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Research Paper

A PLANT LEAF DISEASE IMAGE DETECTION AND CLASSIFICATION WITH CONVOLUTIONAL NEURAL NETWORKS (CNN) AND OPENCV

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ABSTRACT— This paper addresses the challenge of accurately classifying plant leaf diseases by proposing a novel deep learning approach based on Convolutional Neural Networks (CNN). Traditional CNN models often struggle to effectively capture the spatial and posture relationships of plant disease lesions, leading to issues with recognition accuracy and robustness. To overcome this limitation, we introduce an optimized CNN architecture designed specifically for plant leaf disease image classification. The proposed system enhances feature extraction by incorporating advanced convolutional layers that better capture the fine-grained details of leaf lesions. Additionally, a channel attention mechanism is integrated into the network to improve its focus on the most critical features associated with disease detection. To further improve performance, the architecture is designed to handle image transformations such as rotations, scaling, and flipping, ensuring the model's robustness across diverse real-world conditions. In addition to classification, the proposed approach also incorporates disease lesion detection using OpenCV. By utilizing OpenCV for image processing, such as drawing bounding boxes around given image, the model not only classifies the diseases but also locates them accurately the plant leaf images. This step enhances the interpretability of the model and provides more detailed information about the affected regions, which can be useful for precision agriculture applications. The model is trained and tested on multiple plant disease datasets, demonstrating significant improvements in classification accuracy, robustness, and generalization compared to traditional CNN models. The proposed method provides a reliable and efficient solution for automatic plant disease diagnosis, offering significant potential for agricultural applications and crop management.

Index Terms – Plant leaf disease detection, Convolutional Neural Network (CNN), deep learning, OpenCV, channel attention mechanism, image classification, disease lesion detection, computer vision, precision agriculture, feature extraction, agricultural image analysis, crop disease diagnosis.

I. INTRODUCTION

Plant diseases are a major threat to global agriculture, causing significant yield losses and economic impacts on crops. Accurate and timely identification of plant diseases is crucial for effective crop management and disease control. Traditional methods of diagnosing plant diseases rely on expert knowledge, visual inspection, and time-consuming manual processes, which are often not feasible for large-scale agricultural practices. In recent years, the application of deep learning and computer vision techniques has shown great promise in automating the process of plant disease identification through image classification. However, traditional Convolutional Neural Networks (CNNs), despite their success in many image classification tasks, face significant challenges when applied to plant leaf disease classification. These challenges arise from the difficulty of capturing the complex spatial relationships and variations in leaf lesions caused by disease. To address this limitation, we propose an advanced deep learning model that combines the power of Capsule Networks (CapsNet) and Residual Networks (ResNet), two state-of-the-art architectures, to more effectively classify plant leaf diseases. This novel model, referred to as CapsNet-ResNet, aims to leverage the strengths of both networks to improve feature extraction, enhance robustness, and increase the accuracy of disease diagnosis under varying real-world conditions.

II. RELATED WORK

A. *Multiscale feature aggregation capsule neural network for hyperspectral remote sensing image classification*

Models based on capsule neural network (CapsNet), a novel deep learning method, have recently made great achievements in hyperspectral remote sensing image (HSI) classification due to their excellent ability to implicitly model the spatial relationship knowledge embedded in HSIs. However, the number of labeled samples is a common bottleneck in HSI classification, limiting the performance of these deep learning models. To alleviate the problem of limited labeled samples and further explore the potential of CapsNet in the HSI classification field, this study proposes a multiscale feature aggregation capsule neural network (MS-CapsNet) based on CapsNet via the implementation of two branches that simultaneously extract spectral, local spatial, and global spatial features to integrate multiscale features and improve model robustness. Furthermore, because deep features are generally more discriminative than shallow features, two kinds of capsule residual (CapsRES) blocks based on 3D convolutional capsule (3D-ConvCaps) layers and residual connections are proposed to increase the depth of the network and solve the limited labeled sample problem in HSI classification. Moreover, a squeeze-and-excitation (SE) block is introduced in the shallow layers of MS-CapsNet to enhance its feature extraction ability. In addition, a reasonable initialization strategy that transfers parameters from two well-designed, pretrained deep convolutional capsule networks is introduced to help the model find a good set of initializing weight parameters and further improve the HSI classification accuracy of MS-CapsNet. Experimental results on four widely used HSI datasets demonstrate that the proposed method can provide results comparable to those of state-of-the-art methods.

B. Residual vector capsule: Improving capsule by pose attention

The convolutional neural network has significantly improved the accuracy of image recognition; however, it performs in a fragile manner when we apply viewpoint transformation or add noise to the image. Recent studies have proposed new neural networks named capsule. Capsule build the part-whole relationship in the entity through instantiation parameters, and they cluster instantiation parameters layer by layer through routing-by-agreement; therefore, capsule has stronger representational ability and robustness than convolutional neural networks. However, the routing-by-agreement of the capsule network is limited by the prior probability assumption, which performs in an unstable way in recognition accuracy and robustness. To remove the restriction of the prior probability assumption in the routing-by-agreement, we propose a new capsule named the residual vector capsule (RVC), which constructs the routing-by-agreement with self-attention. The experimental results show that compared with other capsule networks, RVC achieves competitive classification accuracy on MNIST, Fashion-MNIST, CIFAR-10 and SVHN, improves the viewpoint invariance of the model on SmallNorb, and significantly improves the robustness of the model against white box attacks on CIFAR-10 and SVHN.

C. Capsule networks—A survey

Capsule networks have drawn increasing attention since the concept is proposed in 2011. They hold advantages over convolutional neural networks (CNNs) on modeling part-to-whole relationships between entities and learning viewpoint invariant representations. A variety of improved designs and applications related to capsule networks have been explored within the past decade. This paper presents a relatively thorough survey of literatures corresponding to the evolution of the capsule networks and their applications. Different design of capsule networks from Hinton's group as well as other researchers are reviewed. Applications of capsule networks in various scenarios and tasks are elaborated, including hyperspectral image processing, medical image processing, facial image processing, text classification, object detection, image segmentation, few-shot learning, etc. The relation and comparison of capsule networks, CNNs, and transformers, and the trend of future development of capsule networks are discussed. We believe this review provides a good reference to researchers who are interested in capsule networks.

D. Plant-CNN-ViT: Plant classification with ensemble of convolutional neural networks and vision transformer

Plant leaf classification involves identifying and categorizing plant species based on leaf characteristics, such as patterns, shapes, textures, and veins. In recent years, research has been conducted to improve the accuracy of plant classification using machine learning techniques. This involves training models on large datasets of plant images and using them to identify different plant species. However, these models are limited by their reliance on large amounts of training data, which can be difficult to obtain for many plant species. To overcome this challenge, this paper proposes a Plant-CNN-ViT ensemble model that combines the strengths of four pre-trained models: Vision Transformer, ResNet-50, DenseNet-201, and Xception. Vision Transformer utilizes self-attention to capture dependencies and focus on important leaf features. ResNet-50 introduces residual connections, aiding in efficient training and hierarchical feature extraction. DenseNet-201 employs dense connections, facilitating information flow and capturing intricate leaf patterns. Xception uses separable convolutions, reducing the computational cost while capturing fine-grained details in leaf images. The proposed Plant-CNN-ViT was evaluated on four plant leaf datasets and achieved remarkable accuracy of 100.00%, 100.00%, 100.00%, and 99.83% on the Flavia dataset, Folio Leaf dataset, Swedish Leaf dataset, and MalayaKew Leaf dataset, respectively.

III. PROPOSED METHODOLOGY

Convolutional Neural Networks (CNNs) are a class of deep neural networks designed specifically for processing structured grid-like data, such as images, videos, and time-series data. CNNs have gained widespread popularity in the field of computer vision, especially for tasks like image classification, object detection, and semantic segmentation, but they have also been successfully applied to other domains such as speech recognition, natural language processing (NLP), and healthcare.

CNNs are inspired by the biological structure of the visual cortex in animals. In the visual cortex, neurons are organized into layers, with each neuron detecting specific features like edges or textures at different levels of abstraction. Similarly, CNNs consist of multiple layers that process data hierarchically, gradually learning increasingly complex features from the raw input. The most defining characteristic of CNNs is their use of convolutional layers, which allow the network to capture spatial hierarchies and relationships in the data, making CNNs particularly effective for image-based tasks.

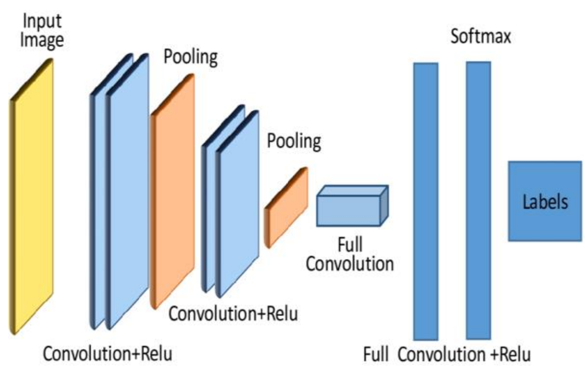

Fig. 1: System Overview

1. Data Collection

Data Collection refers to the process of gathering relevant data for training and testing the model. In the context of plant leaf disease classification, this involves collecting a large and diverse set of labeled images of plant leaves, where each image corresponds to a specific disease or a healthy plant.

2. Reading the Images

It involves loading the collected data (images) into memory so that it can be fed into the model for training and testing. This is done by reading the image files from the dataset directory, converting them to a format that the model can process, and organizing them into appropriate data structures (like arrays or tensors).

3. Preprocessing

It is a crucial step to prepare the images for model input. It involves transforming raw image data into a format that is optimized for neural network training, making the learning process faster and more effective.

4. Model Apply

In this module, the deep learning model is applied to the preprocessed images for training. This involves defining the architecture of the model, CNN training it on the dataset.

5. Model Testing

It involves evaluating the trained model on a separate test dataset that the model has never seen before. This helps assess how well the model generalizes to unseen data and its accuracy in real-world conditions.

6. Prediction

Once the model is trained and tested, it can be used for prediction. This involves feeding new, unseen images into the model and obtaining predicted class labels.

7. Disease Classification

Disease Classification refers to the final stage where the model's predictions are mapped to the actual plant disease categories. This is the goal of the model: to classify the plant leaf as either healthy or diseased and, if diseased, to identify the specific type of disease.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed CNN-based plant leaf disease detection system accurately classifies multiple plant diseases while OpenCV effectively detects and localizes infected regions in leaf images. The integration of channel attention, image preprocessing, and data augmentation improves classification accuracy and model robustness under different environmental conditions. The system demonstrates strong generalization across diverse datasets and provides reliable disease localization.

Fig. 2: Home Page

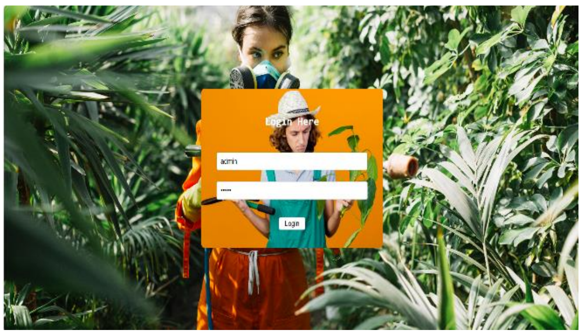

Fig. 3: Login

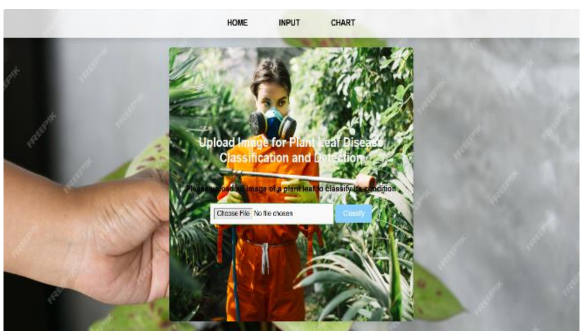

Fig. 4: Upload Image

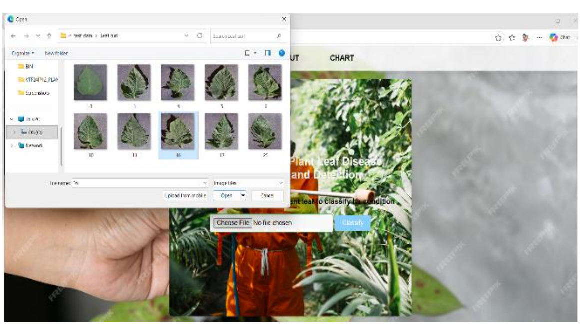

Fig. 5: Select Image

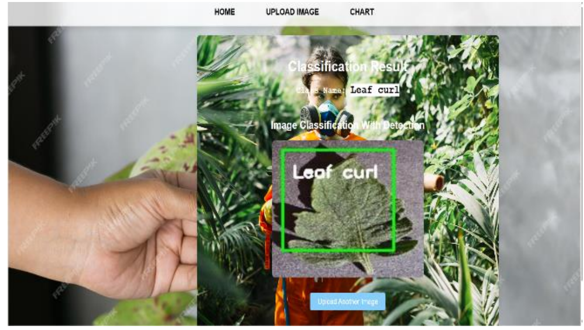

Fig. 6: Result

V. CONCLUSION

This project proposed a novel deep learning-based approach for plant leaf disease classification using Convolutional Neural Networks (CNNs), which significantly improves the accuracy and robustness of disease detection. Traditional CNN models often face challenges in capturing fine-grained details of leaf lesions and maintaining performance under image transformations such as rotation. Our approach addresses these issues by leveraging an optimized CNN architecture, which includes smaller convolutional kernels for better feature extraction and the integration of a channel attention mechanism to focus on the most critical features associated with plant diseases.

REFERENCES

[1] V. S. Dhaka, S. V. Meena, G. Rani, D. Sinwar, K. Kavita, M. F. Ijaz, and M. Woźniak, ‘‘A survey of deep

convolutional neural networks applied for prediction of plant leaf diseases,'' Sensors, vol. 21, no. 14, p. 4749, Jul. 2021.

[2] Ramanjot, U. Mittal, A. Wadhawan, J. Singla, N. Z. Jhanjhi, R. M. Ghoniem, S. K. Ray, and A. Abdelmaboud, ''Plant disease detection and classification: A systematic literature review,'' Sensors, vol. 23, no. 10, p. 4769, May 2023.

[3] C. DeChant, T. Wiesner-Hanks, S. Chen, E. L. Stewart, J. Yosinski, M. A. Gore, R. J. Nelson, and H. Lipson, ''Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning,'' Phytopathology, vol. 107, no. 11, pp. 1426–1432, Nov. 2017.

[4] L. Li, S. Zhang, and B. Wang, ''Plant disease detection and classification by deep learning—A review,'' IEEE Access, vol. 9, pp. 56683–56698, 2021. [5] J.-R. Xiao, P.-C. Chung, H.-Y. Wu, Q.-H. Phan, J.-L.-A. Yeh, and M. T.-K. Hou, ''Detection of strawberry diseases using a convolutional neural network,'' Plants, vol. 10, no. 1, p. 31, Dec. 2020.

[5] M. Turkoglu, M. Aslan, A. Arı, Z. M. Alçin, and D. Hanbay, ''A multidivision convolutional neural network-based plant identification system,'' PeerJ Comput. Sci., vol. 7, p. e572, May 2021.

[6] E. Elfatimi, R. Eryigit, and L. Elfatimi, ''Beans leaf diseases classification using MobileNet models,'' IEEE Access, vol. 10, pp. 9471–9482, 2022.

[7] Z. Xiao, Y. Shi, G. Zhu, J. Xiong, and J. Wu, ''Leaf disease detection based on lightweight deep residual network and attention mechanism,'' IEEE Access, vol. 11, pp. 48248–48258, 2023.

[8] R. Gao, R. Wang, L. Feng, Q. Li, and H. Wu, ''Dual-branch, efficient, channel attention-based crop disease identification,'' Comput. Electron. Agricult., vol. 190, Nov. 2021, Art. no. 106410.

[9] Boyapati, P. K. Building a centralized data operations hub for healthcare enterprise integration. IJSAT-Int. J. Sci. Technol. 16 (2). https://doi.org/10.71097/IJSAT.v16.i2.3219

[10] Shashank A. (2025). Metadata-driven data integration framework: Automating enterprise data integration through declarative approaches. European Modern Studies Journal, 9(4), 9.

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