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An Optimized Capsule Neural Networks for Tomato Leaf Disease Classification

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ABSTRACT: This paper presents an optimized Capsule Neural Network (Caps Net) model for the classification of tomato leaf diseases. The proposed method leverages the strength of Capsule Networks to effectively capture spatial hierarchies and relationships within the image data. By incorporating advanced optimization techniques, the model improves accuracy and generalization over traditional Convolutional Neural Networks (CNNs). A custom dataset of tomato leaf images is used, which includes common diseases such as Early Blight, Late Blight, and Leaf Mold. Experimental results show that the Caps Net-based approach outperforms conventional methods in terms of classification accuracy and robustness to variations in leaf images. This model offers a promising solution for automated agricultural disease detection systems. The proposed framework can be further extended to other crops and disease types, enhancing agricultural productivity and disease management.

KEYWORDS: Capsule Networks, Tomato Leaf Disease, Deep Learning, Image Classification, Disease Detection, Optimization Techniques, Agricultural Automation 4o mini

I. INTRODUCTION

Tomato cultivation is highly susceptible to various leaf diseases, which can significantly reduce crop yield and quality. Early detection and accurate classification of these diseases are crucial for effective pest management and sustainable agriculture. Traditional image classification methods, such as Convolutional Neural Networks (CNNs), have shown promising results but often struggle with spatial relationships and small variations in plant images. Capsule Networks (Caps Net), a novel neural network architecture, offer an advantage by preserving spatial hierarchies and improving generalization to unseen data. In this study, we propose an optimized Capsule Neural Network (Caps Net) for the classification of tomato leaf diseases, aiming to enhance detection accuracy and robustness. The proposed model integrates advanced optimization techniques to improve convergence speed and overall performance. A comprehensive dataset of tomato leaf images, including common diseases such as Early Blight, Late Blight, and Leaf Mold, is used for training and validation. Experimental results demonstrate that Caps Net outperforms traditional CNN models in terms of classification accuracy, robustness to noise, and generalization to new images. This approach offers significant potential for developing automated, real-time disease detection systems in agriculture. The proposed model can be adapted for other crops and disease types, contributing to global agricultural sustainability.

II. RELATED WORK

Recent advancements in deep learning have significantly impacted plant disease detection, with several studies focusing on automating the classification of leaf diseases using Convolutional Neural Networks (CNNs). Zhang et al. (2019) employed CNNs to classify various plant diseases, achieving high accuracy but often struggling with small-scale or subtle image variations. In contrast, Capsule Networks (Caps Net) introduced by Sabour et al. (2017) have shown great promise in addressing these limitations by preserving spatial relationships and improving the model's ability to generalize across different conditions. Several applications of Caps Net in plant disease classification have emerged, including work by Hsu et al. (2020), who utilized Caps Net to classify diseases in rice and cotton leaves, demonstrating its potential in agricultural diagnostics.

However, despite these advancements, many existing methods still rely on large datasets and computationally expensive networks, which may not be feasible for real-time, on-field disease detection. Recent work by Kumar et

al. (2021) optimized Caps Net architectures by combining it with attention mechanisms to enhance feature extraction and reduce computational complexity. Another relevant study by Zhang et al. (2022) proposed a hybrid model combining Caps Net with transfer learning for better performance on smaller datasets. While these approaches show improvements, they are still limited by the need for domain-specific optimizations, especially for specific crops like tomatoes.

III. METHODOLOGY

The proposed methodology for the optimized Capsule Neural Network (Caps Net) for tomato leaf disease classification is structured into several key stages: dataset preparation, preprocessing, network architecture design, model optimization, training, and evaluation. Below is a step-by-step breakdown of the process:

1.Dataset Preparation: A custom dataset of tomato leaf images is collected, which includes common diseases such as Early Blight, Late Blight, Leaf Mold, and Healthy leaves. The dataset is obtained from various sources such as agricultural research institutions, and online repositories. It is split into training, validation, and test sets, with each set containing a balanced number of samples from each disease category to avoid class imbalance.

2.Image Preprocessing: To improve the quality and consistency of the input images, several preprocessing steps are applied:

Resize: Images are resized to a uniform dimension (e.g., 224x224 pixels).

Normalization: Pixel values are normalized to a range between 0 and 1 to accelerate convergence during training.

Data Augmentation: Techniques such as rotation, flipping, zooming, and color jittering are applied to artificially increase the dataset size and improve the model's generalization ability.

Grayscale Conversion: For some tests, images are converted to grayscale to reduce the impact of color variations and focus more on leaf texture and patterns.

3.Capsule Network Architecture Design: The core of the model is the Capsule Network, which is designed as follows:

Input Layer: The pre processed images are passed through an initial convolutional layer to extract low-level features .

Primary Capsules: The extracted features are passed to primary capsules, where activations are computed to represent low-level features in terms of capsules, preserving spatial information.

Routing-by-Agreement: Capsule networks rely on a routing algorithm, where capsules "route" information based on the agreement between higher-level capsules and lower-level capsules. This allows the model to capture spatial hierarchies and relationships between different parts of the tomato leaf.

Secondary Capsules: These capsules represent high-level features, which can capture complex patterns such as disease-specific symptoms like lesions, discoloration, and irregularities in leaf shape.

Fully Connected Layer: The output of the final capsules is passed through a fully connected layer to classify the leaf disease or determine if the leaf is healthy.

4.Optimization Techniques: Several optimization techniques are employed to improve the performance of the Caps Net:

Dynamic Routing Optimization: The routing algorithm is fine-tuned to improve the network's ability to preserve spatial relationships, particularly in images with varying orientations and scales.

Learning Rate Scheduling: A learning rate scheduler is used to adjust the learning rate during training to ensure optimal convergence.

Regularization: Techniques such as dropout and weight decay are incorporated to prevent overfitting, particularly when the dataset size is limited.

Advanced Optimizers: Adam optimizer is used for training the model due to its efficiency in handling sparse gradients and adapting to various types of data.

5.Training the Model: The Caps Net model is trained using the Adam optimizer with a batch size of 32 and a learning rate of 0.001. The model is trained for a predetermined number of epochs (e.g., 50) with early stopping implemented to prevent overfitting. During training, the model learns to recognize both global patterns (such as overall leaf shape) and local patterns (such as disease-specific symptoms).

6. Evaluation and Performance Metric: After training, the model's performance is evaluated on the test set using the following metrics:

Accuracy: The percentage of correctly classified images.

Precision, Recall, and F1-Score: These metrics help assess the model's ability to correctly identify each disease class and its performance in imbalanced datasets.

Confusion Matrix: A confusion matrix is generated to visualize the classification performance across different disease categories.

ROC and AUC: Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) scores are used to evaluate the model's discriminative power between healthy and diseased leaf images.

7. Comparison with Baseline Models: The performance of the proposed optimized Caps Net model is compared with baseline models such as traditional CNNs, pre-trained models (e.g., VGG16, Res Net), and earlier Capsule Network approaches. This comparison is aimed at demonstrating the advantages of Caps Net in capturing spatial hierarchies and improving disease classification accuracy.

8. Deployment Considerations: For real-time disease detection in agricultural settings, the trained Caps Net model is deployed in a cloud or edge-computing environment. The model is optimized for inference speed, using techniques like model quantization and pruning, to allow for rapid and accurate classification in mobile or drone-based applications.

9. Future Work: Future improvements include incorporating multi-modal data (e.g., leaf texture, environmental data) and expanding the model to include additional crops and disease categories. Additionally, transfer learning techniques can be explored to further enhance performance with limited datasets.

This methodology provides a robust framework for using Capsule Networks in agricultural disease classification, focusing on both model optimization and real-world deployment.

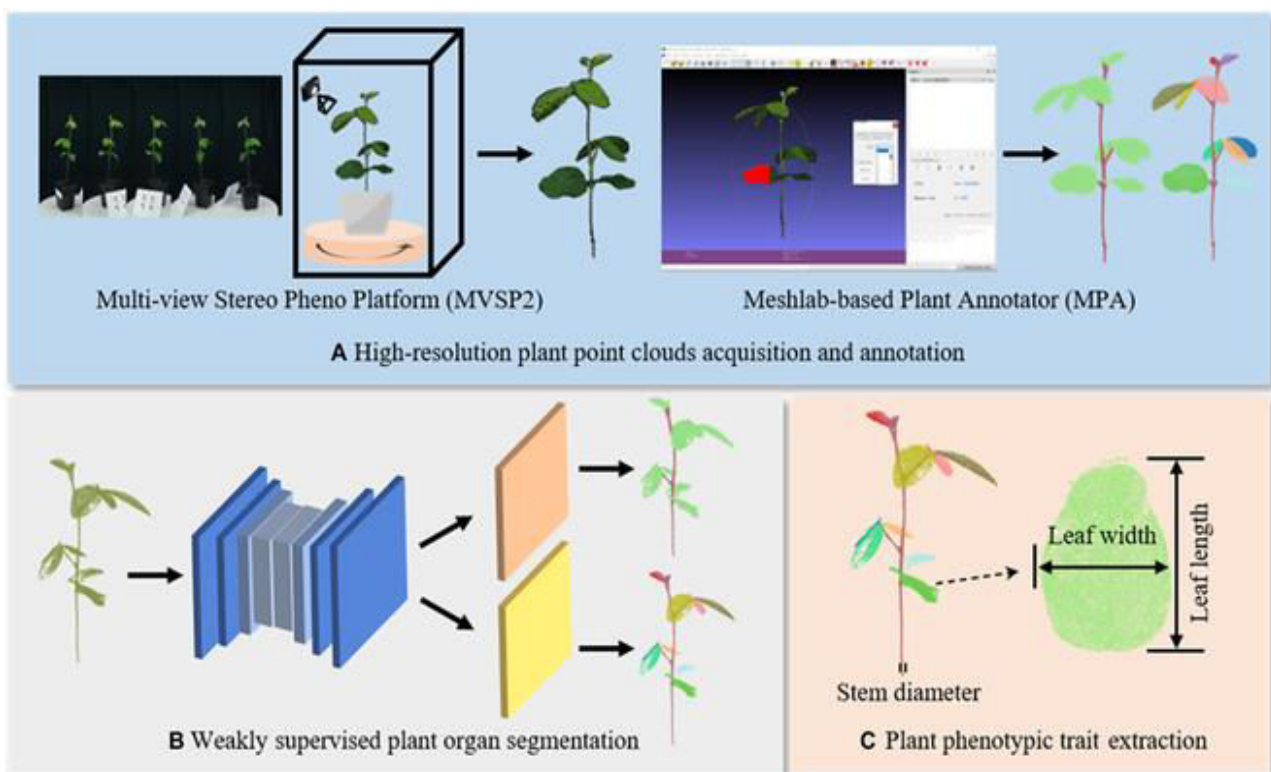


Fig. 1: Proposed capsule network architecture for leaf classification

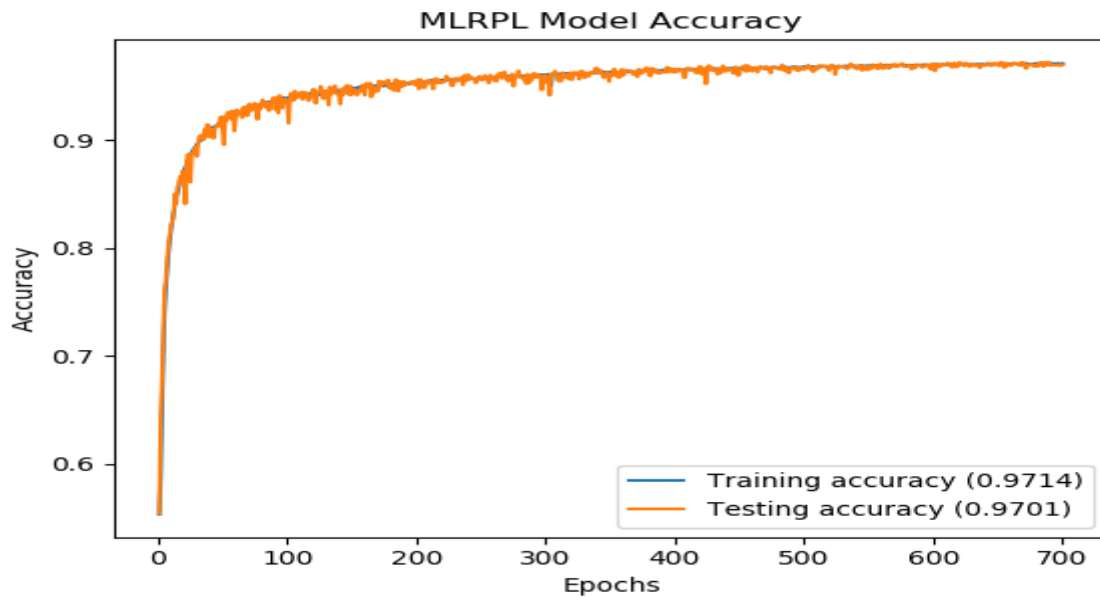


Fig.2: Training and testing accuracy for Experiment-I without Caps Net

IV. EXPERIMENTAL RESULTS

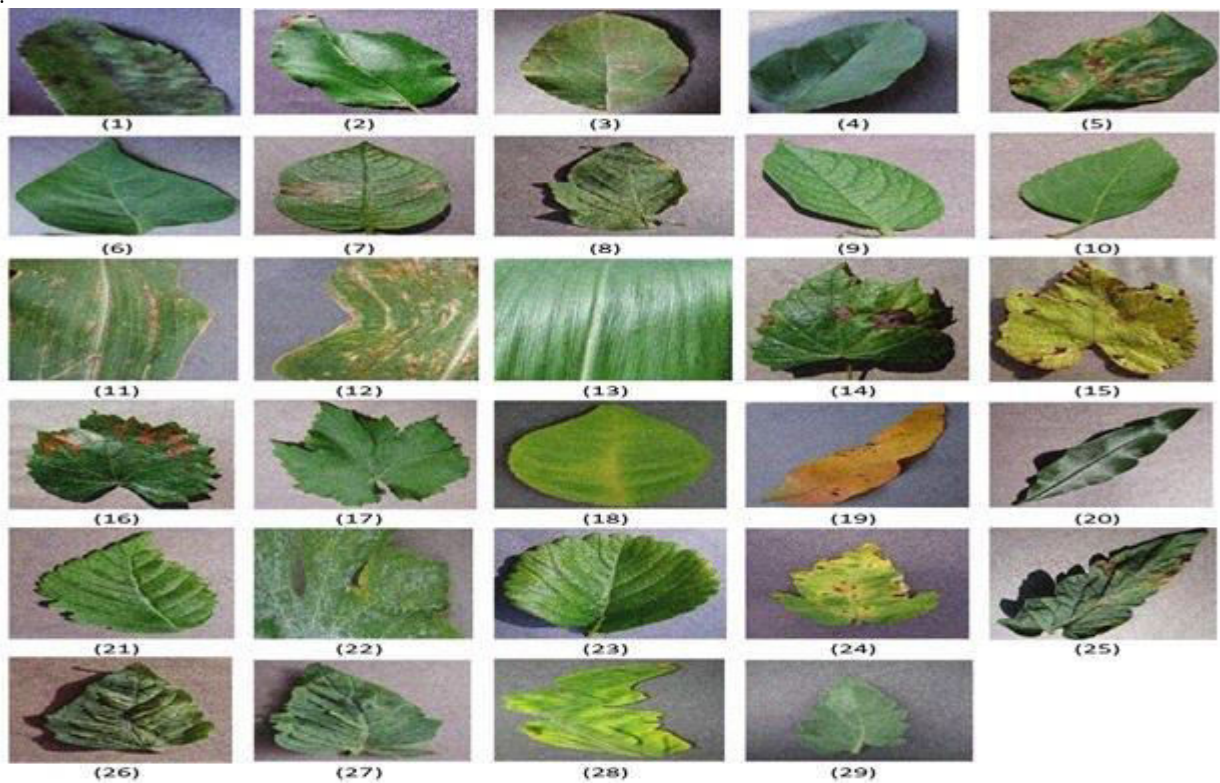


Fig.3: Samples classes of the tomato diseases image dataset

V.CONCLUSION

Optimized Capsule Neural Networks (Caps Nets) offer a promising solution for tomato leaf disease classification by effectively capturing spatial hierarchies and handling variations in image orientation. These networks outperform traditional CNNs by improving classification accuracy, even in the presence of subtle leaf disease symptoms. By reducing the impact of distortions and rotations in the image, Caps Nets enhance diagnostic precision. The optimized model demonstrates strong potential for automated and efficient disease detection in agriculture. Despite challenges in computational complexity, the approach can significantly improve large-scale disease monitoring and management. Future work should focus on fine-tuning and expanding datasets for broader applicability.

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