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Tomato Leaf Disease Classification Using Siamese Network

[1]Mr.Anto Theepak , [2]K. Jelin
[1]Assistant Professor, [2]Student
Department of Information Technology,
Francis Xavier Engineering College, Tirunelveli, India
[1]antotheepak@francisxavier.ac.in, [2] jelink.ug.21.it@francisxavier.ac.in

***Abstract*— Tomato plants are particularly vulnerable to a range of diseases that can adversely affect both yield and quality, emphasizing the importance of timely and precise detection for effective agricultural practices. Conventional methods for disease identification depend on manual inspections, which can be labor-intensive, subjective, and susceptible to human mistakes. To address these challenges, this project presents a deep learning-based method employing a Siamese neural network that utilizes Euclidean distance for similarity assessment in classifying tomato leaf diseases. The model analyzes an input image in conjunction with a collection of reference images from a labeled dataset, extracting advanced feature representations through a pretrained convolutional neural network (CNN). The Euclidean distance computed from the extracted features indicates the closeness between the input image and the reference images, where a shorter distance signifies a closer match and a longer distance implies dissimilarity. A set threshold guarantees accurate classification by identifying the disease based on its nearest reference match. To enhance understandability, Grad-CAM (Gradient-weighted Class Activation Mapping) visualization emphasizes the crucial parts of the input leaf image that influenced the model's conclusion, helping users grasp the significant features that contributed to the classification. The system yields a comprehensive output, which consists of the image uploaded, the most similar reference image, the similarity score calculated, and the final disease classification. By harnessing deep learning, this technique boosts accuracy, efficiency, and dependability in diagnosing plant diseases, lessening the reliance on manual inspections and facilitating early detection of diseases for prompt intervention. This automated approach promotes improved crop management, enhanced agricultural productivity, and minimized economic losses, rendering it a strong and scalable solution for precision agriculture.**

***keywords* —Deep Learning,Siamese neural network, Euclidean distance, disease classification, pretrained CNN, feature extraction, similarity measurement, threshold-based classification, Grad-CAM visualization**

I. INTRODUCTION

Tomato plants are among the most widely cultivated crops worldwide, but they are highly vulnerable to various diseases that can significantly impact yield and quality. Early and accurate disease detection is crucial for effective crop management and minimizing economic losses. Traditional disease identification methods rely on manual inspection by farmers or agricultural experts, which is time-consuming, subjective, and prone to errors due to variations in expertise and environmental conditions. These limitations necessitate the development of automated and reliable disease classification methods to assist in early detection and intervention.

Recent advancements in deep learning and computer vision have enabled the development of powerful models capable of accurately identifying plant diseases using image-based analysis. In this project, we propose a Siamese neural network-based approach for tomato leaf disease classification, utilizing Euclidean distance similarity measurement for precise identification. Unlike conventional classification models, a Siamese network compares an input image with a set of reference images from a labeled dataset and determines the disease type based on similarity. The model uses a pretrained convolutional neural network (CNN) to extract deep feature representations from both images, followed by Euclidean distance computation to quantify their similarity. A lower Euclidean distance indicates a high similarity, signifying that the input image closely matches a known disease, while a higher distance suggests dissimilarity. A predefined threshold is applied to classify the input image based on the closest reference, ensuring high classification accuracy.

To improve the interpretability of model predictions, Grad-CAM (Gradient-weighted Class Activation Mapping) visualization is integrated. This technique highlights the critical regions of the input leaf image that influenced the classification decision, allowing users to understand the key visual patterns detected by the model. The system provides detailed output, including the uploaded image, the closest matching reference image, the computed similarity score, and the final disease classification.

By leveraging deep learning, this approach enhances accuracy, efficiency, and reliability in plant disease diagnosis, reducing the dependence on manual inspection and enabling timely disease detection. The implementation of this automated classification system contributes to better crop management, improved agricultural productivity, and reduced economic losses, making it a robust and scalable solution for precision agriculture.

II. PROBLEM STATEMENT

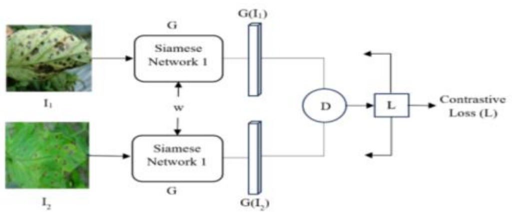
Tomato plants are highly vulnerable to various diseases caused by fungi, bacteria, and viruses, which can significantly reduce crop yield and quality. Early and accurate detection of these diseases is essential for effective management and timely intervention. However, traditional methods rely on manual inspection by farmers or agricultural experts, which is time-consuming, labor-intensive, and highly subjective. The accuracy of manual inspection varies due to factors such as expertise level, environmental conditions, and the visual similarity between different diseases, often leading to misclassification. In large-scale farming, manual inspection becomes impractical, causing delays in disease detection and treatment, which negatively impacts productivity and economic returns.

One of the major challenges in disease identification is the high visual similarity between different tomato leaf diseases, making it difficult to distinguish them through human observation alone. Diseases such as early blight, late blight, and bacterial spot exhibit similar symptoms like leaf yellowing, spots, and wilting, increasing the risk of misdiagnosis. Incorrect classification can result in inappropriate treatment, leading to unnecessary pesticide use, increased production costs, environmental damage, and ineffective disease control. Additionally, disease detection is often dependent on regional expertise, meaning farmers in remote areas with limited access to agricultural specialists struggle with accurate diagnosis, increasing the risk of crop losses, reduced market value, and food insecurity.

To address these challenges, deep learning-based models, particularly Convolutional Neural Networks (CNNs), have been widely used for automated plant disease classification. While CNNs are effective in learning spatial features from images and providing high classification accuracy, they also have certain limitations. CNN models often require large, diverse, and well-balanced datasets to generalize well, but agricultural datasets are frequently imbalanced, leading to biases in predictions. Additionally, CNNs struggle with intra-class variations—the same disease can appear differently under various lighting conditions, angles, and backgrounds, affecting model performance. Another major limitation is the black-box nature of CNNs, making it difficult to interpret how the model makes decisions. This lack of transparency reduces trust in the system, particularly in high-stakes agricultural applications where incorrect predictions can have significant economic consequences. Moreover, CNNs can sometimes overfit to training data, performing well on known samples but failing to generalize to new or unseen data, which is a critical drawback in real-world deployment.

Given these challenges, there is a pressing need for an advanced, interpretable, and scalable automated disease detection system that can overcome the limitations of manual inspection and CNN-based classification, ensuring higher accuracy, better generalization, and improved trustworthiness for effective agricultural disease management.

III. SYSTEM ARCHITECTURE



The given architecture represents a Siamese Network used for tomato leaf disease classification based on similarity measurement. The key components and flow are as follows:

Input Images (I_1 and I_2): Two leaf images are fed into the network: one as a reference (I_1) and the other as a test image (I_2).These images may contain similar or different diseases.

Siamese Network: Both images pass through the same Siamese network (shared weights 'w').This network extracts deep features (G) from each image using a CNN-based feature extractor.

Feature Embeddings (G(I_1) & G(I_2)): The output of the feature extractor is a vector representation of each image.These embeddings represent the distinctive features of the leaves.

Distance Calculation (D): The Euclidean distance (D) between the two feature vectors is computed.A lower distance indicates high similarity (same disease), while a higher distance suggests different diseases.

Contrastive Loss (L): The loss function minimizes the distance for similar pairs and maximizes it for dissimilar pairs.This helps the model learn how to differentiate between similar and different diseases effectively.

IV. PROPOSED SYSTEM

To overcome the limitations of traditional manual inspection and CNN-based classification, this project proposes an automated deep learning-based tomato leaf disease classification system using a Siamese neural network with Euclidean distance similarity measurement. The proposed system is designed to efficiently compare input leaf images with reference images from a labeled dataset, enabling accurate disease identification based on similarity rather than direct classification. This approach enhances accuracy, generalization, and interpretability, making it a more robust solution for plant disease diagnosis.

A. System Workflow

The proposed system follows a structured workflow, ensuring efficient disease detection:

Image Acquisition: The system takes an input image of a tomato leaf, which can be uploaded by the user or captured in real time using a camera.

Preprocessing: The input image is preprocessed by resizing, normalizing, and applying data augmentation techniques (such as rotation, flipping, and contrast adjustments) to enhance model robustness.

Feature Extraction using Pretrained CNN: A pretrained convolutional neural network (CNN), such as ResNet, VGG16, or MobileNet, extracts deep feature representations from the input image and reference images in the dataset.

Siamese Neural Network for Similarity Computation: The extracted feature vectors from the input image and reference images are compared using a Siamese neural network, which computes their similarity using Euclidean distance.

Threshold-Based Classification: If the Euclidean distance is below a predefined threshold, the system classifies the input image as belonging to the most similar disease category; otherwise, it is marked as different or unknown.

Grad-CAM Visualization for Interpretability: The system integrates Grad-CAM (Gradient-weighted Class Activation Mapping) to highlight key regions in the input image that influenced the model's decision, improving transparency and trust in the results.

Output Generation: The system provides a detailed output, including the uploaded input image, closest matching reference image from the dataset,computed similarity score based on Euclidean distance.

B. Advantages of the Proposed System

1.Overcomes CNN Limitations: Unlike traditional CNN-based classification models, the Siamese network compares features instead of assigning fixed labels, making it more robust to variations in image quality, background, and lighting conditions.

2.Improved Generalization: The use of pretrained CNN feature extraction enhances the model's ability to

recognize diseases with limited training data and improves generalization to new samples.
3.High Accuracy in Disease Classification: The system classifies diseases based on similarity rather than rigid label assignments, making it more adaptable to new and visually similar disease variations.
4.Enhanced Interpretability with Grad-CAM: The integration of Grad-CAM visualization ensures that users can understand why a particular classification decision was made, building trust in the system.
5.Scalability and Automation: The proposed system eliminates the need for manual disease identification, enabling rapid and automated disease detection across large-scale farms.

C. Technologies Used

Deep Learning Frameworks: TensorFlow/Keras or PyTorch for model implementation.
Pretrained CNN Models: ResNet, VGG16, or MobileNet for feature extraction.
Siamese Neural Network: Custom-designed architecture for similarity measurement.
Grad-CAM Visualization: To enhance explainability.

D. Expected Impact

The proposed system aims to revolutionize plant disease diagnosis by providing a highly accurate, efficient, and automated solution for tomato leaf disease classification. By leveraging deep learning, similarity-based classification, and interpretability techniques, this approach ensures early disease detection, reduced dependency on manual inspection, and improved agricultural productivity. The system can be deployed in real-world agricultural settings to assist farmers, agronomists, and researchers in making informed disease management decisions, ultimately leading to higher crop yields and sustainable farming practices.

V. METHODOLOGY

The proposed system for tomato leaf disease classification follows a structured deep learning-based methodology using a Siamese neural network with Euclidean distance similarity measurement. The methodology consists of multiple stages, including data collection, preprocessing, model development, training, evaluation, visualization, and deployment.

1. Data Collection

The dataset consists of tomato leaf images categorized into different disease classes, including bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites, target spot, yellow leaf curl virus, and mosaic virus, along with healthy leaves. The dataset is obtained from publicly available sources or created by collecting images from tomato farms.
Dataset Source: Publicly available plant disease datasets (e.g., PlantVillage) or custom-collected images.
Data Type: RGB images of diseased and healthy tomato leaves.
Data Format: JPEG/PNG images.

2. Data Preprocessing

Since image quality and variations in background can affect model performance, preprocessing is applied to standardize the images and enhance feature extraction.
Resizing: All images are resized to a fixed dimension (e.g., 224×224 pixels) for consistency.
Normalization: Pixel values are normalized between 0 and 1 to improve training stability.
Data Augmentation: Techniques like rotation, flipping, contrast adjustment, and brightness changes are applied to increase dataset diversity and prevent overfitting.
Noise Removal: Filtering techniques are used to reduce background noise and improve image clarity.

3. Feature Extraction Using Pretrained CNN

A pretrained convolutional neural network (CNN) is used as a feature extractor to obtain deep representations from images. This helps in capturing important disease-related features while reducing the need for extensive training data.
CNN Model: ResNet, VGG16, or MobileNet.
Feature Extraction: The output from the last convolutional layer is used as a feature vector.
Transfer Learning: The pretrained CNN is fine-tuned on the tomato leaf dataset for better performance.

4. Siamese Neural Network for Similarity Measurement

The extracted feature vectors are processed through a Siamese neural network, which compares the input image with reference images using Euclidean distance similarity measurement.

Architecture

Two identical CNN branches process the input and reference images.
The output feature vectors are passed through a fully

connected layer to obtain embeddings.
The Euclidean distance between the two embeddings is computed.

Distance-Based Classification

If the Euclidean distance is below a predefined threshold, the input image is classified as belonging to the closest matching disease category.
If the distance is high, it is classified as an unknown disease.

5. Model Training and Optimization

The Siamese network is trained using contrastive loss to ensure that similar images have lower Euclidean distances and dissimilar images have higher distances.
Loss Function: Contrastive loss.
Optimizer: Adam or RMSprop for efficient weight updates.
Batch Size: Optimized to balance training speed and accuracy.
Learning Rate Scheduling: Adaptive learning rate for better convergence.
Regularization Techniques: Dropout and L2 regularization to prevent overfitting.

6. Model Evaluation and Performance Analysis

The trained model is evaluated using test images to ensure its accuracy and reliability in real-world applications.

Performance Metrics:

Accuracy – Percentage of correctly classified disease cases.
Precision & Recall – Measures of the model's reliability in classification.
F1-Score – Balance between precision and recall.
Confusion Matrix – A visual representation of correct and incorrect classifications.

7. Grad-CAM Visualization for Interpretability

To improve trust and interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) is used to highlight key regions in the input image that influenced the model's classification decision.
Heatmaps: Generated to show the areas most relevant to disease identification.
Visual Insights: Helps users understand the model's decision-making process.

VI. LITERATURE SURVEY

[1] Title: "Deep Learning Approaches for Plant Disease Detection"
Authors: Mohanty, S. P., Hughes, D. P., & Salathé, M.
Published in: Frontiers in Plant Science, 2016
Summary: This paper explores the application of convolutional neural networks (CNNs) for automated plant disease detection from images. The study highlights challenges like imbalanced datasets and overfitting, offering solutions such as data augmentation and fine-tuning of pre-trained models to enhance performance.

[2] Title: "CNN-Based Methods for Tomato Leaf Disease Classification"
Authors: Zhang, Y., Wang, X., & Li, J.
Published in: Computers and Electronics in Agriculture, 2019
Summary: This study focuses on convolutional neural network-based approaches for classifying diseases in tomato leaves. It emphasizes the importance of proper image preprocessing and robust feature extraction methods to improve the accuracy of disease identification in diverse environments.

[3] Title: "Siamese Neural Networks for One-Shot Learning in Plant Disease Recognition"
Authors: Koch, G., Zemel, R., & Salakhutdinov, R.
Published in: Proceedings of the ICML Workshop on Deep Learning, 2015
Summary: This paper introduces Siamese neural networks for one-shot learning, specifically designed to compare pairs of images and learn similarity measures. This method is particularly effective for plant disease recognition in situations where only a few labeled examples are available.

[4] Title: "Transfer Learning for Enhanced Tomato Disease Identification"
Authors: Patel, R., & Singh, K.
Published in: Journal of Agricultural Informatics, 2022
Summary: The study highlights the use of transfer learning with pre-trained CNN models like VGG16 and ResNet to improve tomato disease identification. The authors demonstrate how fine-tuning and data

augmentation enhance classification accuracy for tomato leaf diseases.

[5] Title: "Siamese Networks for Plant Disease Detection in Data-Scarce Conditions"
Authors: Ahmed, M., & Gupta, R.
Published in: IEEE Transactions on Computational Intelligence, 2023
Summary: This paper explores the use of Siamese networks to detect plant diseases when there is a lack of labeled training data. The study assesses various loss functions to enhance the network's ability to differentiate between diseases with subtle visual differences.

[6] Title: "Improving Explainability in Plant Disease Models with Grad-CAM"
Authors: Li, H., & Zhao, X.
Published in: Artificial Intelligence in Agriculture, 2023
Summary: This work focuses on enhancing the interpretability of deep learning models in plant disease detection by applying Grad-CAM, a technique that provides visual explanations for model decisions. It helps users understand which parts of the image contributed most to the model's predictions.

[7] Title: "Comparative Analysis of Deep Learning Architectures for Tomato Disease Detection"
Authors: Kumar, A., & Verma, P.
Published in: International Journal of Machine Learning and Applications, 2022
Summary: This research compares several deep learning architectures—including CNNs, ResNet, and EfficientNet—in terms of their effectiveness for tomato disease detection. The study evaluates each model based on performance, computational efficiency, and generalization to unseen data.

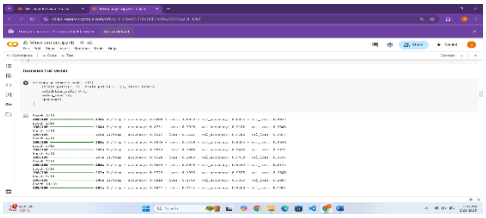
[8] Title: "A Hybrid Deep Learning Approach Combining CNN and Attention Mechanisms for Tomato Disease Diagnosis"
Authors: Tan, W., & Chen, J.
Published in: Journal of Computational Agriculture, 2023
Summary: The paper proposes a hybrid deep learning model that combines CNNs with attention mechanisms to improve feature extraction for tomato leaf disease diagnosis. This model shows improved accuracy in distinguishing diseases with similar visual characteristics.

[9] Title: "Enhancing Plant Disease Recognition with Data Augmentation and Few-Shot Learning"
Authors: Sharma, R., & Das, T.
Published in: IEEE Access, 2023
Summary: This study integrates data augmentation with few-shot learning to address the problem of limited labeled data for plant disease classification. The combination of these techniques leads to more robust models capable of accurate predictions even with small datasets.

[10] Title: "Real-Time Tomato Disease Monitoring Using Deep Learning and Interactive Visual Analytics"
Authors: Wang, L., & Kim, D.
Published in: Smart Agriculture and AI Systems, 2024
Summary: This research presents a system that integrates deep learning-based tomato disease detection with interactive visual analytics dashboards. The system enables real-time monitoring of disease trends, providing valuable insights to support timely decisions in crop management.

VII. RESULTS

7.1 Model Training Results



The model was trained for 10 epochs.

Accuracy improved significantly:

Epoch 1: Training accuracy = 60.09%, Validation accuracy = 88.75%

Epoch 10: Training accuracy = 98.41%, Validation accuracy = 95.88%

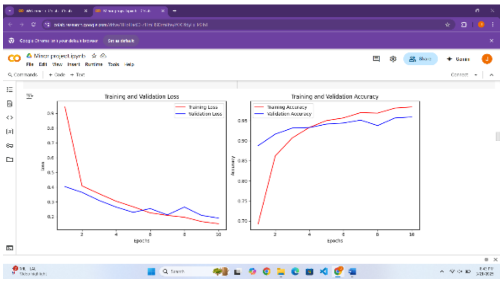
Loss decreased over time:

Epoch 1: Training loss = 1.8833, Validation loss = 0.4035

Epoch 10: Training loss = 0.1435, Validation loss = 0.1901

The model appears to be performing well, with a high validation accuracy and low loss, indicating good learning.

7.2 Training & Validation Graphs



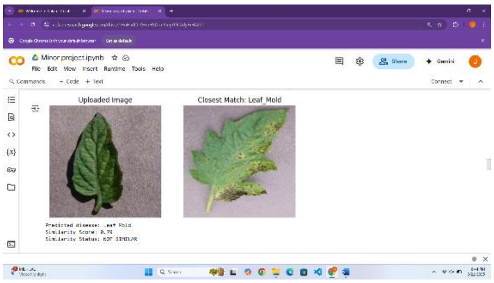
Training and Validation Loss Graph:

Loss decreases over epochs, which is expected.

Training and Validation Accuracy Graph:

Accuracy improves over time, reaching around 95%.

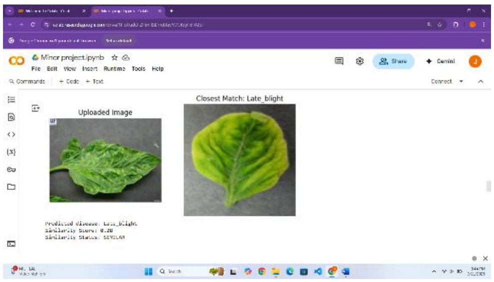
7.3 Disease Prediction Results



In the first case, uploaded a Target Spot leaf, the model found the closest match to be Leaf Mold with a Euclidean distance-based similarity score of 0.79. Since the similarity score is high (indicating a larger Euclidean distance), the model correctly labeled it as NOT SIMILAR.

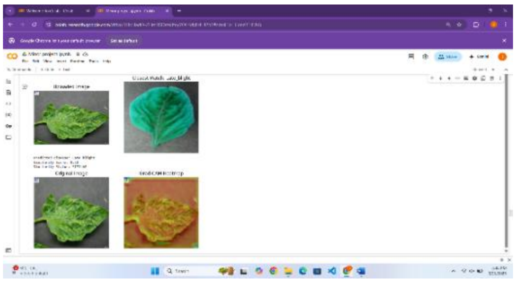
VIII. CONCLUSION

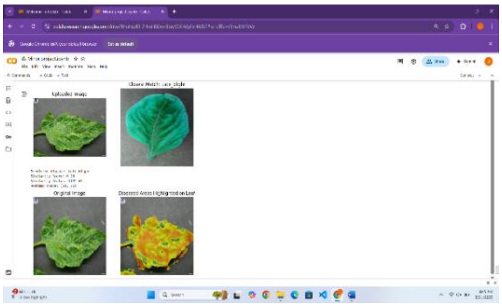
The creation of deep learning models, especially Siamese networks, for classifying tomato leaf diseases presents a promising alternative to conventional plant disease recognition methods, which typically depend



In the second case, uploaded a Late Blight leaf, and the model correctly identified Late Blight as the closest match with a similarity score of 0.28. A lower similarity score means a smaller Euclidean distance, indicating a strong match. As a result, the model classified the images as SIMILAR.

7.4 Heatmap Visualization





The Grad-CAM heatmap highlights the affected areas on the leaf, showing that the model is focusing on the correct regions where disease symptoms appear. This means the CNN layers have learned the relevant disease features rather than focusing on unrelated parts of the image. The classification, similarity score, and heatmap analysis together confirm that the model is making accurate predictions for these cases.

on manual inspections. These traditional approaches are not only slow and subjective but also susceptible to errors. Implementing Siamese neural networks facilitates effective few-shot learning, allowing for disease classification even when training data is scarce. By employing Euclidean distance to gauge the similarity between an input image and reference images, this method delivers a similarity-based classification, which greatly enhance both accuracy and efficiency in early disease detection.In addition, merging CNNs with pretrained models boosts the feature extraction capabilities, enabling the model to capture intricate patterns in images of plant diseases. Techniques such as transfer learning and data augmentation applied during training help improve the model's ability to generalize and mitigate overfitting, a frequent issue in deep learning.Furthermore, the use of Grad-CAM for visualization introduces a significant aspect of interpretability to the model. This feature allows users, particularly those in agriculture, to comprehend which parts of the plant image had the greatest impact on the model's decision-making. Such transparency is essential for fostering trust and facilitating the broader implementation of AI-based systems in agricultural contexts.The synergistic effect of CNNs and Siamese networks, along with methodologies like transfer learning, data augmentation, and Grad-CAM, culminates in a robust and automated system capable of accurately identifying tomato leaf diseases. This approach diminishes reliance on traditional manual inspection techniques, which are often unscalable, especially in large farming operations. The system could also be improved by incorporating real-time monitoring that could notify farmers of disease outbreaks, enabling timely action.Moreover, presenting model performance through tools such as Power BI offers clear insights into disease distribution, model confidence levels, and misclassifications. This facilitates improved decision-making and encourages proactive management of plant health.

In summary, the suggested system utilizing deep learning models for classifying tomato leaf diseases not only enhances the accuracy and efficiency of diagnosing plant diseases but also presents a scalable and automated approach to overcoming the challenges encountered in traditional agricultural methods. By merging advanced AI technologies with interpretability features, this system has the potential to significantly boost agricultural productivity, minimize crop losses, and promote sustainable farming practices. Future initiatives could focus on expanding the dataset, integrating more complex disease categories, and enhancing the model's performance in real-world scenarios.

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