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Abstract:
This is a comprehensive review of the application of deep learning techniques in the identification and classification of plant diseases. It highlights the significant progress made in this field due to advancements in deep learning and imaging technologies. Moreover, the study focuses on the application of convolutional neural networks (CNNs) for plant disease detection and diagnosis using leaf images. These advancements have revolutionized plant disease detection and classification, enabling rapid, objective, and efficient analysis. This synthesis of research highlights the exceptional importance of CNNs in understanding and managing agricultural challenges review covers various aspects, such as the evolution of image processing methods, the development of different learning architectures, their applications in plant disease detection, challenges in the field, and future directions. It emphasizes the effectiveness of deep learning models in improving the accuracy and efficiency of plant disease recognition, addressing limitations of traditional methods, and the potential for real-world applications in agricultural settings underscoring the critical role of these technologies in sustainable agriculture and food security.

Introduction :

The prevalence of plant diseases poses significant challenges to agricultural productivity, often leading to increased food insecurity if not promptly identified and managed. This paper delves into the critical issue of plant disease identification, a key aspect of agricultural decision-making and management. Traditionally, plant disease identification relies on visible patterns of abnormalities on various parts of the plant, such as leaves, stems, flowers, or fruits, with leaves often being the primary source for disease identification. However, conventional methods involving agricultural and forestry experts or farmer-based identification are subjective, time-consuming, laborious, and often lead to inefficiencies and misjudgments, potentially causing environmental pollution and economic losses.

This review paper addresses the limitations of traditional image processing techniques used for plant disease recognition, which, despite achieving high accuracy in disease recognition, suffer from cumbersome processes, heavy reliance on spot segmentation, and artificial feature extraction,*alongside difficulties in testing*the models in complex environments. In contrast, recent advancements in deep learning (DL) technology have shown significant progress in the field of plant disease recognition. The user-friendly nature of DL technology, coupled with the ability to automatically extract image features and classify plant disease spots, has made it an increasingly popular research area. This shift is attributable to the availability of larger datasets, the adaptability of multi-core graphics processing units (GPUs), and advancements in training deep neural networks.

Convolutional Neural Networks (CNNs), a subset of deep learning techniques, have emerged as the preferred method for image recognition and classification, demonstrating exceptional abilities in this domain. However, challenges remain in terms of dataset diversity for training CNNs. To address this, transfer learning has been employed effectively, adapting pre-trained CNNs on smaller, diverse datasets for disease recognition, we employed various deep learning architectures, including Convolutional Neural Network (CNN), MobileNet, and Xception, to analyze plant disease and insect datasets. MobileNet and Xception, both of which are derivatives of the CNN architecture, are utilized as pre-trained models. These models adhere to the principles of transfer learning, a methodology that leverages the knowledge acquired from previously trained models on a base dataset and applies it to a new, relevant dataset. Our investigation involved the application of these deep learning models to two distinct datasets focused on plant diseases and insects. Upon analyzing the outcomes of these algorithms, a comparative*assessment was conducted to evaluate their effectiveness. It was observed that Xception emerged as the most successful model in this context. This finding underscores the potential of advanced deep-learning techniques in the field of agricultural research, particularly in the rapid and accurate identification of plant diseases and insect infestations.
This review aims to fill the gaps identified in the existing literature by providing a comprehensive overview of the application of image processing, hyperspectral imaging, and deep learning techniques in plant leaf disease recognition. This approach is recognized for its efficiency, providing rapid results and enhanced performance in various applications.

Literature review:

The Role of CNNs in Plant Disease Detection

This research paper[1] approaches for early detection and identification of plant diseases and pests using image processing and Convolutional Neural Network (CNN) models. The work is particularly focused on crops like Corn, Peach, Grape, Potato, and Strawberry, which are significant to the agricultural economy of Bangladesh.

The motivation for this research stems from the increasing demand for food globally and the challenges faced by farmers in protecting crops from diseases and pests, which result in substantial financial losses. Traditional methods for disease identification are manual and time-consuming, leading to delayed treatment. This paper proposes a machine learning-based solution to expedite the detection process, thereby aiding farmers in timely disease management.

The study utilizes CNN, a deep learning algorithm, for training datasets consisting of images of diseased and healthy leaves of the mentioned crops. The model achieved a high accuracy rate of 94.29%, demonstrating its effectiveness in distinguishing between healthy and diseased plant conditions. This approach is particularly beneficial for Bangladeshi farmers, who primarily rely on manual, non-scientific methods for crop cultivation and disease detection.

In the introduction, the paper highlights Bangladesh's reliance on agriculture, with a significant portion of its economy driven by this sector. The country's agrarian landscape is diverse, with crops like rice, wheat, potato, maize, peach, grape, and strawberry being widely cultivated. The research emphasizes the challenges in crop protection, particularly for maize (corn), which is susceptible to various diseases affecting its growth and yield. The paper also discusses the importance of peaches, grapes, and strawberries, all of which are vulnerable to different diseases and pests.

The literature review section delves into previous research works relevant to plant disease detection, highlighting the need for innovative models and techniques in this field. The proposed methodology section explains the approach taken in this study, including image acquisition, fundamental image processing, and the architecture of the CNN model used. The model incorporates various layers and activation functions, optimized for effective disease identification.

The paper describes the process of image expansion and model training in detail, emphasizing the importance of optimization and learning rate in achieving high accuracy. The system architecture is crafted using a multi-level CNN model, with specific configurations for convolutional and pooling layers. The paper also discusses the layer visualization process, showcasing the gradual transformation of images through the model.

The results and discussion section provides an analytical analysis of the model's performance. The model demonstrates high training and validation accuracy, with minimal signs of overfitting or underfitting. The accuracy graph and confusion matrix further validate the model's effectiveness. A comparative analysis with other models shows that the proposed model outperforms existing solutions in terms of accuracy.

The paper concludes by affirming the model's potential to aid farmers and agricultural specialists in rapid disease detection and management. The future goal of the research includes developing an open multimedia system and software for automatic plant disease detection and solution provision.

Overall, this study presents a significant advancement in agricultural technology, particularly in disease and pest detection, leveraging the capabilities of deep learning and image processing. This approach not only enhances crop protection strategies but also contributes to increasing agricultural productivity and reducing economic losses due to crop damage.

Utilizing Xception in Advancing Plant Disease Detection

This paper[3] presents a comprehensive study on the development of a detection tool for the early identification of diseases and pests in crops, employing various deep-learning architectures. The primary objective is to construct an accurate and efficient detection model to mitigate the economic losses faced by agriculturists due to plant diseases and pests. The study leverages Convolutional Neural Network (CNN), VGG16, InceptionV3, and Xception architectures, with the latter three being pre-trained models based on the CNN framework. These models utilize transfer learning, which involves applying knowledge from models previously trained on a base dataset to a new dataset, ensuring rapid results and improved performance.

Two distinct plant datasets, focusing on diseases and insects, were utilized to evaluate the effectiveness of these algorithms. Among these, the Xception model demonstrated superior performance, achieving an accuracy of 82.89% for disease detection and 77.9% for pest identification. This underscores Xception's efficacy in the context of plant health monitoring.

The introduction emphasizes the critical challenge plant diseases and pests pose to agriculture and food security. Traditional methods of insect identification, relying on expert taxonomists and morphological analysis, are inefficient for large-scale applications. Agricultural pests, primarily mites or insects, cause substantial commercial damage and their growth depends on various factors including external pressure, local weather, greenhouse design, and crop management practices. Rapid pest identification is crucial for maintaining yield productivity and reducing pesticide use. However, traditional eye observation methods are inadequate for large crop areas.

The paper discusses the use of Deep Convolutional Neural Networks for disease and pest identification, noting the computational challenges involved in training large neural networks. Despite these challenges, once trained, these networks can quickly classify images, making them suitable for smartphone applications. Deep learning methods address the limitations of traditional image recognition and classification methods, which are capable of extracting only the underlying features. By performing unsupervised learning on images, deep learning techniques can acquire multi-level image attribute feature information. Traditional disease and pest detection algorithms largely depend on manually designed attributes, which are challenging to implement and lack the ability to learn and extract features autonomously. In contrast, deep learning models automatically learn features from large datasets without manual intervention.

The paper is divided into four sections: materials and methods, results, and conclusion. The study uses data from the Kaggle repository, specifically the Tomato Leaf Disease and Pests Identification datasets. The data preprocessing steps include data acquisition, importing relevant Python libraries, reading the data, applying Label Binarizer, converting images to arrays, rescaling, and data augmentation. Data splitting was performed using a 70:30 train-test split ratio.

Different algorithms were explored, including CNN, VGGNet, InceptionV3, and Xception. VGGNet, known for its accuracy in ImageNet, uses multiple small kernel-size filters. InceptionV3 focuses on reducing computing power by modifying previous architectures and introducing factorized convolutions, smaller convolutions, asymmetric convolutions, and grid size reduction. Xception, an extension of Inception, replaces standard Inception modules with depth-wise separable convolutional layers, featuring a simpler, modular design and residual connections.

The results indicated that the Xception model outperformed others in both datasets, with CNN coming second in the disease dataset. VGG16 and InceptionV3 followed in terms of accuracy. The conclusion of the study suggests that the Xception model is the most suitable for detecting and identifying tomato leaf diseases and pests, highlighting its potential application in agricultural technology.

MobileNet

The comprehensive plant-disease recognition process combines traditional and deep features, leveraging the strong interpretability of traditional features and the robustness of deep features in this study[4].

Key components of the process include:

1. The OSTU algorithm is based on the naive Bayes model, designed to identify leaf locations and remove interference from complex backgrounds.
2. A multi-dimensional feature model that interprets traditional features to capture leaf characteristics.
3. A MobileNet V2 network with a dual attention mechanism, enhances the model's performance in spatial and channel dimensions at the network level for better plant-disease recognition.

The process was tested using the Plant Village open database, showing an average sensitivity (SEN) of 94%, which surpasses other algorithms by 12.6%.

Two main approaches: are classification and clustering. Classification methods focused on analyzing inter-class differences and were divided into traditional-feature and deep-feature-based algorithms, with various representative algorithms discussed for each. Clustering methods, on the other hand, built models by analyzing intra-class differences, with algorithms based on traditional features and deep feature extraction.

The experimental data were sourced from the Plant Village public database, including 61 categories classified by species, disease, and degree. The dataset comprised 31,718 images in the training set and 4,514 in the test set. The proposed classification algorithm involves three steps: leaf area focusing using the OSTU algorithm, traditional feature extraction using multi-scale and multi-directional Gabor filters, and classification using a dual attention network.

It showed that the proposed algorithm was effective in plant disease classification, particularly in complex backgrounds. However, the limited experimental dataset, covering only a fraction of diseases, highlighted the need for a more extensive dataset to integrate traditional and deep features further.

Conclusion:

In this essay, we have shown the fundamental understanding of deep learning and gave an extensive overview of current Deep learning research that has been done in the field of plant leaf disease detection. Deep learning methods can identify plants as long as there is enough data available for training. diseases of the leaves with great precision. The significance of gathering huge, highly variable datasets, data augmentation, transfer learning, and CNN activation map visualization in raising the accuracy of categorization, and the significance of detection of plant leaf disease in a tiny sample and its significance of hyperspectral imaging to identify plant diseases early have been spoken about. Meanwhile, there are furthermore some shortcomings.

On their datasets, most of the DL frameworks put out in the literature have good detection effects, however, the effects are not excellent on additional datasets, indicating a weakly resilient model. Better robustness DL models are therefore required to adapt. The majority of the studies made use of the PlantVillage dataset. to assess the DL models' performance. Even so, this collection includes several photos of various plant species along with their illnesses, and it was collected in a lab. As a result, it is anticipated that create a huge dataset of plant diseases in actual circumstances. The issues that prevent the broad application of hyperspectral imaging (HSI) in the early identification of plant diseases still need to be addressed, even though some research utilizes DL frameworks and hyperspectral pictures of sick leaves. That is to say, it is challenging to get labeled datasets for early plant disease detection, and even highly skilled specialists are unable to identify invisible disease pixels and mark the locations of invisible disease symptoms, which is crucial for HSI to identify plant disease.

5. EXPERIMENTAL ANALYSIS:

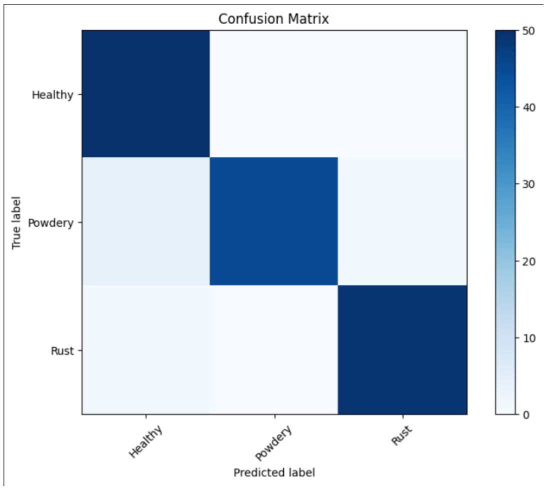
To find the best process, a comparative analysis of the neural networks was done using the Accuracy, Precision, Recall, and F1 scores of the models. The dataset was run for 10 epochs on all the models for an equal comparison.

Table 1: Model Performance Metrics

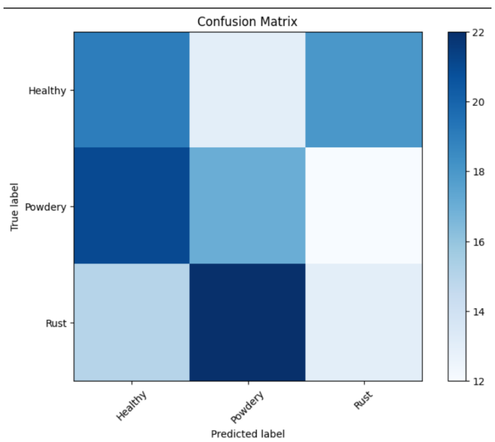
Model Name	Accuracy	Precision	Recall	F1
CNN	91%	92%	91%	92%
MobileNet v2	96%	96%	96%	96%
Xception	88%	32%	33%	32%

Table 1 shows the comparison of From Table 1, Accuracy, Precision, Recall, and F1 scores of the models. From Table 1, we can see that all the models accomplish high levels of accuracy on the testing data, with MobileNet achieving 96% accuracy. CNN and Xception were also close with 91 and 88% accuracy.

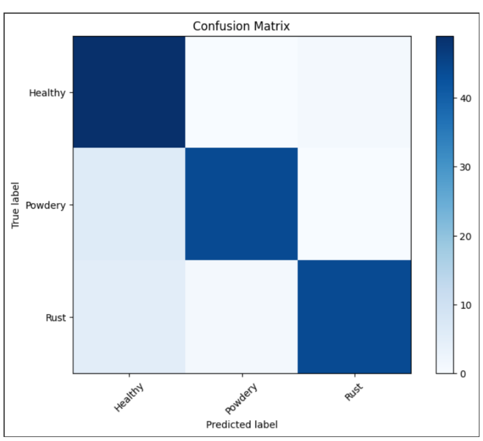
For precision, recall, and F1 score, MobileNetV2 again comes up with the best scores with 96% accuracy on all the metrics of the R2 scores. This shows that MobileNetV2 is very precise in distinguishing between the classes and has a low chance of missing any data from any classes. CNN also shows similar levels of results in this matrix, with precision, recall, and f1 scores being 92%, 91%, and 91% subsequently. Xception here shows a different type of result, as it has only 32% precision, 33% recall, and 32% F1 score. Showing that it fails to precisely distinguish between the classes.



MobileNet V2



Xception



CNN

Pictures 1 to 3 show the convolution matrix between the True labels and Predicted Labels between the classes of the models. Here we see that MobileNetV2 and CNN have predicted the labels accurately thus boosting their precision and recall of these two Models. Xception on the other hand is very inaccurate while predicting the classes according to their true labels. We can see that between rust and powdery, also between powdery and healthy. Thus the recall and precision of the model stagnates.

Conclusion:

In this research, we saw the usability of Deep Learning models in categorizing and thus detecting plant diseases. Through extensive research, it has been established that deep learning models are well-versed in such tasks, and particularly MobileNetV2 model works very well in distinguishing diseased plants from healthy plants. Moreover, the 96% accuracy of MobilNetV2 and 91% accuracy of CNN suggest the dataset we used is of high quality. The high performance and success of MobileNetV2 suggest that this model can work for mobile architectures and thus can be utilized for underdeveloped areas.

XceptionNet's underperformance presents a unique challenge to this work. The model analysis using Explainable AI(XAI) would be a target in future works to better utilize this model. Also, few more heavy architectures would be utilized to better understand the significance of heavier architecture in these situations.

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