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# MULTI-LEAF DISEASE DETECTION AND RECOMMENDS PESTICIDE USING DEEP LEARNING

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## ABSTRACT

This research describes a proposed system that uses deep learning and image processing methods to identify and categorize plant leaf diseases. The approach that is suggested comprises of two categorization methods and compares them. The first approach comprised of multiple steps leading up to the classification stage and was based on the support vector machine (SVM) algorithm. Because they are the most prevalent plant species worldwide and in Iraq specifically, tomatoes, peppers, and potatoes are the specific plant species that we use in our work. Convolution neural networks (CNNs) were employed in the second approach for classification. Fifteen classes were identified using these two methods: three classes for healthy leaves and twelve classes for illnesses of various plants that were found, such as fungi, bacteria, etc. The comparison's outcome demonstrates that the CNN algorithm is preferred over the SVM algorithm in terms of speed and accuracy, creating a system that is reliable and accurate for the identification and categorization of plant leaf diseases. The effectiveness of the system is evaluated using evaluation measures such as accuracy, precision, recall, and F1-score. Additionally discussed are the moral and environmental aspects of using pesticides.

This strategy's practical use is illustrated by case studies and real-world examples, which also highlight how it may be used to increase agricultural yields, lower resource consumption, and support sustainable farming methods.

Finally, this study highlights how CNNs can revolutionize both pesticide recommendation and the detection of multi-leaf diseases. The integration of advanced technology with agricultural methods in this study promotes sustainable farming practices and global food security.

**KEYWORDS:** Deep Learning, Convolutional Neural Networks (CNNs), Multi-Leaf Disease Detection, Pesticide Recommendation, Agriculture, Plant Disease Diagnosis, Image Analysis, Data Augmentation, Transfer Learning.

# I. INTRODUCTION

With agriculture feeding the world's expanding population, food security is based on a solid foundation. But this important industry continues to encounter obstacles, the most significant of which being the rise and spread of plant diseases. When it comes to agriculture, multi-leaf diseases are a serious concern since they can harm a wide range of crops, including common crops like tomatoes, potatoes, and wheat. These illnesses lower crop output while also lowering the standard of agricultural products.

Conventional techniques for managing pests and detecting diseases in agriculture frequently depend on manual examination and specialized knowledge. Although beneficial, these techniques have several built-in drawbacks, such as subjectivity, labor-intensive procedures, and a human mistake risk.

In addition to offering practical pesticide recommendations, this research focuses on addressing the crucial need for quick and accurate multi-leaf disease detection in crops. This study aims to transform the agricultural environment by utilizing the potential of deep learning, namely Convolutional Neural Networks (CNNs). Because CNNs are so good at image interpretation, they are a great option for automating the diagnosis of plant diseases based on symptoms seen on the leaves.

The principal aim of this study is to design a CNN-based system for the automatic and precise detection of multi-leaf diseases in crops. With the use of plant image analysis, the system can be trained to differentiate between diseased and healthy leaves, providing farmers and other agricultural experts with an invaluable tool.

Furthermore, by using a pesticide recommendation system, this research goes beyond illness detection. Based on the identified disease, crop species, and other contextual parameters, the system recommends suitable pesticide treatments.

The concepts of CNNs, deep learning, and the research technique will all be covered in detail in the parts that follow. We'll look at the difficulties and possibilities in detecting multi-leaf diseases, enhancing data, and the moral implications of using pesticides. Through case studies and actual situations, the study also emphasizes the usefulness of the suggested strategy, demonstrating how

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it can increase agricultural yields, use less resources, and support sustainable farming methods. Global food security is ultimately a goal that is furthered by this research's combination of cutting-edge technology with agricultural practices.

Artificial neural networks that are especially well-suited for image analysis are called convolutional neural networks. Computer vision and medical diagnostics are two areas in which their capacity to automatically learn and identify complex patterns in images has proven invaluable. When it comes to agriculture, CNNs can be extremely helpful in the early diagnosis of diseases, allowing farmers to take preventative action to avoid crop damage and output losses. The goal of this project is to provide timely, accurate, automated pesticide recommendations and multi-leaf disease detection. There are many possible advantages to this strategy. More sustainable farming methods, higher crop yields, and a decreased need for broad-spectrum insecticides can all result from it. By assisting farmers in protecting their crops from pests and illnesses, it can also improve global food security.

# **II. OBJECTIVES**

- > Develop a specialized CNN model for accurate Multi-leaf disease identification.
- > Curate a diverse dataset with images of healthy and diseased plants.
- > Apply data augmentation techniques to enhance model performance.
- > Optimize model parameters for efficient disease classification.
- > Validate the model's effectiveness through comparative analysis.

The following are the goals of a study that employed cutting-edge technology and deep learning techniques to detect multi-leaf diseases and propose pesticides in agriculture:

Automated Disease Detection: Provide a system that can identify and categorize multi-leaf diseases in crops automatically. This will decrease the need for manual inspection and enable quick and precise identification.

High Detection Accuracy: To guarantee dependable and timely diagnosis and enable timely disease intervention, achieve a high degree of accuracy in disease identification.

Pesticide Recommendation: Put into place a system that combines disease identification with pesticide recommendations, providing customized advice for efficient pest control.

Environmental and Health Considerations: To reduce the impact on ecosystems, non-target creatures, and human health, give priority to environmentally responsible and safe pesticide recommendations.

# III. METHODOLOGY

#### 3.1 Data collection

A large dataset of plant photographs, including pictures of both healthy and diseased leaves, is first gathered for the research. To ensure the robustness of the system, these photos are gathered from a variety of crop types and geographical locations. Each photograph contains carefully documented metadata, including disease kind, plant species, and geographic location. To get rid of redundant information and discrepancies, the dataset is organized and cleansed.

3.2 Dataset Preprocessing

To artificially expand the quantity and diversity of the obtained dataset, data augmentation techniques are performed. To replicate different climatic conditions and illness severities, techniques including rotation, flipping, and scaling are used. To guarantee consistency throughout the collection, preprocessing procedures including resizing, normalizing, and standardizing images.

#### 3.3 Data Architecture Selection and Customization:

A critical first step is choosing a suitable CNN architecture. To meet the unique needs of multi-leaf disease detection, researchers can take a tried-and-true architecture such as VGG, ResNet, or Inception and modify it. In order to improve the performance of the network, customization involves changing the quantity of layers, filters, and activation functions.

3.4 Transfer Learning and Model Training

Utilizing CNN models that have already been trained, usually on extensive picture datasets such as ImageNet, transfer learning is facilitated. Using the plant disease dataset, researchers refine the pre-trained model, which acts as a base. Training entails providing labeled data to the network, applying suitable loss functions (such as cross-entropy loss), and maximizing model weights by gradient descent-based methods.

# 3.5 Pesticide Recommendation System

Pesticides and their attributes, like cost, toxicity, and efficacy, are entered into a database. Based on the type of crop, the illness that has been discovered, and other contextual information, researchers create a recommendation system that identifies



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- Peer Reviewed Journal

appropriate pesticides. In order to minimize environmental damage, the system's recommendations promote effective disease control.

#### 3.6 Evaluation and Validation

Accuracy, precision, recall, F1-score, AUC-ROC, and other well-known evaluation measures are used in conjunction with a separate validation dataset to thoroughly assess the system's performance. In terms of sustainability and disease control, the efficacy of the pesticide recommendations is also evaluated.

#### 3.7 User Interface and Usability Testing

Professionals in agriculture and farmers can engage with the system with ease because to its straightforward interface design. We perform usability testing to make sure the interface satisfies end users' needs and presents findings and suggestions in an understandable and practical way.

#### 3.8 Real-World Testing and Integration

The effectiveness of the method is confirmed in actual farming environments with a range of crop types and weather circumstances. To make the system more functional and user-friendly, user feedback is actively sought for and refined.

#### 3.8 Documentation and Reporting

The model architecture, results, hyperparameters, dataset specifics, and full technique are all well documented. The results, difficulties, and suggestions for implementing the created system in farming operations are compiled into an extensive research paper.

The research aims to improve crop management and food security by using this thorough technique to develop a workable and efficient solution for multi-leaf disease diagnosis and pesticide recommendation.



#### Fig 1: CNN Architecture

#### 3.9 Model Training

Model training is a crucial phase in deep learning where the algorithm learns patterns and relationships within the data. A Convolutional Neural Network (CNN) is trained to classify leaf diseases. The model is fed batches of preprocessed images from the training set, and it adjusts its internal parameters through a process called back propagation. This process iterates over multiple epochs, refining the model's ability to accurately classify images. The choice of optimizer (Adam) and loss function (sparse categorical cross-entropy) guide this training process, aiming to minimize the error between predicted and actual labels. The model's performance is evaluated on a separate validation set to monitor its progress.

# **IV. RESULTS**

Illnesses are the biggest threat to agriculture and agricultural output. This is the driving force behind our decision to use computer capabilities and technologies to quickly and robustly develop a system. This system compares two distinct algorithms for the classification and detection of plant leaf diseases. These two algorithms are Convolutional Neural Network (CNN) and Support Vector Machine (SVM). In terms of performance and accuracy, the comparison findings favored the deep learning CNN method; we obtained a screening accuracy of 98%, whereas SVM's accuracy was only 57.11%, with an explanation provided for the latter's inaccuracy.



**EPRA International Journal of Research and Development (IJRD)** - Peer Reviewed Journal

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# Fig.2: Interface to Upload a Leaf





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### Fig 4: Tomato Leaf which is effected with disease

Figure 4 This image displays a tomato leaf afflicted by blight, evident in its distinct dark lesions, signaling a potential fungal infection by the CNN it preprocess the image and extract the relevant features from the leaf and predict the disease and recommends Pesticide.

### Fig.5: Tomato leaf disease and its causes

Figure 5 A Tomato leaf is shown suffering from late blight, characterized by water-soaked lesions and sporulation on the undersides.

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	Confidence: 21.770000457763672						-
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○ Disease Detector	<ol> <li>Early blight can be caused by two different closely related fungi, Alternaria tomatophila and Alternaria solani.</li> </ol>						
	<ol> <li>Alternaria tomatophila is more virulent on tomato than A. solani, so in regions where A. tomatophila is found, it is the primary cause of early blight on tomato. However, if Atomatophila is absent, A.solani will cause early blight on tomato.</li> </ol>						-
	How to prevent/cure the disease						
	1. Use pathogen-free seed, or collect seed only from disease-free plants						
	2. Rotate out of tomatoes and related crops for at least two years.						
	<ol><li>Control susceptible weeds such as black nightshade and hairy nightshade, and volunteer tomato plants throughout the rotation.</li></ol>						
	4. Fertilize properly to maintain vigorous plant growth. Particularly, do not over-fertilize with potassium						
	and maintain adequate levels of both nitrogen and phosphorus.						
	5. Avoid working in plants when they are wet from rain, irrigation, or dew.						ŝ



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**Fig.6: Recommends Pesticide** 

Figure 6 This picture shows pesticide that is recommended for the curing of leaf disease .

# V. CONCLUSION

Consequential leaf disease detection and pesticide recommendation using Convolutional Neural Nets (CNNs) have demonstrated encouraging outcomes. The CNN can detect and precisely diagnose the type of disease on the leaves after being trained on a sizable dataset of photos of both healthy and damaged plants. Decreased crop losses and increased yields are possible as a result of the early disease detection and prompt pesticide treatment. In addition, depending on the kind of disease found, the CNN can be used to suggest particular insecticides. In addition to financial savings and environmental advantages, this customized strategy may result in less pesticide use and more efficient pest management.

Overall, the use of CNNs for multiple leaf disease detection and pesticide recommendation holds great potential for improving agricultural productivity and sustainability. However, further research and testing are needed to optimize the model's performance and ensure its practicality and scalability for real-world applications.

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