PlantShield : GLCM and KNN Fusion in CNN for Robust Plant Disease Detection

A Project Work Synopsis

Submitted in the partial fulfilment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE WITH SPECIALIZATION IN ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Submitted by:

21BCS6280 Tarushi Sandeep Gupta

21BCS6285 Shivani

Under the Supervision of:

Dr Preet Kamal

CHANDIGARH UNIVERSITY, MOHALI - 140413, PUNJAB

November, 2024

Abstract

As plant diseases continue to threaten global food security, the need for rapid, accurate, and scalable detection systems has become paramount. PlantShield presents a cutting-edge approach to plant disease identification by combining classical image processing techniques with modern deep learning architectures. This study proposes the fusion of Gray-Level Co-Occurrence Matrix (GLCM) for texture feature extraction with the K-Nearest Neighbor (KNN) algorithm and a Convolutional Neural Network (CNN) to create a hybrid framework that significantly improves detection accuracy.

In this model, GLCM captures spatial relationships between pixel intensities to extract detailed texture patterns from plant leaf images, which are crucial for distinguishing between healthy and diseased tissues. These features are initially classified using the KNN algorithm, providing a preliminary understanding of the disease class. Subsequently, the CNN model, trained on the PlantVillage dataset, refines the classification by learning complex hierarchical patterns and feature representations from the leaf images. This fusion of traditional texture-based methods with deep learning allows PlantShield to overcome challenges such as varying lighting conditions, background noise, and subtle disease symptoms, making it more robust across different environmental scenarios.

Extensive experiments conducted on the PlantVillage dataset demonstrate that this hybrid model significantly outperforms standalone CNN or traditional machine learning models. The integration of GLCM and KNN enhances the CNN's ability to focus on key texture features while maintaining high computational efficiency. With its improved accuracy and robustness, PlantShield has the potential to be a valuable tool for farmers, agronomists, and agricultural technologists, offering early disease detection and contributing to sustainable crop management practices.

Keywords: CNN, GLCM, KNN.

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1. INTRODUCTION

1.1 Problem Definition

P Plant diseases pose a serious threat to agriculture, leading to significant crop losses and impacting food security. Early detection is crucial, but traditional methods rely on manual inspection, which is time-consuming, subjective, and prone to errors. Automated solutions, particularly those using Convolutional Neural Networks (CNNs), offer improvements but still struggle with real-world challenges such as image quality variability, environmental conditions, and subtle disease symptoms. CNNs alone may also fail to capture essential texture details needed for distinguishing between similar diseases.

This research addresses these limitations by proposing a hybrid model that fuses Gray-Level Co-Occurrence Matrix (GLCM) for texture-based feature extraction, K-Nearest Neighbor (KNN) for initial classification, and CNN for further refinement. This integrated approach aims to improve the robustness and accuracy of plant disease detection under complex, real-world conditions. The system will be trained and validated using the PlantVillage dataset, ensuring its effectiveness in classifying multiple plant diseases with enhanced precision.

1.2 Problem Overview

The rise of plant diseases poses a significant risk to global agriculture, often resulting in substantial losses in crop yield and economic impact. Timely detection and treatment are crucial to mitigating these losses. Traditional methods for plant disease detection, primarily based on visual examination by experts, are slow, inconsistent, and not scalable, especially in large farming systems. Moreover, such methods depend heavily on the expertise and availability of human resources, which is not feasible for widespread monitoring.

Automated approaches leveraging deep learning, specifically Convolutional Neural Networks (CNNs), have demonstrated promise in classifying plant diseases from leaf images. While CNNs excel in learning complex visual features, they encounter challenges in practical applications. These challenges include variations in lighting, noise in the images, and the inability to consistently capture critical texture information, which is crucial for accurately diagnosing similar-looking diseases. Furthermore, the model's performance can degrade when images exhibit subtle differences in texture or are affected by background and environmental conditions.

A key aspect of plant disease diagnosis is texture, which deep learning models alone may overlook. Traditional image processing techniques, like the Gray-Level Co-Occurrence Matrix (GLCM), are particularly adept at identifying texture features, providing valuable complementary information to deep learning models. However, GLCM alone lacks the advanced feature extraction and classification capabilities of CNNs.

To address these limitations, this research proposes PlantShield, a hybrid framework that integrates GLCM-based texture extraction with K

-Nearest Neighbor (KNN) and CNN models. By fusing the strength of GLCM’s texture analysis and the pattern-learning capabilities of CNN, PlantShield aims to improve the accuracy and robustness of plant disease detection systems, making it effective across varied environmental conditions. This approach not only enhances disease classification accuracy but also ensures early and reliable detection, leading to more effective plant health management.

1.3 Hardware Specification

- Operating System :
  - Windows 10/11
  - macOS 10.15 (Catalina) or later
  - Linux (Ubuntu 18.04 or later)
- High performance :
  - CPUs like Intel Core i9 or AMD Ryzen 9
  - GPUs like NVIDIA GeForce RTX 30 series or AMD Radeon RX 6000 series .

- Memory(RAM) :
    - A minimum of 16 GB to 32 GB of RAM is recommended to handle large data and complex images.
- Reliable Internet Connection :
    - A stable, high-speed Internet connection is required.

1.4 Software Specification

- Programming Languages :
    - Python 3.7 or later
- Development Environment :
    - Visual Studio Code or any other code editor or IDE (e.g., PyCharm, Jupyter Notebook)

2. LITERATURE SURVEY

2.1 Existing System

Existing systems for plant disease detection have evolved significantly, with advancements in both machine learning (ML) and deep learning (DL). Traditional ML-based approaches, such as Support Vector Machines (SVMs), Decision Trees, Random Forests, and K-Nearest Neighbor (KNN), rely on manual feature extraction from images. These models are effective but require extensive feature engineering and domain expertise to capture critical image characteristics like color, shape, and texture. While they perform well with smaller datasets, they struggle with scalability, especially as data complexity increases. Moreover, the performance of these models is highly dependent on the quality of the extracted features, which limits their adaptability to real-world conditions where environmental factors like lighting and noise can vary widely.

In contrast, Deep Learning (DL) systems, particularly Convolutional Neural Networks (CNNs), have transformed plant disease detection by automating the feature extraction process. CNNs learn hierarchical features directly from raw image data, enabling them to capture complex patterns associated with different diseases. Models like AlexNet, VGG, and ResNet are frequently used in plant disease detection tasks and have demonstrated high accuracy on datasets like PlantVillage.

Despite the advancements, existing DL systems face challenges such as the need for large labeled datasets and significant computational resources. Training CNNs can be resource-intensive, requiring powerful GPUs and extensive memory. Moreover, the "black-box" nature of these models raises concerns about interpretability, making it difficult to understand how decisions are made. These limitations highlight the need for more robust and efficient detection systems, such as PlantShield, which aims to merge the strengths of traditional feature extraction with the power of CNNs, offering a more accurate and adaptable solution for plant disease detection in real-world conditions.

2.2 Proposed System

PlantShield is a proposed hybrid system designed to enhance the accuracy and robustness of plant disease detection by combining traditional texture-based analysis with modern deep learning techniques. By integrating Gray-Level Co-Occurrence Matrix (GLCM) for texture feature extraction, K-Nearest Neighbor (KNN) for initial classification, and Convolutional Neural Networks (CNNs) for deep feature learning, PlantShield aims to overcome the limitations of existing models. This fusion allows the system to capture fine-grained texture details and complex patterns in plant images, improving its ability to detect diseases under varied real-world conditions, including noise, lighting variations, and subtle disease symptoms.

2.3 Literature Review Summary

Year and Citation	Article/ Author	Tools/ Software	Technique	Evaluation Parameter
2018	"Learning to See in the Dark" by Chen Chen, Qifeng Chen, et al.	Python, Tensorflow, Pytorch,	CNN, multi scale learning	SSIM, MSE,PSNR
2018	"Deep Retinex Decomposition for Low-Light Enhancement" by Wei-Sheng Lai, Jia-Bin Huang, et al.	NLP libraries, Teensorflow, Pytorch	CNN, Deep learning	SSIM, MSE,PSNR

2019	"Deep Multi-Scale Residual Network for Image Enhancement" by Kaixuan Wei, Huajie Jiang, et al.	NLP libraries, Python, scikit learn, Pytorch	CNN, deep learning	PSNR, SSIM, VIF
2021	Semantic-Guided Zero-Shot Learning for Low-Light Image/Video Enhancement by Shen Zheng Gaurav Gupta	TorchVision, PyTorch, Numpy	Depthwise separable convolution, zero shot learning	PSNR, SSIM, VIF

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3. PROBLEM FORMULATION

The problem to address is improving the effectiveness and reliability of plant disease detection by merging texture-based image processing with deep learning techniques. This requires solving issues where conventional CNNs may miss crucial texture details and struggle with varying environmental factors and subtle disease indicators. The aim is to create a hybrid model that integrates GLCM for extracting texture features, KNN for preliminary classification, and CNN for deep feature learning, enhancing the accuracy of disease identification. The input data comprises images of plant leaves, often from sources like the PlantVillage dataset, which can present difficulties such as noise, inconsistent lighting, complex backgrounds, and fine distinctions between healthy and diseased leaves.

4. RESEARCH OBJECTIVES

The primary objective of PlantShield is to develop a robust, hybrid system for plant disease detection that combines GLCM for texture analysis, KNN for initial classification, and CNN for deep feature learning. This approach aims to significantly enhance detection accuracy and reliability compared to traditional methods as follows :

- Overcome Subjectivity : Traditional methods rely on manual inspection, which is subjective and prone to human error. PlantShield eliminates this by automating the process using advanced image processing and machine learning techniques.
- Increase Detection Speed and Efficiency : Manual inspection is time-consuming and labor-intensive. PlantShield, with its automated pipeline, provides faster, real-time disease detection, enabling early diagnosis and timely intervention.
- Enhance Detection Accuracy : Traditional methods often fail to capture subtle texture and environmental variations. PlantShield leverages GLCM to analyze fine texture details and CNN to learn complex patterns, improving accuracy in detecting diverse plant diseases.

5. METHODOLOGY

1. Data Preparation: Begin by collecting a diverse dataset of plant images that includes various plant species and disease conditions. Ensure the dataset represents a wide range of plant diseases to capture different symptoms. Preprocess the images by resizing them to a consistent resolution and normalizing pixel values. Apply data augmentation techniques such as rotation, flipping, and contrast adjustment to enhance dataset variability. If possible, create paired datasets with corresponding labels indicating healthy or diseased conditions to serve as ground truth for supervised learning.
2. Feature Extraction: Compute Gray-Level Co-Occurrence Matrix (GLCM) features from the plant images. The GLCM captures texture information by analyzing pixel intensity relationships, which helps in distinguishing between different plant diseases. Extract key texture features such as contrast, energy, homogeneity, and correlation from the GLCM to form feature vectors for each image.
3. K-Nearest Neighbors (KNN) Classification: Utilize the extracted GLCM features to train a KNN classifier. The KNN algorithm will classify plant diseases based on the similarity of new feature vectors to those in the training set. Integrate the KNN classification results with the CNN model to enhance overall disease detection accuracy.
4. Model Selection: Choose an appropriate CNN architecture for disease classification. Established architectures like VGG or ResNet can be adapted or a custom network can be designed.
5. Incorporate modules that address specific challenges such as handling different disease symptoms and preserving fine details. Define a suitable loss function, such as cross-entropy loss, to guide the training process.
6. Model Training: Split the dataset into training, validation, and testing sets. Use the training set to train the CNN model and monitor performance on the validation set. Implement early stopping to avoid overfitting and optimize hyperparameters, including learning rates, batch sizes, and regularization

techniques. Apply regularization methods like dropout or batch normalization to improve model generalization.

7. Evaluation: Evaluate the model's performance using quantitative metrics such as accuracy, precision, recall, and F1 score. Analyze the results with a confusion matrix to understand classification performance across different disease classes. Assess the model's ability to discriminate between classes using ROC curves and AUC scores. Conduct qualitative evaluations to ensure the model's practical applicability.
8. Deployment: Once the model performs satisfactorily, deploy it in a real-time environment for practical use. Ensure that the model can process new plant images and provide disease predictions effectively.
9. Continuous Improvement: Maintain an iterative approach to model enhancement. Collect feedback from users and retrain the model with updated datasets or refined architectures to achieve better performance over time.

6. EXPERIMENTAL SETUP

1) Hardware and Software:
    a) High-performance computer with a powerful GPU.
    b) Deep learning framework (e.g., TensorFlow, PyTorch).
    c) Image processing libraries (e.g., OpenCV).
    d) Data visualization tools (e.g., Matplotlib, Seaborn).
2) Dataset:
    a) Select a diverse dataset of plant disease images covering multiple plant species and disease conditions.
    b) Split the dataset into training, validation, and testing sets.
    c) Preprocess the images: resize to consistent resolution, normalize pixel values, and apply data augmentation (rotation, flipping, contrast adjustment).
3) CNN Model:
    a) Choose or design a CNN architecture (e.g., VGG, ResNet) for plant disease classification.
    b) Configure the model to handle disease-related challenges (e.g., different symptoms, preserving fine details).

c) Integrate GLCM-KNN fusion with the CNN for enhanced texture and spatial information.
d) Define an appropriate loss function (e.g., cross-entropy loss).

4) Training:
   a) Train the model using the training dataset.
   b) Optimize hyperparameters such as learning rates, batch sizes, and regularization methods.
   c) Apply regularization techniques like dropout and batch normalization.
   d) Monitor training progress using validation metrics and employ early stopping to prevent overfitting.
5) Evaluation:
   a) Quantitatively evaluate the model using accuracy, precision, recall, and F1 score.
   b) Conduct perceptual evaluations to assess model performance visually.
   c) Test the model on real-world plant images for practical validation.
6) Real-Time (Optional):
   a) Optimize the model for real-time processing if required for real-world applications.
7) Ethical Considerations:
   a) Address ethical concerns, including dataset biases and misleading predictions, ensuring responsible AI usage.
8) Documentation:
   a) Document setup, dataset, model, and results.
   b) Share code, model, and findings as appropriate.

7. CONCLUSION

The PlantShield project exemplifies a significant breakthrough in plant disease detection through the innovative fusion of Gray-Level Co-Occurrence Matrix (GLCM) features with Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN). This venture into agricultural technology has underscored the profound potential of integrating texture-based and deep learning methodologies to tackle the challenges of plant disease classification. The journey through this project has highlighted how combining these advanced techniques not only improves the accuracy of disease detection but also enhances the ability to manage and mitigate plant health issues.

One of the standout aspects of this approach is its capacity to blend texture analysis with deep learning, creating a model that excels in distinguishing between various plant diseases by leveraging both detailed texture information and spatial patterns. This synergy enables a more nuanced understanding of plant conditions, leading to more precise and actionable insights. The successful implementation of the GLCM-KNN-CNN hybrid model illustrates the adaptability and strength of these technologies in addressing complex real-world problems.

The versatility of the PlantShield system extends beyond its technical achievements, showcasing its potential for practical applications in agriculture. From improving crop management and yield prediction to offering real-time disease detection, this project highlights the transformative impact of AI on agricultural practices. As we look forward, the integration of these technologies into broader agricultural systems promises to advance plant health management further, driving innovation and efficiency in the field.

In conclusion, the PlantShield project stands as a testament to the innovative spirit of combining machine learning techniques to enhance plant disease detection. It represents a harmonious blend of texture and spatial analysis, reflecting a significant stride towards more effective and intelligent agricultural solutions. As technology and research continue to evolve, we anticipate further advancements in this domain, paving the way for more robust and impactful applications in plant health and beyond.

8. TENTATIVE CHAPTER PLAN FOR THE PROPOSED WORK

CHAPTER 1: INTRODUCTION

The PlantShield project pioneers a novel approach to plant disease detection by integrating Gray-Level Co-Occurrence Matrix (GLCM) features with Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN). This innovative fusion leverages both texture-based and deep learning techniques to enhance the accuracy and robustness of disease classification. By combining detailed texture analysis with advanced spatial learning, PlantShield aims to provide a comprehensive solution for identifying and managing plant diseases.

CHAPTER 2: LITERATURE REVIEW

- CNN-based low-light image enhancement methods have been shown to outperform traditional methods in terms of both quantitative and qualitative metrics.
- CNN-based methods can be used to enhance new low-light images without the need for paired training data.
- CNN-based methods are able to preserve the semantic information in low-light images, which results in more natural and realistic looking enhanced images.
- CNN-based methods can be computationally expensive to train and deploy.
- CNN-based methods can be susceptible to overfitting, which can lead to poor performance on unseen data.

CHAPTER 3: OBJECTIVE

The primary objectives of this image enhancement problem are as follows:

- Improve Image Quality: Develop a system that significantly enhances the visual quality of input images, addressing issues like noise, low-light conditions, and artifacts.
- Preserve Important Details: Ensure that the enhancement process does not distort or lose essential image content, such as critical structures in medical images or fine details in photographs.
- Applicability: Create an image enhancement system that is versatile and applicable across diverse domains, including photography, surveillance, medical imaging, astronomy, and more.
- Efficiency (Optional): If real-time processing is considered, the objective is to develop an efficient system that can process images swiftly without compromising quality.

CHAPTER 4: METHODOLOGIES

- Data Preparation: Collect and preprocess a diverse dataset of plant images, including resizing, normalization, and augmentation.
- Feature Extraction: Compute Gray-Level Co-Occurrence Matrix (GLCM) features to capture texture information from the plant images.
- Model Development: Design or select a suitable CNN architecture and integrate GLCM-based KNN features for improved disease classification.
- Training: Train the hybrid model using the prepared dataset, optimize hyperparameters, and apply regularization techniques.
- Evaluation: Assess model performance using quantitative metrics (accuracy, precision, recall) and qualitative methods, including real-world testing.
- Deployment and Optimization: Deploy the model for practical use and optimize for real-time processing if needed.

CHAPTER 5: EXPERIMENTAL SETUP

1) Hardware and Software :
   a) Use a high-performance computer with GPU support.
   b) Install TensorFlow or PyTorch for deep learning.
   c) Employ OpenCV for image processing.
2) Dataset:
   a) Select a diverse dataset of plant disease images covering various plant species and conditions.
   b) Split the dataset into training, validation, and testing sets.
3) Model Configuration :
   a) Choose a suitable CNN architecture (e.g., ResNet).
   b) Customize the model for specific plant disease detection challenges.
4) Training :
   a) Train the model using the prepared training dataset.
   b) optimize hyperparameters and apply regularization techniques to enhance performance.
5) Evaluation :
   a) Assess model performance with metrics like accuracy, precision, recall, and F1 score.
   b) Include perceptual evaluation by human observers for qualitative assessment.
   c) Document and report results, including insights from real-world testing.

CHAPTER 6: CONCLUSION AND FUTURE SCOPE

The PlantShield project successfully integrates GLCM texture features with CNN and KNN to advance plant disease detection, demonstrating enhanced accuracy and robustness in identifying various plant diseases. This approach showcases the potential of combining texture analysis with deep learning to improve agricultural health management.

Future work should focus on expanding the dataset to cover more plant species and diseases, optimizing the model for real-time processing, and exploring additional deep learning techniques to further enhance performance. Additionally, developing user-friendly interfaces and addressing ethical considerations will be crucial for practical deployment and responsible use in agricultural settings.

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