



Research Article

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Detection of Leaf Disease Using Deep Learning

Prof. Syeda Ayesha Unisa*¹, Aishwarya N², Abhi Keshav Royal Komala³, Abhyuday Tomar⁴, Anuj Raturi⁵¹Assistant Professor, Department of Computer Science and Engineering, RV Institute of Technology and Management, Visvesvaraya Technological University, Bengaluru, Karnataka, India.^{2,3,4,5}Student, Department of Computer Science and Engineering, RV Institute of Technology and Management, Visvesvaraya Technological University, Bengaluru, Karnataka, India.

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Unisa, S. A., Aishwarya, N., Komala, A. K. R., Tomar, A., & Raturi, A. (2024). Detection of Leaf Disease Using Deep Learning. *Indiana Journal of Multidisciplinary Research*, 4(3), 98-103.**Abstract:** Agriculture is a pillar of the Indian economy, but plant diseases jeopardize its viability. Early disease diagnosis is critical for maintaining crop output and food security. This paper presents a method for disease diagnosis in apple, grape, maize, and potato plants utilizing Convolutional Neural Networks (CNN) and MobileNet, with a focus on their efficacy in deep learning-based disease detection. The CNN and MobileNet models are trained on the PlantVillage dataset, which contains leaf pictures from four crops across 14 categories. MobileNet improves detection by utilizing transfer learning, especially in resource-constrained contexts. The models learn to recognize visual patterns associated with plant illnesses, allowing for early and accurate diagnosis. Following training, the accuracy of both the CNN and MobileNet models is assessed and compared. The results show that the proposed approach is useful for reliably identifying illnesses across several crops. This study uses advanced deep learning techniques to address the issues presented by plant diseases in Indian agriculture. The proposed technology provides a viable solution for early disease identification, allowing for timely interventions to reduce crop losses and provide food security for a growing population.**Keywords:** Deep Learning, CNN, MobileNet, Plant-Village Dataset

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INTRODUCTION

Plant diseases are a major danger to agricultural output, resulting in severe economic losses and food poverty. Early diagnosis of these diseases is critical for carrying out timely interventions and preventing future spread. This research presents a unique method for detecting leaf disease in crops using deep learning models, notably Convolutional Neural Networks (CNN) and MobileNet. The work focuses on using CNN and MobileNet architectures, which have shown useful in image recognition tasks, to properly diagnose illnesses in apple, grape, maize, and potato plants. By training these models on a dataset of leaf photos with diverse disease symptoms, the system learns to distinguish visual patterns that indicate plant diseases. The experimental results show that the proposed approach is effective at detecting leaf diseases across multiple crop types. The combination of CNN and MobileNet allows the system to achieve high accuracy in illness categorization, making it a dependable tool for early disease detection in agricultural contexts. This research helps to overcome the issues provided by plant diseases in agriculture by utilizing modern deep learning techniques. By providing a reliable solution for early disease identification, the proposed approach has the potential to greatly increase agricultural yields and assure food security for the expanding population.

MATERIALS AND METHODS

Plant diseases are a serious problem since they lower agricultural yield and result in significant losses

for farmers. Deep learning technology presents one potential fix for this issue. Crop systems can reduce losses and ensure continued output by developing reliable models that can diagnose conditions and provide remedies. This analysis examines recent developments in deep learning algorithms aimed at precisely identifying plant illnesses and offering prompt remedies. By summarizing current literature, this study aims to highlight significant achievements and limits in applying deep learning to disease identification and control in agriculture.

1. The research paper discusses the creation of a resource-constrained convolutional neural network (CNN) on the Open-MV Cam H7 Plus platform for the purpose of developing a real-time plant disease classification system. With its high accuracy (95%) and minimal memory consumption and inference time, the CNN is a good fit for a portable embedded precision agricultural system.
2. The study uses a CNN algorithm to categorize processed photos of early blight, healthy, and late blight potato leaves. To facilitate efficient model training and assessment, the dataset is split into training (75%) and testing (25%) sets. The approach is centered on teaching the model to discriminate between healthy and unhealthy leaves. The main goal is to classify these groups with high accuracy so that farmers have an invaluable tool for quickly identifying and treating illnesses.

- The research introduces CRFormer, a segmentation approach for detecting grape leaf disease in smart agriculture. With 88.78% IOU on the Field-PV dataset and lower processing needs, CRFormer surpasses other approaches on datasets thanks to its use of a lightweight decoder, MultiPath Feed-Forward Network, and Large-Kernel Mining attention operation.

The robustness and effectiveness of CRFormer are validated by ablation studies.

- This research uses Convolutional Neural Networks (CNNs), including models like CNN, Alex-Net, and VGG16, to detect plant illnesses in crops including apple, grape, corn, and potato in order to address the need for greater food supply in India owing to population expansion. The study highlights how important these CNN models are for effective disease detection, which is essential for maintaining agricultural productivity and guaranteeing food security.
- Five prevalent apple leaf diseases pose a threat to yield. Traditional methods of detection are unreliable and slow. In order to accomplish realtime illness diagnosis with 78.8% accuracy and 23 FPS speed, this study presents a new deep learning model, INAR-SSD, that makes use of cutting-edge methodologies. This discovery provides a potent instrument for better apple health and early detection.
- The real-time AI system proposed in this paper aims to counter the threat of crop disease in India. It employs a deep learning model that analyses photos of maize leaves and is tailored for the Raspberry Pi 3. The method achieves 88.46% accuracy in disease recognition by honing the model and implementing it on specialized hardware, paving the way for smartphone and drone-based crop monitoring.

PROPOSED SYSTEM

Our suggested method aims to predict plant illnesses by detecting them in potato, maize, apple, and grape plants using leaf pictures. We use deep learning techniques, notably Convolutional Neural Network (CNN) and MobileNet, a CNN-based transfer learning method. Following the training of the dataset with these algorithms, we present precautions for the identified plant illnesses. The block diagram below depicts the proposed technique.

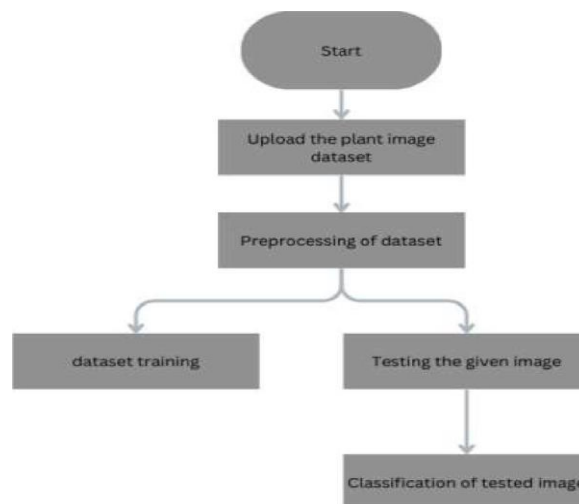


Figure 1: Block Diagram

This technique consists of two modules: system users and users who utilize the model in the end. The technique initially allows System users to create a dataset of photos of plant leaves that are classified as normal or ill. The dataset is then separated into training and testing subsets, with test sizes 70% training data and 30% testing data. Pre-processing is the process of reducing and editing pictures prior to model training. The pre-processed training dataset is used to train deep learning models like CNN and MobileNet. These algorithms are taught by collecting information from images and categorizing it as normal or ill. These algorithms are trained by extracting data from photographs and classifying them as normal or diseased. Once trained, the models can anticipate how to classify fresh photos. The system gives anticipated output as well as accuracy data, allowing users to evaluate the performance of trained models. After training and collecting reliable data, users may learn about the accuracy of training algorithms. This module allows users to evaluate the performance of models using training data. Users can upload photos for categorization.

The trained models then use the uploaded picture to determine whether the plant leaf is healthy or unhealthy. Following classification, viewers may examine the picture categorization results, as well as any related warnings. The system provides information on the found disease, allowing users to take appropriate disease management and mitigation measures. The modular architecture of the proposed system allows for faster data processing, more accurate categorization, and more user-friendly interaction, all of which increase plant disease detection and management efficiency.

Algorithms Used: CNN and MobileNet
Convolutional Neural Network (CNN)

Step 1a: Convolutional Operation. In this first section, we look at the fundamental building element of CNNs convolutional operations. In this section, we'll investigate feature detectors, which are like filters in neural networks, as well as feature maps. Learning the properties of these maps helps us understand how patterns are recognized inside pictures, the hierarchical levels of detection, and how these discoveries are then mapped.

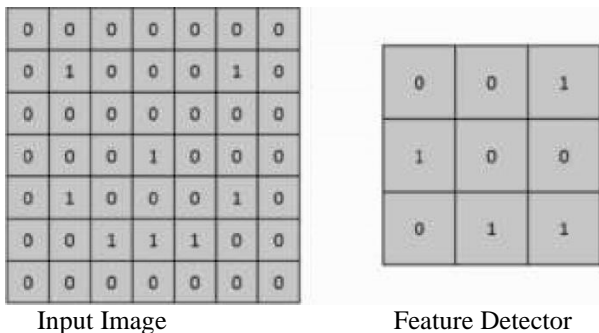


Figure 2: Convolutional Layer

Step 1b: ReLU layer: The next part describes the Rectified Linear Unit (ReLU) layer. We explain the importance of ReLU layers and their purpose in Convolutional Neural Networks, which improves understanding of linearity dynamics in this setting.

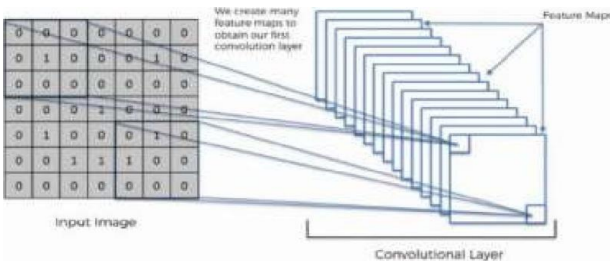


Figure 3: Convolutional Layer Creation

Step 2: Pooling Layer Pooling is the subject of this phase, with an emphasis on the basic mechanics and particular of max pooling. We discuss several pooling methodologies, including mean (or sum) pooling, and present practical demonstrations with interactive tools to enhance learning.

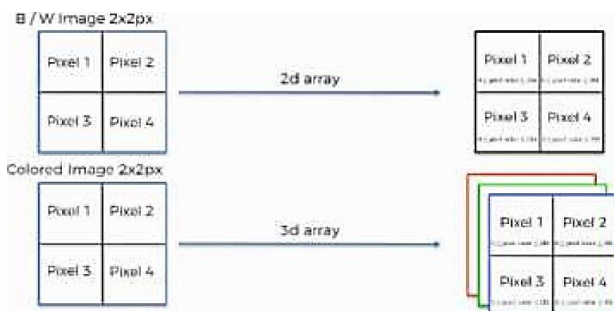


Figure 4: CNN Scan Images

Step 3: Flattening A concise explanation of the flattening process follows, illustrating the shift from pooling to flattened layers in convolutional neural networks.

Step 4: Full Connection Here, we combine all the previous notions, offering insight into how Convolutional Neural Networks work holistically. Understanding this phase enables a thorough understanding of how the resulting "neurons" learn picture categorization.



Figure 5: Final Output

SUMMARY

The final chapter presents a quick overview of the previously discussed themes, cementing comprehension. Furthermore, an optional session on SoftMax and Cross Entropy is advised since it provides additional insights for dealing with Convolutional Neural Networks. While not required, understanding these ideas improves proficiency in CNN applications.

MobileNet: Mobile Net is a convolutional neural network architecture that enables efficient deep learning on mobile and embedded devices. It was created by Google researchers to give a lightweight yet strong solution for tasks like picture categorization, object identification, and others, particularly in resource-constrained contexts such as mobile phones, 10T devices, and robots. MobileNet provides a compelling method for deploying deep learning models on resource-constrained devices, allowing for a wide range of computer vision and other applications. Its economy, versatility, and speed make it a popular choice among developers looking to deploy deep learning algorithms in real-world settings with limited computational resources.

System Requirements:	
Operating System	Windows 10
Server-side script	Python 3.6
Libraries Used	NumPy, Keras, 10, OS.
IDE	Visual Studio Code

Hardware requirements:	
RAM	4 GB
ROM	256 GB
Processor	Intel Core i3 or more

Advantages

The suggested system presents multiple advantages:

1. By analysing leaf photos, the categorization method allows farmers to take earlier action to avoid disease spread and reduce crop losses.

2. Deep learning algorithms can learn complicated patterns and characteristics from leaf photos, resulting in more accurate disease classification than older techniques. This precision guarantees that ill plants are correctly identified, eliminating misdiagnosis and wasteful treatments.
3. Once taught, the categorization system can automate the process of identifying unhealthy plants, removing the need for manual inspections, and saving farmers money on labour.
4. The system can be scaled to handle enormous amounts of leaf pictures from a variety of plant species, making it appropriate for usage in a variety of agricultural environments and crop kinds.
5. Compared to traditional laboratory-based illness detection approaches, leaf disease categorization using deep learning algorithms is less expensive and more accessible, using only a digital camera or smartphone to gather photos.
6. The system creates useful data on disease frequency and distribution, allowing farmers, researchers, and policymakers to gain insights into disease dynamics, spatial patterns, and long-term trends that may help them make decisions and allocate resources.
7. By detecting ill plants early, the categorization system allows farmers to take preventive actions such as tailored pesticide treatment, crop rotation, and disease-resistant crop types, decreasing reliance on broad-spectrum herbicides and boosting sustainable agriculture.

RESULTS

The research paper presents a website designed to analyse uploaded images of plant leaves and classify the diseases present. Specifically, the system accurately identifies apple scab, a fungal disease affecting apple trees, from an image showing a leaf with white spots. The website provides detailed information about apple scab, including its fungal cause and its propensity to thrive in wet conditions. It offers recommendations for treatment, such as fungicides, pruning infected areas, and maintaining orchard sanitation. Additionally, the website presents both organic and inorganic fungicide options, providing users with a range of treatment choices. The classification model that powers the website is trained on a dataset that contains 70% training data and 30% testing data. It includes four crop types: apple, maize, grape, and potato, each with its own disease category. Apple disease types include apple black rot, apple healthy, cedar apple rust, and the apple scab. Maize is classified as common rust, gray leaf spot, healthy, and northern leaf blight, whereas grape illnesses include black measles, black rot, healthy, and Isariopsis leaf spot. Potato diseases are divided into two categories: healthy blight and late blight.



Figure 6: Home Page

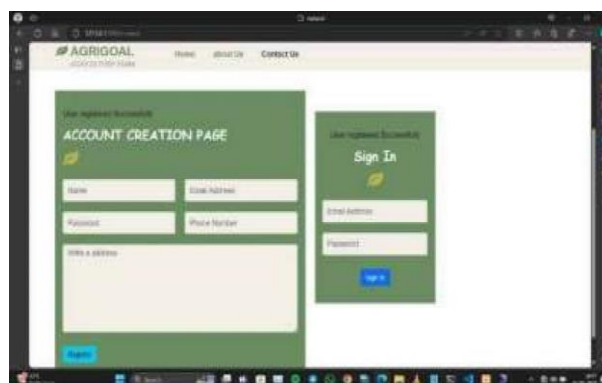


Figure 7: Sign Up

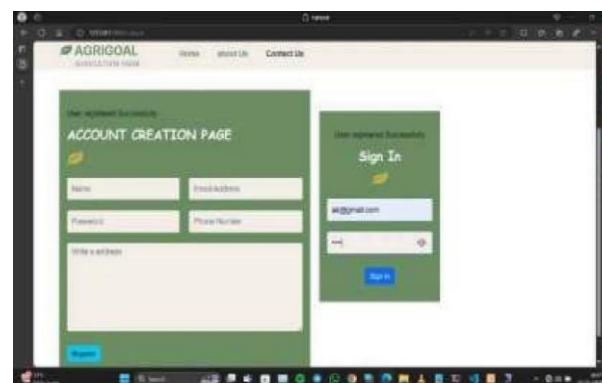


Figure 8: Sign in



Figure 9: Choose file

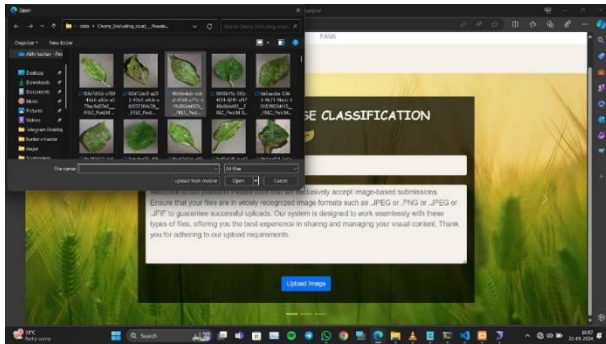


Figure 10: Select image

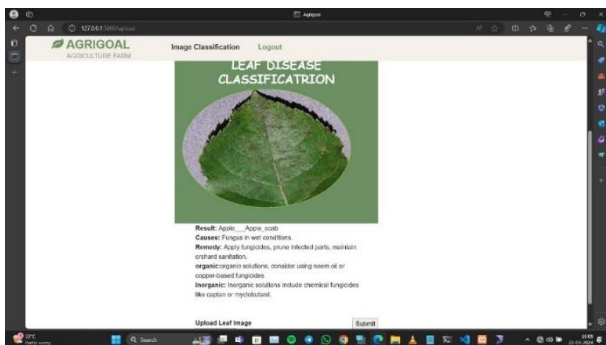


Figure 11: Final Result

The categorization model utilizes two algorithms, CNN and MobileNet, with MobileNet outperforming CNN at around 97% accuracy against 83%. As a result, the website's interface uses MobileNet to categorize leaf illnesses based on user image submissions. Users receive fast feedback on the diagnosed ailment, its causes, and advised preventative measures, which include both organic and inorganic therapies. Overall, the study article demonstrates a strong system capable of properly recognizing plant illnesses from leaf photos and giving relevant information and treatment recommendations to users, so contributing to improved disease management and agricultural output.

DISCUSSION

The "Leaf disease classification using deep learning" project, which uses CNN and MobileNet models, has interesting future directions. Key areas of improvement include improving the model to support in various ways. Integration of Spectral Imaging: Investigate the use of spectral imaging techniques such as hyperspectral or multispectral imaging to capture precise spectral fingerprints of plant leaves. By examining these spectral fingerprints, the classification system may detect small metabolic changes associated with illness presence, resulting in more accurate and timely disease identification. Creating automated remediation suggestions: Improve the categorization system such that it can not only detect unhealthy plants but also make automatic suggestions for disease prevention and treatment. This may entail combining decision support algorithms that examine disease severity, environmental factors, and historical data to

provide personalized remediation options, such as appropriate pesticide treatment schedules or disease resistant crop types. Implementation of Active Learning Techniques: Implement active learning approaches to increase the categorization system's efficiency over time. Active learning algorithms may autonomously choose the most informative examples for annotation, allowing the model to iteratively improve its performance with little human interaction. This method can assist alleviate data imbalance concerns and decrease the labeling work necessary while training new models. Deploying Edge Computing Solutions: Investigate the use of edge computing systems to provide real-time disease detection and classification directly on agricultural IoT equipment or in the field. By analyzing leaf photos locally rather than using cloud infrastructure, the categorization system may offer farmers with fast feedback, allowing for quick decision-making and action. Edge computing also provides benefits in terms of data privacy, security, and low latency.

CONCLUSION

To summarize, the "Leaf Disease Classification Using Deep Learning" research represents a significant leap in agricultural technology, providing farmers with a potent tool for early disease identification and management. The technology uses deep learning algorithms to detect plant illnesses in real time, allowing for rapid intervention and reducing crop losses. The project's ability to serve a wide range of applications in agriculture, water management, and crop management emphasizes its importance in tackling the issues that farmers confront. Furthermore, the insights into the causes of plant diseases and preventive methods provide useful information for implementing proactive initiatives. Farmers can improve agricultural yields by understanding the factors that contribute to disease occurrence and implementing preventive measures such crop rotation, disease-resistant plant types, and proper watering methods.

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