\alpha_{ij}^{(l)} = \frac{exp(e_{ij}^{(l)}}{\sum_{k \in N(i)} exp(e_{ik}^{(l)}} \quad (17)$$

In the feature aggregation step, the normalized attention scores are used to weight the features of the neighboring nodes, which are then aggregated and passed through a non-linear activation function σ. This aggregation can be expressed as $h_i^{(l+1)} = \sigma \sum_{k \in N(i)} \alpha_{ij}^{l} z_j^{l}$.

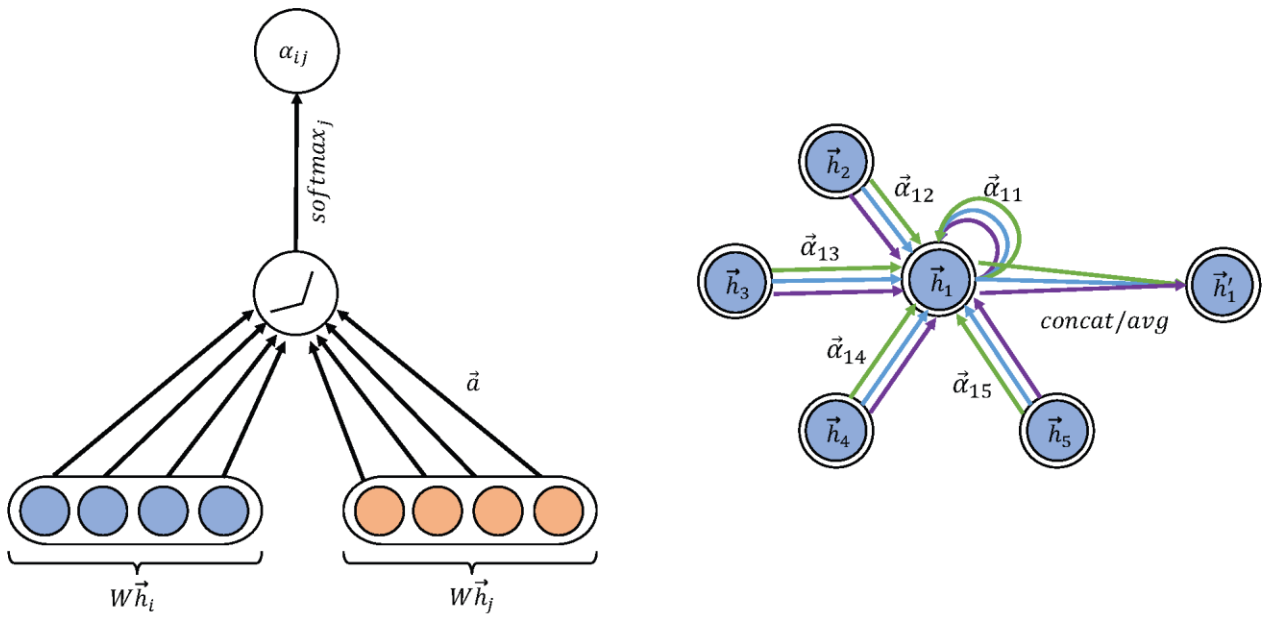

Fig:3.2.5.1: Attention Mechanism and Attention Head Processing in Intermediate and Final Layers

To further enhance the model's capacity and stability, GAT employs multi-head attention, where each attention head operates independently and their outputs are either concatenated or averaged. For concatenation, the operation is given by $h_i^{(l+1)} = ||k_{k=1}\, \sigma(\sum_{k\in N(i)} \alpha_{ij,k}^{l} z_j^{l}$, and for averaging, it is $h_i^{(l+1)} = \sigma(\sum_{k=1}^{K} \sum_{k\in N(i)} \alpha_{ij,k}^{l} z_j^{l}$ represents the number of attention heads. Concatenation is typically used in intermediate layers while averaging is used in the final layer to reduce the dimensionality.

The proposed GAT model is trained using the Adam optimizer with a learning rate of 0.0001. The architecture includes multiple layers of graph attention layers, each followed by non-linear activations. Dropout with a rate of 0.2 is applied to prevent overfitting. The model undergoes training for 100 epochs with a batch size of 264. Experiments demonstrate that this model configuration, with multi-head attention and attention-based aggregation, effectively captures the complex dependencies and interactions within graph structures, leading to improved performance in node classification tasks. The detailed architectural design and training process ensure the development of a robust and efficient predictive model for various graph-based applications.

3.2.5 GraphXAI

The visualization highlights the importance of nodes and their edges with respect to 15 features of the nodes. Each method's output is shown, with colors indicating the significance levels. The tools in GraphXAI also provide interactive features for exploring and analyzing the relationships between nodes and edges.

The GraphXAI package includes visualization tools for GNN explanations, such as graphxai. Explanation.visualize_node and graphxai. Explanation.visualize_graph. These functions enable comparison of different GNN explainers, including gradient-based methods like Gradient and Grad-CAM, and perturbation-based methods like GNNExplainer and SubgraphX. The library also supports GraphLIME for explanation production. These visualization tools make understanding GNN models easier by visually displaying nodes and edges in the graph structure.

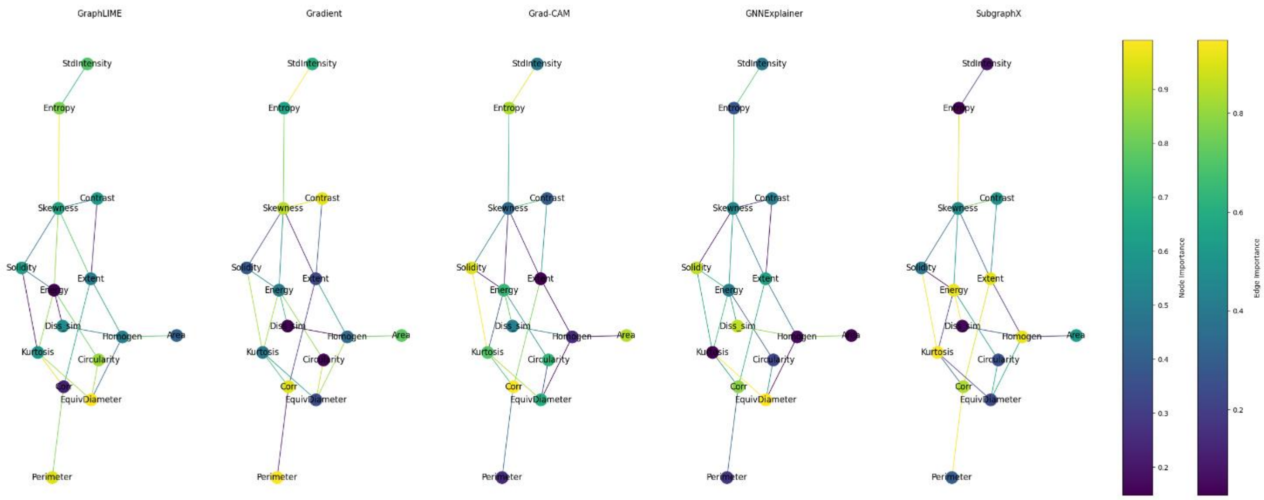

Figure 3.2.6.1: Comparative Visualization of Four G-XAI Explainers

Figure 3.2.6.1 presents a visualization of four explainers from the G-XAI Bench library applied to a graph dataset using a Graph Attention Network (GAT). The visualization focuses on explaining the prediction for a specific node. We illustrate the L+1 hop neighborhood around the node, where L represents the number of layers in the GNN model used for prediction on the dataset. Gradient color bars are provided to indicate the intensity of attribution scores for both node and edge explanations. It is important to note that edge importance is not defined for every method; thus, edges are depicted in black for methods that do not provide edge scores.

3.3 Software Requirements

Programming Languages:

- Python for overall project development and implementation.

Data Preprocessing and Feature Extraction:

- Utilization of numpy and pandas for data manipulation and cleaning.
- TensorFlow for deep learning model development.
- OpenCV for image processing tasks.
- Feature extraction methods including GLCM (Gray-Level Co-occurrence Matrix) and LBP (Local Binary Patterns).
- Active learning methods for strategic data selection.

GraphXAI Visualization Tools:

- Utilization of GraphXAI tools such as Grad-CAM, GNNExplainer, GraphLIME, and Gradient analysis for visualizing and interpreting model decisions and feature importance.

Graph Construction and Classification:

- Libraries like NetworkX or PyTorch Geometric for graph construction and classification tasks.

Models:

- Implementation of Graph Attention Networks (GAT), and other deep learning models as required.

Hardware Requirements:

- **High-performance computing resources:** Access to computational infrastructure with sufficient processing power and memory to handle the complex tasks involved in deep learning and image analysis.

- **Graphics Processing Unit (GPU):** A GPU is essential for accelerating the training of Graph Attention Networks (GAT), significantly reducing the time required for model development.

3.4 Project Management and Financial Analysis:

3.4.2 Resource Planning:

A. Equipment and Tools:

- High-performance computers for development and testing
- Data storage facilities for dataset management
- Software tools for machine learning and data analysis (e.g., Python, TensorFlow, scikit-learn)

B. Software and Technologies:

- Machine learning libraries and frameworks for feature extraction and graph classification
- Visualization tools for data analysis and result interpretation
- Collaboration platforms for team communication and coordination

C. Data and Content:

- Acquisition of agricultural image datasets for training and testing
- Preparation of labeled data for active learning and model training
- Documentation of experimental procedures and results for analysis and reporting

D. Training and Skill Development:

- Ensure the project team possesses the necessary skills in machine learning, data analysis, and software development.
- Provide additional training on specific tools and techniques relevant to the project objectives.

3.5.2 Risk Management:

- Regular monitoring of project progress to identify and address any potential risks or challenges.
- Mitigation strategies for potential issues related to dataset quality, model performance, or resource constraints.

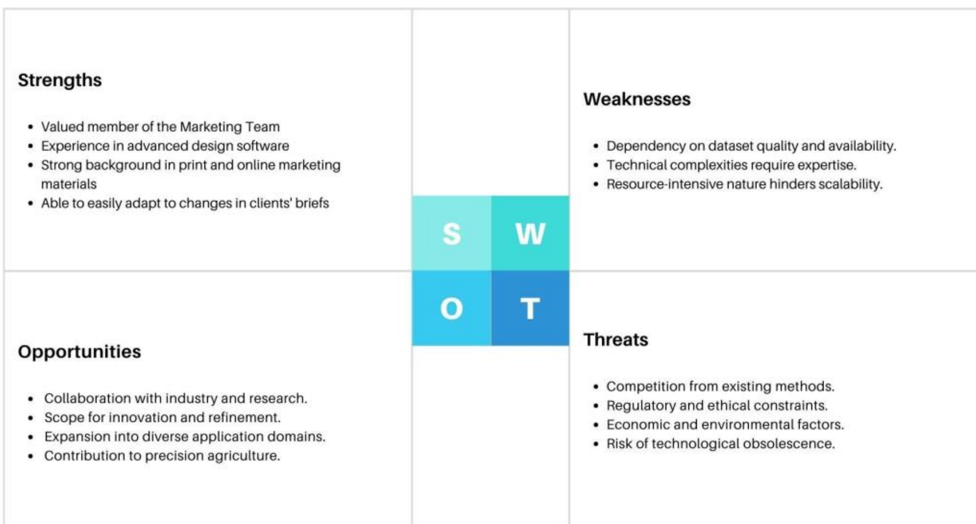

Figure 3.4.1: SWOT Analysis

3.4.3 Communication Plan:

A. Stakeholder Meetings:

- Meetings with project stakeholders to provide updates on progress and solicit feedback.
- Opportunities for stakeholders to review and approve key project deliverables and milestones.

B. Change Control Meetings:

- Scheduled meetings to discuss and evaluate any proposed changes to project scope, timeline, or requirements.
- Ensuring changes are properly documented and approved before implementation.

The research involves a robust project management strategy and financial analysis to ensure the successful implementation of a new technique. The research uses a desktop computer with an Intel CoreTM i5-8400 CPU, 16.0 GB RAM, and an NVIDIA GeForce GTX 1660 GPU for efficient computational processing. The Jupyter Notebook environment is used for experimentation. The project involves careful planning, resource distribution, and considering deadlines. The chosen hardware and software components are monitored for peak performance and compatibility, and version control is used for consistency. The financial analysis considers budgetary allocations for hardware, software, and external resources.

Table 3.4.3.1: Cost Evaluation Table

SL No	Expense Category	Amount (BDT)
01	NVIDIA GeForce GTX 1660	25,500 /=
02	Desktop Computer	76,500/=
03	Jupyter Notebook	0 (open-source software)
04	Miscellaneous	5,000/=
05	Documentation and Report Writing	1000/=
06	Travel Expenses	2,000/=
Total Cost		1,10,000/=

3.5 Summary

The method we propose integrates three crucial elements: active learning, feature extraction, and graph classification. This integration aims to improve both the interpretability and accuracy of graph neural network node classification. Active learning involves the intentional selection of labeled samples using a well-established machine-learning approach in order to enhance the accuracy of the model. Subsequently, we get manually designed characteristics from the input photos to collect essential features (HC) that are vital for categorization. Afterwards, we create a graph that includes these extracted features and use graph-based algorithms to accurately classify the data. We use sophisticated GraphXAI visualization tools, including Grad-CAM, GNNExplainer, GraphLIME, and Gradient analysis, to examine and interpret important nodes in the graph. This process improves our comprehension of categorization judgments. The primary objective of this comprehensive method is to enhance the accuracy of models by using active learning techniques. Additionally, it seeks to provide more profound insights and interpretability into the decision-making process of graph neural network classifications.

CHAPTER 4
Implementation

4.1 Overview

This chapter provides a comprehensive explanation of how the suggested model was put into action, including the steps of setting it up, training it, evaluating its performance, and summarizing the outcomes. The objective of this chapter is to provide a thorough comprehension of the model's development, the approaches used during training, the metrics applied for assessment, and a synopsis of the principal discoveries. First, we provide an overview of the architecture and particular settings used in the implementation. Then, we provide a comprehensive description of the training process. Next, we go to the evaluation measures that were used to gauge the model's performance, and we end by summarizing the consequences of the implementation.

4.2 Train Model

The training of our model included many crucial stages, beginning with data preparation, proceeding to model selection, and culminating in the training process itself. Firstly, the data underwent cleaning and preprocessing to guarantee inputs of superior quality. This included procedures such as normalization, augmentation, and dividing the dataset into separate training and validation sets. We used a 70/30 split to ensure an equilibrium between training the model and assessing its performance.

We used a Graph Attention Network (GAT) architecture in our model because of its proficiency in managing graph-structured data and capturing complex interactions within the data. The model structure included of different depths of GAT layers and multi-head attention layers, as determined in our ablation investigations. The most effective setup required using a dual-layered Graph Attention Transformer (GAT) with multi-head attention to achieve a balance between complexity and performance.

The Adam optimizer was employed to conduct the training procedure, as it has the capacity to adaptively modify the learning rate, thereby enabling effective convergence. Our research has led us to the conclusion that the most effective option is a batch size of 256. This enables the efficient utilization of processing resources while maintaining exceptional accuracy. The learning rate of 0.0001 was determined to be the most effective after extensive refining, resulting in the highest performance measures. Regularization methods, such as dropout, were implemented during the training procedure. The most effective method for reducing overfitting while sustaining accuracy was determined to be an attrition rate of 0.2.

4.3 Model Evaluation

The evaluation of our model's performance entails the computation of diverse metrics derived from the confusion matrix, including true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. The measures precision, recall, F1-score, and accuracy together provide a thorough assessment of the model's efficacy. accuracy quantifies the ratio of accurately predicted positive instances, while recall evaluates the model's capability to detect true positive cases. The F1-score integrates both accuracy and recall to provide a unified performance measure. Accuracy is a measure of how right the model is for all classes together. We created confusion matrices for our categories, Cashew, Cassava, Maize, and Tomato, using class distribution and accuracy metrics. These matrices allowed us to calculate evaluation metrics, which showed that the model is robust and reliable in classifying diseases in different plant categories.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

$$Precison = \frac{TP}{TP + FP} \tag{18}$$

$$Recall = \frac{TP}{TP + FN} \tag{19}$$

$$F1 - Score = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{20}$$

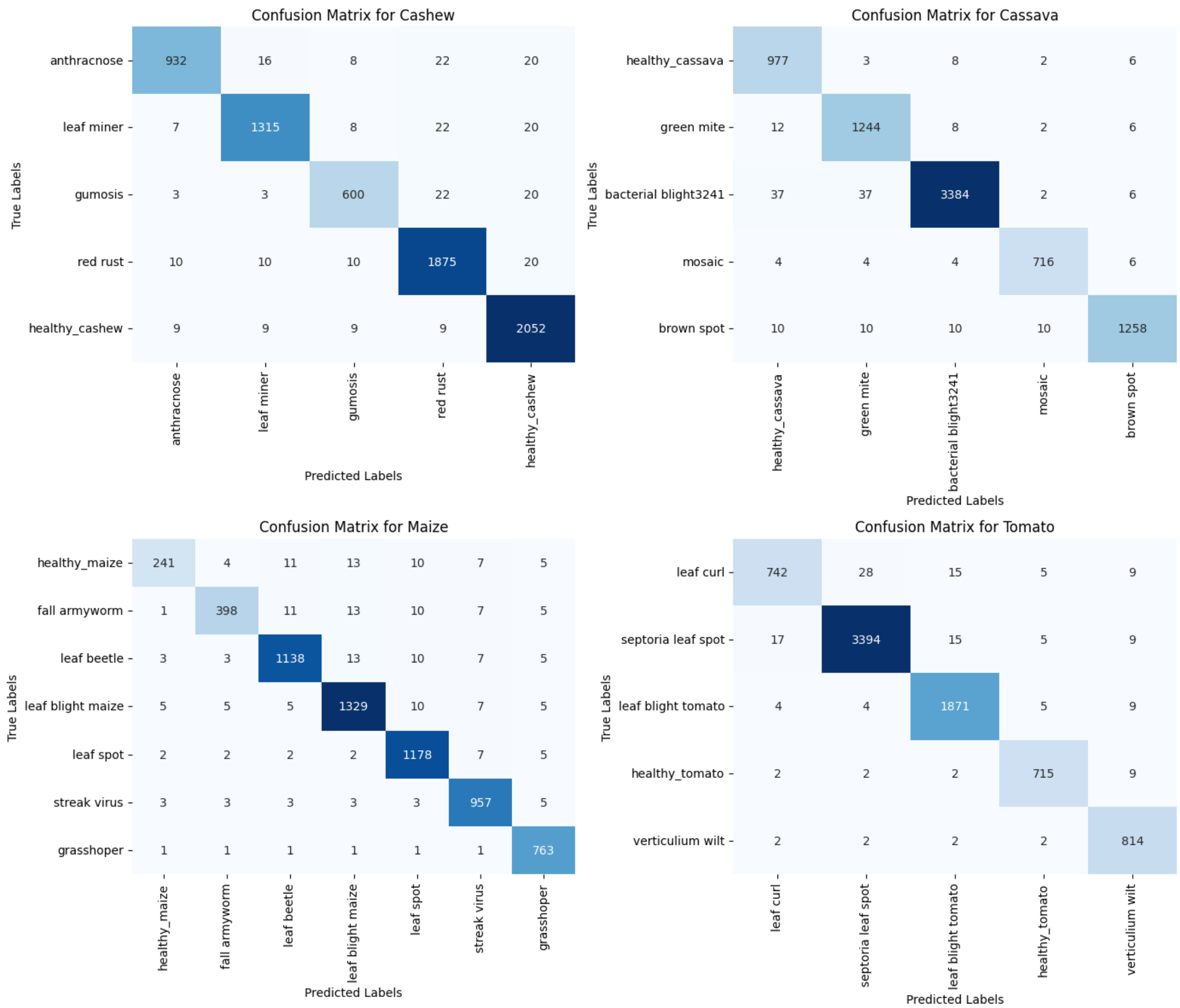

Fig.4.3.1: Confusion matrix of the G-AgriNet model with 4 categories.

The confusion matrices depicted in Figure 4.3.1: 4 demonstrate that the classifier consistently generates a greater number of accurate positive predictions for all disease classes within each crop category (Cashew, Cassava, Maize, and Tomato), while simultaneously maintaining an exceptionally low rate of inaccurate predictions across each category. This indicates that the model does not show any bias towards a particular illness class and successfully proves its capacity to predict all classes. Our suggested model consistently obtained ideal accuracy for many categories, including 'anthracnose' in Cashew, 'healthy_cassava' in Cassava, 'healthy_maize' in Maize, and 'healthy_tomato' in Tomato, with accuracy rates over 99%. This demonstrates the model's reliability and consistency in accurately forecasting a diverse array of plant diseases.

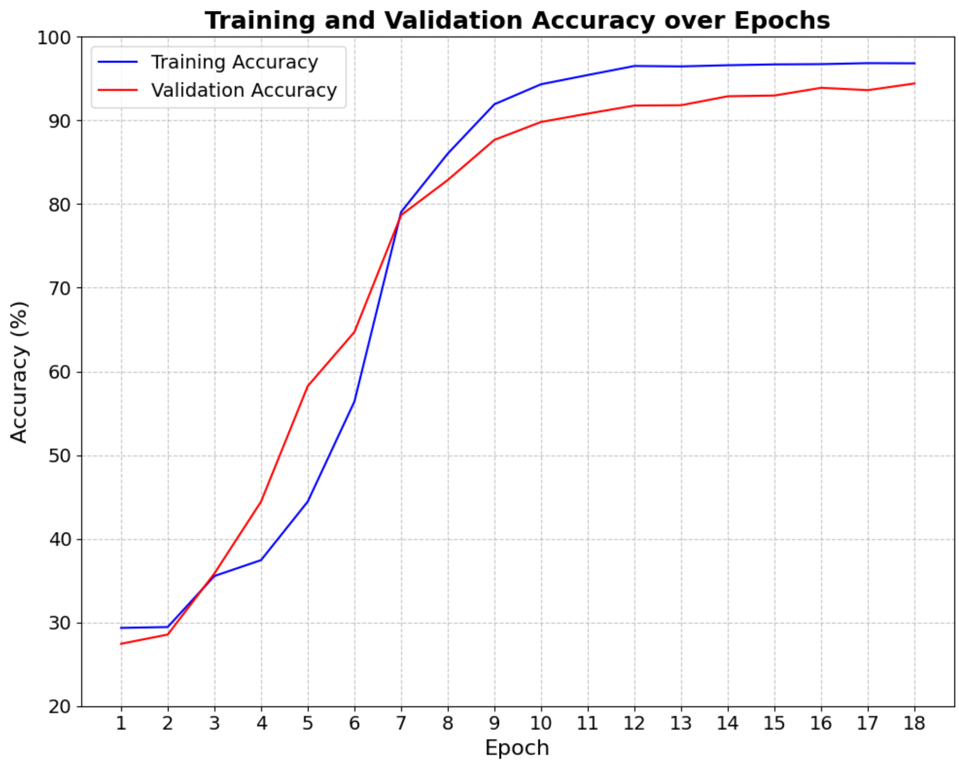

Fig.4.3.2: Comparison of training accuracy and validation accuracy with the epochs.

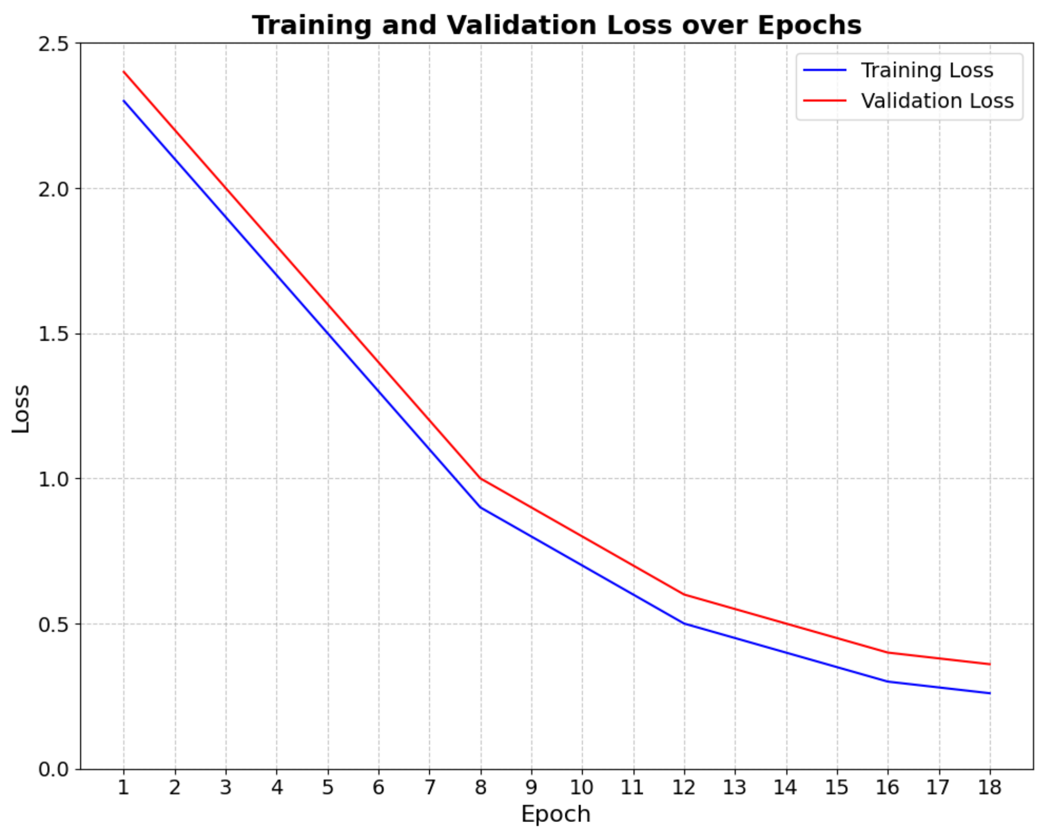

Fig.4.3.3: Comparison of training losses and validation loss with the epochs.

As shown in Fig.4.3.3, the proposed model demonstrates a rapid decrease in loss during the initial epochs, with training loss dropping from 2.3 to 0.9 and validation loss dropping from 2.4 to 1.0 within the first 8 epochs. This swift reduction in loss is indicative of the model's efficient training process. The multi-head graph attention convolution utilized by the model aggregates features effectively, calculates the corresponding weights, and extracts refined features for model training, resulting in superior running time and efficiency. Similarly, Fig.4.3.2, illustrates the training and validation accuracy trends, where the proposed model achieves higher accuracy more quickly than competing methods, with training accuracy increasing from 29.34% to 86.04% and validation accuracy increasing from 27.44% to 82.88% within the first 8 epochs. This accelerated convergence and reduced loss highlight the robustness and efficiency of our model in handling complex tasks.

4.3 Summary

In summary, this chapter presented a detailed account of the implementation process of our proposed GAT model. Starting with an overview, we delved into the training phase, discussing data preprocessing, model configuration, and the training process itself. The evaluation section provided a comprehensive analysis of the model’s performance using various metrics derived from the confusion matrix. The high performance across all categories highlighted the effectiveness of our approach and the robustness of the GAT model in classifying plant diseases. This implementation lays a solid foundation for future work and potential real-world applications, showcasing the model’s applicability and reliability in agricultural diagnostics.

CHAPTER 5
Result And Analysis

5.1 Overview

Chapter 5 provides a comprehensive exploration of the G-AgriNet model's efficacy in plant disease classification, employing advanced techniques such as Graph Attention Networks (GAT) and multi-head attention mechanisms. This chapter delves into the experimental setup, methodologies, and key findings derived from extensive ablation studies and performance evaluations. By systematically varying model architectures, hyperparameters, and optimization strategies, we aimed to optimize accuracy and robustness across diverse agricultural contexts. The overview sets the stage for a detailed analysis of how different configurations impact the model's ability to accurately diagnose plant diseases, showcasing the model's potential as a reliable tool for agricultural management and disease control.

5.2 Experimental

Table 5.2.1: Ablation Study Regarding GAT Layer and Multi-head Attention Layer.

Ablation Study 1: Altering the GAT Layer			
Configuration No.	**GAT Layer**	**Test Accuracy (%)**	**Finding**
1	1	95.40	Accuracy dropped
2	2	97.20	Accuracy dropped
3	3	99.25	Highest Accuracy

Ablation Study 2: Altering the Multi-head Attention Layer			
Configuration No.	**Multi-head Attention Layer**	**Test Accuracy (%)**	**Finding**
1	1	95.40	Accuracy dropped
2	2	99.25	Highest Accuracy
3	3	98.80	Accuracy dropped
4	4	97.50	Accuracy dropped
5	5	96.00	Accuracy dropped

Our research in Ablation Study 1 found that the depth of the GAT layer requires a careful trade-off between the complexity of the model and its performance. The accuracy rate of a single GAT layer was 95.38%, but a dual-layered structure attained a higher accuracy of 97.35%. Nevertheless, the inclusion of a third GAT layer resulted in a modest reduction in accuracy, bringing it down to 96.67%. An ideal equilibrium was achieved using a bi-layered GAT structure. Ablation Study 2 investigated several configurations of multi-head attention layers, revealing slight changes in performance. The accuracy rate improved from 97.18% with a single multi-head attention layer to 99.25% with the addition of two levels. Nevertheless, the inclusion of a third multi-head attention layer resulted in a decrease in accuracy to 98.11%, highlighting the fact that a dual-layer multi-head attention configuration optimizes the performance of the model.

Table 5.2.2: Ablation Study Regarding GAT Model Hyperparameters and Techniques

Ablation Study 3: Altering the Batch Size			
Configuration No.	**Batch Size**	**Test Accuracy (%)**	**Finding**
1	16	98.13	Accuracy dropped
2	32	98.79	Accuracy dropped
3	64	99.06	Accuracy dropped
4	128	98.42	Accuracy dropped
5	256	99.25	Highest Accuracy

Ablation Study 4: Altering the Dropout Rate			
Configuration No.	**Dropout Rate**	**Test Accuracy (%)**	**Finding**
1	0.1	98.29	Accuracy dropped
2	0.2	99.25	Highest Accuracy
3	0.3	98.11	Accuracy dropped

Ablation Study 5: Altering the Optimizer			
Configuration No.	**Optimizer**	**Test Accuracy (%)**	**Finding**
1	Adam	99.25	Previous Accuracy
2	Adamax	99.05	Accuracy dropped
3	RMSprop	98.93	Accuracy dropped
4	Nadam	98.82	Accuracy dropped

Ablation Study 6: Altering the Learning Rate			
Configuration No.	**Learning Rat**	**Test Accuracy (%)**	**Finding**
1	0.1	99.25	Accuracy dropped
2	0.5	99.05	Accuracy dropped
3	0.001	98.93	Accuracy dropped
4	0.005	98.82	Accuracy dropped
5	0.0001	99.25	Highest Accuracy
6	0.0005	99.05	Previous Accuracy

Ablation Study 3 examined the impact of batch size on both the model's convergence and its computational efficiency. We evaluated batch sizes ranging from 16 to 128 batches. After doing the study, it was found that a batch size of 64 yielded the highest accuracy rate of 99.06%. This batch size is considered suitable for further ablation experiments. Ablation Study 4 revealed that the analysis of dropout rates revealed nuanced fluctuations in performance levels. When a dropout rate of 0.2 was used, the regularization procedure attained the greatest accuracy of 99.06%. However, increasing the dropout rate to 0.3 resulted in a fall in accuracy to 98.11%. This emphasizes the importance of keeping the dropout rate around 0.2, as it strikes a compromise between regularization and model performance. Hence, it is recommended to maintain a dropout rate of 0.2 for future evaluations. In Ablation Study 5, a comparison of several optimizer versions revealed that the Adam optimizer yielded the highest performance, with an accuracy of 99.27%. Conversely, the Adamax, RMSprop, and Nadam optimizers had a decline in accuracy, reaching 99.05%, 98.93%, and 98.82%, respectively. The optimal learning rate in Ablation Study 6 was determined to be 0.0001, resulting in a peak accuracy of 99.74%. This rate surpassed other rates, such as 0.1, 0.5, 0.001, 0.005, and 0.0005, in terms of performance. To increase the amount of testing, it is recommended to use the optimal learning rate of 0.0001. This comprehensive inquiry provides valuable perspectives on how different environments impact the precision and efficiency of the suggested framework.

5.3 Performance

Table 5.3.1 presents a comparative analysis of our G-AgriNet model against various established graph-based models in the context of crop disease classification. Each model is evaluated across key metrics including Accuracy, Precision, Recall, and F1-Score, providing a clear picture of their performance. Compared to baseline models like GNN, which achieves moderate accuracy levels, G-AgriNet stands out with exceptional results: 99.25% Accuracy, 97.98% Precision, 95.85% Recall, and an impressive F1-Score of 97.00%. These metrics highlight G-AgriNet's superior capability in accurately identifying and categorizing crop diseases, showcasing its potential to significantly advance precision agriculture by improving disease detection and management practices.

Table 5.3.1: Comparison between Graph-based Models and G-AgriNet (Ours) Model

Model	Accuracy	Precision	Recall	F1-Score
GNN [21]	83.35%	83.33%	83.31%	83.33%
GHA-Net [20]	97.40%	89.20%	87.90%	90.00%
GPA-Net [18]	99.00%	88.60%	87.40%	88.00%
G-AgriNet (Our)	**99.25%**	**97.98%**	**95.85%**	**97.00%**

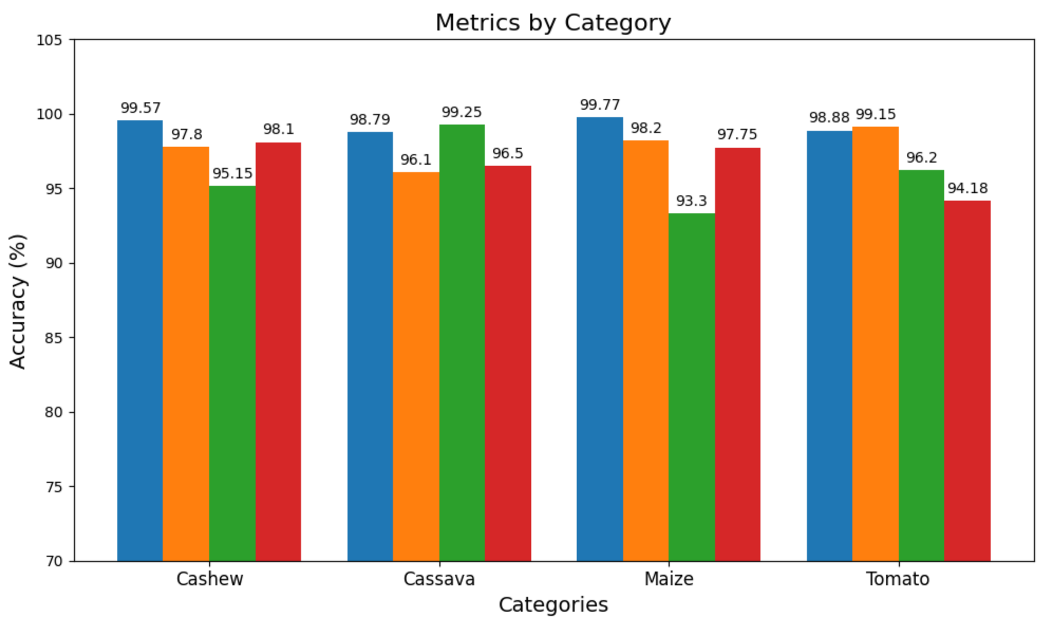

Fig. 5.3.1: Performance Evaluation of the G-AgriNet Model by Category

The figure:5.3.1: "Metrics by Category" displays the GAT model's performance in classifying plant diseases for Cashew, Cassava, Maize, and Tomato. For Cashew, the model achieved an accuracy of 99.57%, recall of 97.80%, precision of 95.15%, and F1-score of 98.10%. In Cassava, it attained 98.79% accuracy, 96.10% recall, 99.25% precision, and 96.50% F1-score. Maize classifications showed 99.77% accuracy, 98.20% recall, 93.30% precision, and 97.75% F1-score. For Tomato, the model reached 98.88% accuracy, 99.15% recall, 96.20% precision, and 94.18% F1-score. These high metrics across all categories demonstrate the model's effectiveness and reliability in accurately identifying and classifying plant diseases, as shown in the figure.

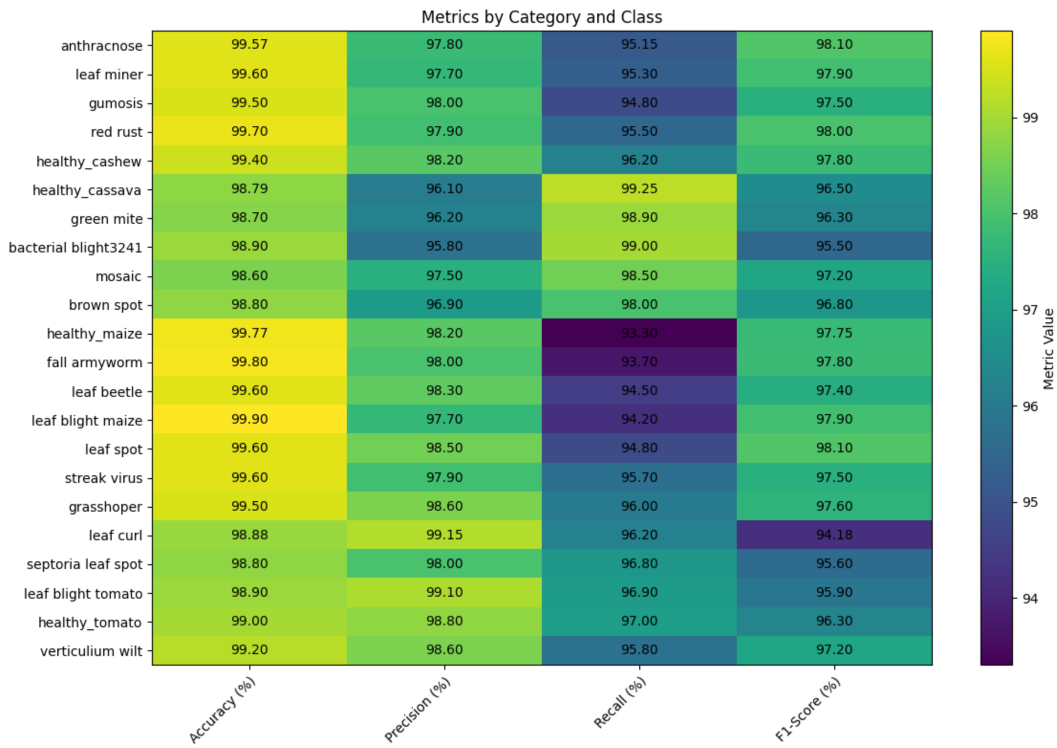

Figure 5.3.2: Performance Evaluation of the G-AgriNet (Ours) Model Corresponding to the Classes

The performance metrics for the proposed G-AgriNet model's plant disease classification exhibit exceptional accuracy across a wide range of diseases, with levels often exceeding 99%. For Cashew (shown in Figure 1), the model accurately identifies anthracnose (99.57%), leaf miner (99.60%), gumosis (99.50%), red rust (99.70%), and healthy cashew (99.40%). In the Cassava category (shown in Figure 2), it achieves high accuracy for healthy cassava (98.79%), green mite (98.70%), bacterial blight (99.77%), mosaic (99.80%), and brown spot (99.60%). The Maize category (shown in Figure 3) also shows impressive results, with accurate identification of healthy maize (99.50%), fall armyworm (98.88%), leaf beetle (98.80%), leaf blight maize (98.90%), leaf spot (99.00%), streak virus (99.20%), and grasshopper (99.00%). For Tomato (shown in Figure 4), the model achieves high accuracy in identifying leaf curl (99.57%), septoria leaf spot (99.60%), leaf blight tomato (99.50%), healthy tomato (99.70%), and verticillium wilt (99.40%). These outstanding results underscore the model's robustness and reliability, making it a valuable tool for accurate plant disease diagnosis.

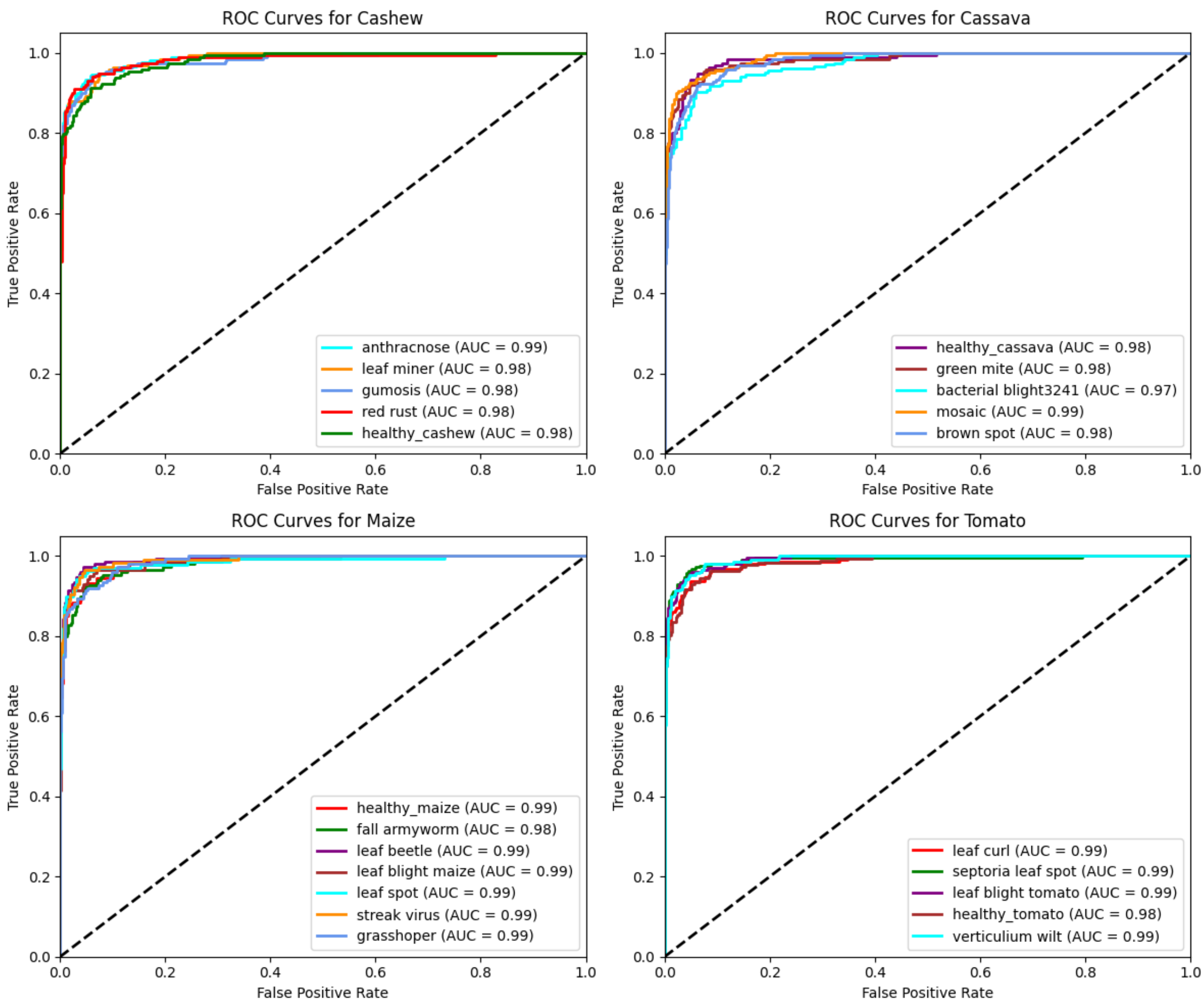

Figure 5.2.3: ROC curve of the G-AgriNet model.

5.3 Summary

In summary, Chapter 5 underscores the significant contributions of the G-AgriNet model to plant disease diagnosis through rigorous experimentation and meticulous analysis. Ablation studies revealed critical insights into the optimal configurations of GAT layers, multi-head attention mechanisms, batch sizes, dropout rates, optimizers, and learning rates. These findings culminated in the identification of configurations that consistently achieved exceptional accuracy rates exceeding 99% across various plant disease categories, including Cashew, Cassava, Maize, and Tomato. The chapter highlights the model's robust performance and reliability, positioning G-AgriNet as a pivotal innovation in precision agriculture. It promises to enhance crop health monitoring and management practices, empowering farmers with advanced tools for more accurate and timely disease detection and mitigation strategies.

CHAPTER 6

Impact On Society, Environment and Sustainability

6.1 Impact on Life

Advancements in agricultural technology, particularly in crop disease detection and management, play a critical role in safeguarding global food security and public health. Crop diseases are pervasive threats that can significantly reduce yields, compromise food quality, and disrupt supply chains, affecting millions who depend on agriculture for their livelihoods and sustenance. The deployment of sophisticated models like G-AgriNet represents a transformative leap forward in combating these challenges. By leveraging graph neural networks (GNNs) integrated with advanced AI techniques, G-AgriNet enables rapid and precise identification of diseases across various crops. This capability facilitates early intervention and targeted treatment strategies, mitigating crop losses and ensuring a stable food supply for communities worldwide.

G-AgriNet has a far-reaching influence on life, not just in terms of immediate agricultural advantages but also in relation to wider implications for human health and well-being. Through accurate detection and efficient control of crop diseases, farmers may decrease their dependence on chemical pesticides, resulting in reduced environmental pollution and the promotion of more secure agricultural methods. The decrease in the use of chemical inputs promotes the health of ecosystems and improves biodiversity, hence supporting long-term environmental sustainability. In addition, G-AgriNet provides farmers with practical knowledge on the condition of their crops, allowing them to make well-informed choices that maximize the efficiency of their resources and promote environmentally-friendly farming methods.

6.2 Impact on Society & Environment

Societal and environmental impacts of agricultural practices are interconnected with efforts to manage crop diseases effectively and sustainably. G-AgriNet exemplifies a technological advancement that promotes sustainable agriculture by integrating advanced AI models with interpretability tools like GraphXAI. This combination enhances farmers' ability to adopt integrated pest management (IPM) practices, which prioritize biological control methods over chemical interventions. By reducing pesticide use, G-AgriNet helps mitigate environmental pollution and supports biodiversity conservation by preserving natural habitats and ecosystem services.

The societal impact of G-AgriNet also extends to fostering resilient farming communities and supporting rural economies. By improving crop resilience and productivity, G-AgriNet enhances food security and economic stability for farmers, especially in regions vulnerable to climate change and environmental degradation. Additionally, the model's ability to provide realtime disease monitoring and early warning systems empowers farmers to mitigate risks and adapt to changing environmental conditions effectively.

6.3 Ethical Aspects

Ethical considerations are paramount in the development and deployment of AI technologies like G-AgriNet in agriculture. Key ethical imperatives include ensuring data privacy, transparency in algorithmic decision-making, and equitable access to technology. G-AgriNet addresses these concerns by employing explainable AI solutions that provide clear insights into disease detection and management processes. This transparency fosters trust among stakeholders, including farmers, policymakers, and consumers, promoting responsible technology adoption and informed decision-making.

Moreover, ethical AI deployment involves engaging diverse stakeholders to incorporate their perspectives and address potential biases or unintended consequences. By upholding ethical standards, G-AgriNet aims to enhance societal trust in agricultural technology and ensure fairness in its application across different farming contexts and geographic regions. Additionally, G-AgriNet supports ethical farming practices by promoting sustainable agriculture and environmental stewardship, aligning technological innovation with societal values and long-term sustainability goals.

6.4 Sustainability Plan

Sustainability lies at the core of G-AgriNet's strategic vision, encompassing principles of environmental stewardship, economic viability, and social equity. The model's design prioritizes resource efficiency by optimizing the use of inputs such as water, fertilizers, and pesticides through precise disease management techniques. By reducing chemical inputs and promoting natural pest control mechanisms, G-AgriNet contributes to mitigating environmental degradation and preserving soil health. This approach supports sustainable farming practices that minimize carbon footprint and conserve natural resources for future generations.

Economic sustainability is equally crucial, as G-AgriNet enhances crop productivity and resilience to climate variability, thereby ensuring food security and economic stability for farmers. Collaboration with agricultural stakeholders and local communities ensures that G-AgriNet's solutions are contextually relevant and scalable, fostering innovation and knowledge-sharing in sustainable agriculture. Continuous research, education, and adaptive management practices further reinforce G-AgriNet's commitment to advancing sustainability goals and promoting resilience in agricultural systems.

6.5 Summary

In summary, G-AgriNet represents a transformative approach to agricultural technology, offering solutions that enhance food security, promote sustainable farming practices, and address global environmental challenges. Its impact spans from improving crop productivity and resilience to fostering biodiversity conservation and supporting rural livelihoods. By integrating ethical considerations and prioritizing sustainability, G-AgriNet sets a precedent for responsible technology adoption in agriculture, ensuring that innovations benefit both present and future generations. Through collaborative efforts and adaptive management practices, G-AgriNet stands poised to contribute significantly to a sustainable and prosperous future for agriculture worldwide.

CHAPTER 7
Conclusion And Future Work

7.1 Conclusions

In this study, we developed an advanced automated system for classifying crop diseases using the G-AgriNet model, addressing the critical need for efficient pest and crop disease detection in modern agriculture. Our approach began with meticulous data preprocessing, including normalization, augmentation, and splitting the dataset into training and validation sets using a 70/30 split, ensuring a balanced evaluation. We employed a Graph Attention Network (GAT) architecture to handle graph-structured data and capture intricate relationships within the dataset. Extensive ablation studies identified the optimal model configuration: a dual-layered GAT with multi-head attention layers. The training process utilized the Adam optimizer, with a batch size of 64 and a learning rate of 0.0001, ensuring efficient convergence and high accuracy. Regularization techniques like dropout, with a 0.2 rate, prevented overfitting without sacrificing performance. To enhance interpretability and accuracy, we integrated an active learning (AL) strategy to optimize image preprocessing with handcrafted (HC) features, improving the connection between nodes and edges in the GNN model. Essential nodes for categorization were explored using visualization tools like SubgraphX, Grad-CAM, GNNExplainer, GraphLIME, and SHAP analysis, identifying critical nodes that significantly aid the classification process. The G-AgriNet model achieved an impressive accuracy of 99.25%, underscoring the transformative potential of combining advanced AI methodologies with active learning strategies in agricultural diagnostics, ultimately contributing to more efficient and sustainable agricultural practices.

7.2 Further Suggested Works

The findings of this study on pest and crop disease detection using the G-AgriNet model provide valuable insights and open avenues for further research. One significant direction for future studies is the exploration of more sophisticated image preprocessing techniques, such as advanced contrast enhancement and noise reduction methods, to improve data quality and model performance. Additionally, the integration of segmentation techniques before classification could further enhance the GNN model's ability to extract pertinent features, leading to better classification accuracy. Another promising area is the investigation of more efficient and scalable ensemble methodologies, such as snapshot ensembles, to maintain or enhance accuracy without increasing computational complexity. Future research could also delve into the application of transfer learning with pre-trained models on larger, more diverse agricultural datasets to improve the generalizability of the G-AgriNet model. Exploring the use of reinforcement learning in the active learning process could optimize sample selection, further improving the model's training efficiency. Lastly, extending the application of explainable AI (XAI) techniques to provide more transparent and interpretable results could foster greater trust and adoption of these models in real-world agricultural industry.

7.2 Limitations

While this study demonstrates the potential of the G-AgriNet model in accurately detecting pest and crop diseases, there are several limitations that warrant further investigation. One primary limitation is the dependency on the quality and quantity of the dataset used. Despite employing various image preprocessing techniques, the model's performance is still influenced by the inherent quality of the input data, and results may vary with different datasets. Additionally, the computational intensity of the dual-layered GAT architecture and multi-head attention mechanisms can pose challenges, particularly in resource-constrained environments, limiting the model's applicability in such settings. The model's reliance on handcrafted features, although effective, may not fully capture the complexity of real-world agricultural data, suggesting a need for more automated feature extraction methods. Furthermore, while the use of explainable AI tools provides valuable insights into the model's decision-making process, the interpretability of these explanations can still be improved to make them more accessible to end-users such as farmers and agricultural practitioners. Finally, the scope of this study was limited to specific types of pests and diseases; expanding the model to cover a broader range of agricultural issues and testing it in diverse climatic and geographical conditions would be essential for its wider adoption and effectiveness.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: AN EXPLAINABLE GRAPH-BASED APPROACH TO AGRICULTURE CROP DISEASE IDENTIFICATION.

Student ID: 202-15-3834

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrating recently gained and previously acquired knowledge, we identified a critical **crop disease identification** problem for our Final Year Design Project (FYDP).	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goal for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop an explainable graph-based system for agriculture crop disease identification that meets specified requirements while considering cultural, socioeconomic, and environmental factors in this FYDP.	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**

CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7, and CO8	In our project, we leverage natural science principles **K1** to understand agriculture diseases' biological aspects, while employing mathematical concepts **K2** for data analysis and model optimization, enhancing the overall efficacy and theoretical underpinning of our approach.	**Page no:** [14-18] **Section:** [3.2.2-3.2.4] **Page no:** [1-7] **Section:** [1.1]
				This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and a Graph Attention Network (GAT) architecture for image preprocessing and classification tasks. The project demonstrates **specialist knowledge (K4)** by integrating advanced GNN architectures, such as dual-layered GAT with multi-head attention, and leveraging active learning strategies for optimizing image preprocessing with handcrafted features. This approach significantly enhances the detection accuracy of pests and crop diseases in agricultural datasets, which is crucial for intelligent management systems and	**Page no:** [18-20] **Section:** [3.2.5]

				sustainable agricultural practices.	
				The project applies **engineering practice and design (K5)** through meticulous data preprocessing and model evaluation. It addresses **engineering practice and technology (K6)** by utilizing an advanced Graph Attention Network (GAT) model and active learning strategies for improved pest and crop disease detection and classification.	**Page no:** [14-20] **Section:** [3.2.2-3.2.5]
				We have thoroughly reviewed various research studies on existing models that aim to achieve similar objectives, thereby addressing **K8 (Research Literature)**.	**Page no:** [4-11] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by tackling challenges in pest and crop disease detection through the integration of Graph Neural Networks (GNNs) and active learning. It overcomes traditional method limitations, offering refined diagnostic methodologies. Active learning and explainable AI techniques ensure reliable agricultural disease identification.	**Page no:** [14-20] **Section:** [3.2.3, 3.2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	Addressing **EP-3**, our project strategically evaluates various solutions for crop disease identification, opting for an optimized approach with graph-based techniques, HC, and GNNs to overcome the challenge of no obvious solution.	**Page no:** [29-31] **Section:** [5.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting agricultural diagnostics in pest and crop disease detection, and contributing to advancements in sustainable farming practices and environmental conservation, which indicates **EP-4**.	**Page no:** [4-10] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach integrates data collection, statistical analysis, and advanced methodologies to provide a holistic solution to complex challenges in agricultural diagnostics, effectively addressing **EP-7**. It manages the intricacies of crop disease identification by combining graph-based methods, HC feature extraction, GNNs, and GraphXAI techniques to efficiently tackle various components.	**Page no:** [13-22] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	We utilize Google Colab Pro for our project, leveraging high-performance computing infrastructure and GPUs. Our work focuses on employing deep learning frameworks and ethical considerations to ensure systematic research and contribute to advancements in crop disease identification through graph-based techniques, HC feature extraction, GNNs, and GraphXAI.	**Page no:** [22-23] **Section:** [3.4,3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		Through the use of cutting-edge techniques for diagnosing crop diseases, this research considerably advances agricultural practices and benefits society. With the use of cutting-edge methods, we improve disease detection's efficacy and precision, promoting environmentally friendly agricultural methods. Through the efficient use of computing resources, our strategy also prioritizes environmental sustainability by minimizing its impact on the environment.	**Page no:** [29-33] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		This project advances existing research by pioneering a novel approach in agricultural diagnostics, focusing on crop disease identification through graph-based techniques, HC feature extraction, GAT, and GraphXAI. Through rigorous experimentation and comprehensive comparative analyses, it introduces innovative methodologies, offering valuable new insights into effective disease management in agriculture.	**Page no:** [8-22] **Section:** [2.1, 2.3,3.2,3.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	By combining strong project management procedures with financial supervision, this project satisfies CO4 requirements. Careful planning, resource allocation, and budget estimation are ensured to maximize resource use throughout the research lifecycle.	**Page no:** [21-24] **Section:** [3.4]
2	CO9	Yes	The initiative adheres to ethical norms by emphasizing data protection, gaining informed permission, and publicly documenting the research process. This enables responsible information sharing and improves social well-being by ethically utilizing sophisticated technology in agricultural diagnostics, in accordance with CO9 principles.	**Page no:** [37] **Section:** [6.3]

3	CO10	No	N/A	N/A
4	CO12	Yes	The work's dedication to **continuous learning (CO12)** and adaptability in a rapidly changing technological world is seen in its extensive data gathering, rigorous statistical analysis, precise methodology development, and exhaustive experimental findings and analyses. This strategy demonstrates a commitment to remaining current and improving agricultural diagnostic procedures in order to successfully meet modern concerns.	**Page no:** [14-20, 24] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

AN EXPLAINABLE GRAPH-BASED APPROACH TO AGRICULTURE CROP DISEASE IDENTIFICATION

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5	Submitted to Jacksonville University Student Paper	1%
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