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A NOVEL METHOD IN THE FIELD OF DEEP LEARNING FOR THE IDENTIFICATION OF LEAF DISEASES

B Uma Maheswari[1], Venkatesh.Savithri[2], K.Nishitha[3]
Assistant professor, Department of MCA,
Audisankara College of Engineering and Technology,
Gudur, Andhra Pradesh, India

ABSTRACT

A new strategy that leverages Convolution Neural Networks (CNNs) has been developed to accurately classify diseases across various types of leaves. This technique provides agriculturalists with an effective instrument for the early detection and accurate treatment of plant diseases by swiftly and accurately recognizing diseases from leaf images. By employing deep learning methods, this system aids in minimizing economic losses and enhancing agricultural output. Moreover, it showcases the possibility of utilizing deep learning for the detection of plant diseases in different crops, promoting environmentally friendly farming practices.

Keywords: Classification, class imbalance, Leaf disease, CNN, Mobile net

1. INTRODUCTION

Deep learning, a branch of machine learning characterized by its use of artificial neural networks with multiple layers, has emerged as a transformative technology in the realm of data analysis and artificial intelligence. By leveraging the power of deep neural architectures, deep learning models can automatically learn to represent data in a hierarchical manner, capturing intricate patterns and complex structures that traditional machine learning techniques often struggle to discern.

The resurgence of deep learning over the past decade can be attributed to several key factors: the availability of large datasets, advancements in computational power, and innovative algorithmic developments. Deep learning's proficiency in handling vast amounts of unstructured data has catalyzed significant progress in various fields, including computer vision, natural language processing, and autonomous systems.In computer vision, convolution neural networks (CNNs) have set new benchmarks in image classification, object detection, and segmentation tasks. Recurrent neural networks (RNNs), along with their variants like long short-term memory networks (LSTMs), have revolutionized natural language processing by improving performance in language modeling, translation, and speech recognition.

Furthermore, the introduction of generative adversarial networks (GANs) has opened new avenues for data generation and augmentation, enabling the creation of realistic synthetic data.

Recent advancements in farming methods have seen a significant increase in the adoption of state-of-the-art technology, including the application of sophisticated artificial intelligence for identifying leaf diseases. The study concentrates on cultivating two vital crops, rice and tomatoes, aiming to tackle the challenges posed by plant illnesses by incorporating advanced technology solutions. Recognizing the importance of the health of crops for global food security, it is essential to identify diseases promptly to minimize yield reductions. An effective approach for fast and accurate identification of diseases is the employment of specialized deep learning models for rice and tomato species. By investigating the relationship between artificial intelligence and farming, this research paves the way for the development of efficient, self-operating systems that improve the management of plant diseases. Upgraded agricultural practices have led to significant improvements in the outcomes of this research, which has the potential to transform farming techniques, ensuring crop production that is both sustainable and safeguards the lives of farmers worldwide.

II . LITERATURE SURVEY

[1] This literature review examines recent advancements in Convolution Neural Network (CNN) models for classifying agricultural leaf diseases. Various CNN designs, transfer learning techniques, and datasets utilized for model training are evaluated. Additionally, the review investigates current progress and its potential to address challenges in real-world scenarios.

[2] This analysis examines various CNN designs, such as AlexNet, VGGNet, ResNet, and Inception Net, in the domain of leaf disease classification. It evaluates the advantages and disadvantages of each architecture, assessing their performance on benchmark datasets. The insights gained from this study aid in selecting the most effective CNN model for accurate leaf disease detection.

[3] The research review centers on transfer learning and explores various techniques to adapt pre-trained CNN models in order to classify leaf diseases. It examines strategies like domain adaptation, feature extraction, and fine-tuning, providing an in-depth analysis of their effectiveness in enhancing model performance when dealing with plant disease datasets.

[4] This literature review examines the challenges associated with CNN-based leaf disease categorization, such as insufficient labeled data, class imbalances, and environmental variations. It explores the existing methodologies proposed in the literature to tackle these concerns and offers valuable perspectives on potential strategies for developing models that possess enhanced flexibility and robustness.

III. EXISTING METHOD

In the research project "Leaf Disease Classification by Using Deep Learning with CNN Algorithms," Convolutional Neural Networks (CNNs) are employed to accurately identify plant diseases by analyzing leaf images. To categorize these diseases, scientists make adjustments to popular CNN architectures like AlexNet, VGGNet, ResNet, and InceptionNet. Transfer learning plays a crucial role in achieving faster convergence and improved performance. This involves pre-training the networks on extensive datasets such as ImageNet and fine-tuning them using datasets specific to plant diseases, particularly in scenarios with limited labeled data.

It is common practice to use high-quality datasets containing well-annotated images of damaged leaves, such as PlantVillage and FER2013. The model's robustness is significantly improved by incorporating these datasets. Transfer learning, when combined with a range of datasets, can address challenges like imbalanced class distribution, limited access to labeled data, and environmental changes. Recent advancements focus on enhancing model accuracy and interpretability by integrating spectrum and multi-modal imaging data, ensembles, and attention mechanisms. Despite progress, there are still unresolved issues, including the need for more diverse datasets, addressing class imbalances, and ensuring the model's relevance in real agricultural settings. Overall, these strategies underscore the importance of leveraging deep learning—particularly CNNs—for precise and efficient leaf disease classification in agriculture.

Drawbacks:

1. Limited Model Interpretability: When adopting complicated designs, CNNs frequently function as opaque systems, making it challenging to understand how they make decisions. Lack of interpretability is problematic in fields like agriculture where trust and useful insights depend on knowing how models arrive at their results.
2. Sparse Data Availability and Class Imbalances: In agricultural contexts, obtaining large and diverse labeled datasets for CNN training might be challenging. Furthermore, models may be biased towards more common diseases as a result of class imbalances, which occur when some diseases are underrepresented, making it more difficult for them to identify rarer ones.
3. Overfitting and Generalization Issues: When trained on small datasets, CNNs are particularly prone to overfitting. In real agricultural applications, overfitted models may perform well on training data but fail to generalize to new, unknown data, which compromises their dependability
4. High Computational Demands: Researchers or practitioners with limited computer resources may find it difficult to train deep CNN models due to their substantial computational requirements. This restriction may prevent CNN-based techniques from being widely used.
5. Sensitivity to Environmental Variability and Image Quality: CNNs are susceptible to changes in ambient noise, illumination, and image quality. For CNN models to be useful in agricultural settings—where environmental variables are sometimes unpredictable—it is essential that they continue to be resilient to these variances.

IV. PROPOSED METHODOLOGY

"Leaf Disease Classification using Deep Learning and CNN Algorithms" is a system that aims to improve generalization, handle data scarcity, and improve interpretability of models. We design strategies to address class imbalances, include attention mechanisms for finer-grained feature separation, and investigate ways to extend sparsely labeled datasets. In addition, we recommend investigating interpretability tools for models in order to clarify decision-making procedures. The focus will be on making sure the model is resilient to changes in the environment and can be effectively applied to a range of agricultural situations. All these improvements work together to improve leaf disease categorization in precision agriculture in terms of accuracy, reliability, and usefulness.

Advantages:

1. Improved Interpretability of Models: By include attention processes, CNN models gain more interpretability and may be used to identify the precise characteristics that influence illness categorization choices.

2. Handling Class Imbalances: The suggested system's strategies take care of the dataset's class imbalances to make sure the model picks up on both common and uncommon illnesses.

3. Data Augmentation for Small Labelled Datasets: By enhancing the variety of the training data, methods like synthetic data creation may be used to augment small labelled datasets and enhance model performance.

4. Ensuring Robustness to Environmental Variations: By emphasizing robustness, CNN models are made more suitable for use in actual agricultural applications by being adaptable to changes in environmental variables.

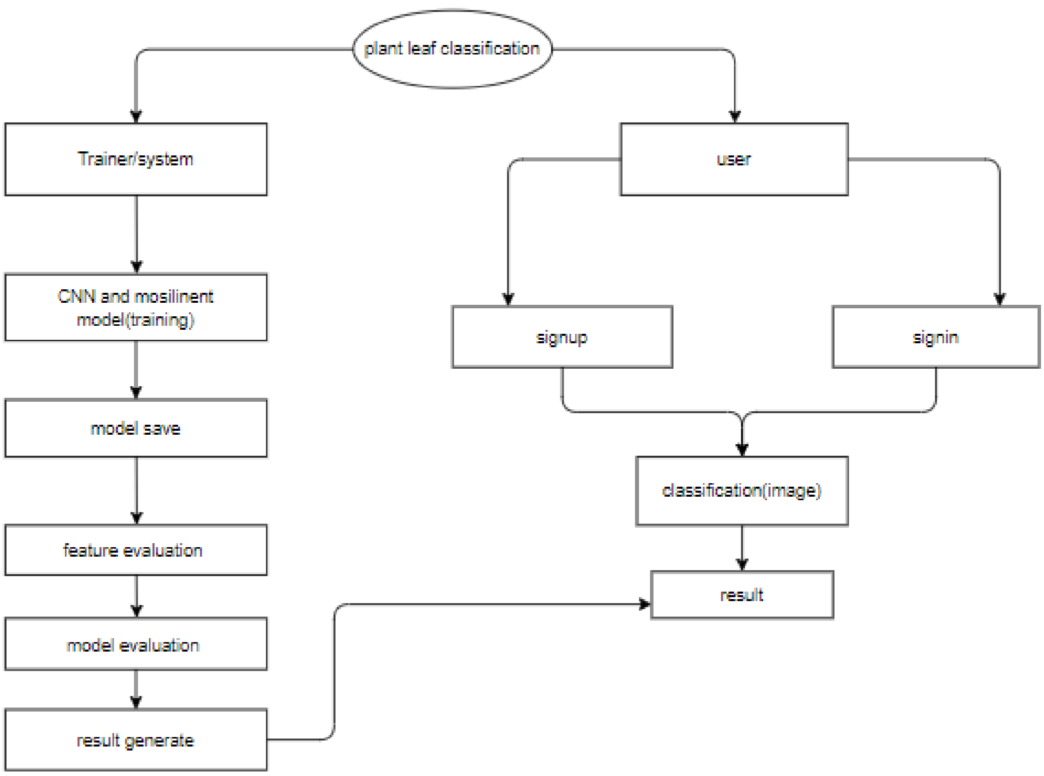


Fig 1. Block diagram of proposed method

5. Expanding Generalization to Various Agricultural Settings: By giving priority to generalization, the suggested method seeks to create models that can accurately classify leaf diseases across a range of agricultural contexts and plant species.

6. Improving Accuracy and Reliability: The system minimizes incorrect findings by improving interpretability, providing balanced training data, and being resilient. These factors all help to increase accuracy and reliability in illness categorization.

V. IMPLEMENTATION

1. System:

1.1 Creation of the Dataset: The dataset is made up of pictures of plant leaves that have been classified as being in healthy or sick conditions. It is divided into
subsets for training and testing, with a test proportion usually between 20% and 30%.

1.2 Data Preprocessing: To make sure that the images are compatible with the input format of the model, they are resized and reshaped.

1.3 Model Training: A variety of algorithms, such as deep learning (CNN, MobileNet) and machine learning (SVM), are trained using the preprocessed training dataset as input.

1.4 Classification: To evaluate accuracy, the model makes predictions on the test dataset and compares the outcomes.

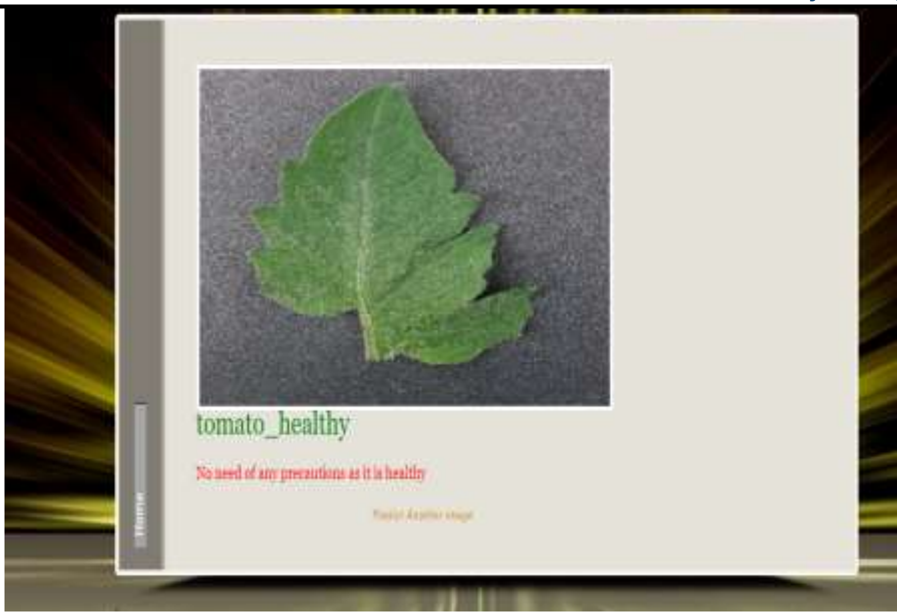
2. Interface with Users:

2.1 Training Accuracy Display: The accuracy metrics of algorithms that have been trained are visible to users.

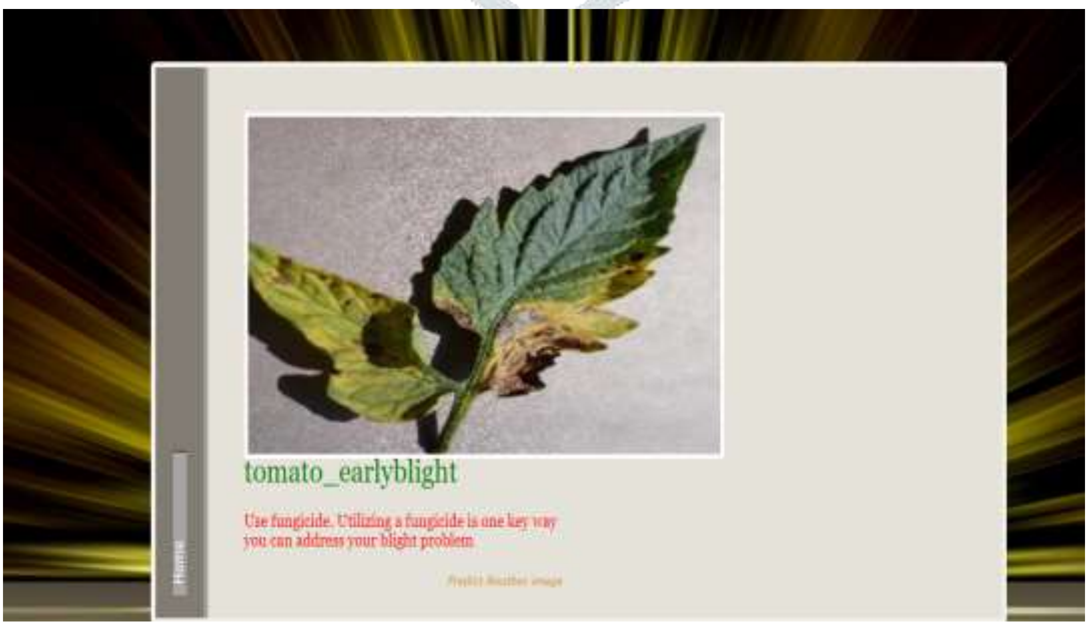
2.2 Image Upload: In order to classify photographs, users upload them.

2.3 Viewing Results and Precautions: Users get access to the results of categorized images as well as the related safety measures

VI. EXPERIMENTAL RESULTS


tomato_healthy
No need of any precautions as it is healthy


tomato_earlyblight
Use fungicide. Utilizing a fungicide is one key way you can address your blight problem


tomato_earlyblight
Use fungicide. Utilizing a fungicide is one key way you can address your blight problem

VII. CONCLUSION

This research successfully integrates machine learning and deep learning techniques to develop a prediction model for identifying plant leaf photos with illnesses. To train the picture dataset, we employed the CNN, MobileNet, SVM, and ResNet algorithms. The model's performance was evaluated by examining the classification of input pictures after training. Additionally, comprehensive guidelines for farming practices were provided, specifically tailored to address infected foliage and ensure safety measures. This approach holds the promise of streamlining and precisely predicting plant diseases in the coming years. These methods offer an avenue to streamline tasks and reduce human effort, all while upholding a remarkable level of precision.

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