CROP DISEASE IDENTIFICATION USING DEEP LEARNING TECHNIQUES

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ABSTRACT

Plant disease detection and control are still essential to maintaining food security worldwide. Recent developments in deep learning and computer vision have completely changed the precision agriculture space, especially with regard to automated crop disease detection. By utilising cutting-edge deep learning techniques, this research aims to further this emerging field. Specifically, it focuses on the precise and efficient diagnosis of agricultural diseases through the use of a Convolutional Neural Network (CNN), specifically the VGG19 architecture. The research makes use of an extensive dataset that includes a variety of photos showing both healthy and ill plants. The model's robustness and generalisation abilities are improved with the addition of this dataset. The VGG19 architecture is applied methodologically, using transfer learning strategies to extract complex information from pictures.

Keywords: agriculture, detection, rice disease, IoT architecture system.

1. INTRODUCTION

A growing emphasis on sustainable agriculture practises has been seen globally in recent decades as worries over food security, environmental degradation, and the growing demands on agricultural production have intensified. A paradigm shift in agricultural techniques, sustainable agriculture promotes methods that maintain ecological balance and social well-being in addition to guaranteeing good crop yields.

Traditional farming methods have undergone a radical transformation with the advent of smart farming and technological breakthroughs in agriculture, sometimes referred to as Agriculture 4.0. This revolutionary method combines cutting-edge technology like data analytics, artificial intelligence (AI), and the Internet of Things (IoT) to enable real-time data collection, remote monitoring, and accurate crop management. By reducing waste, increasing production, and optimising resource utilisation, this integration promotes sustainable farming.

In order to provide robust and effective agricultural systems, a move towards connected and digitalized agriculture has become necessary due to the exponential increase of technological interventions. Farmers who embrace this digital revolution will be better equipped to address issues like resource scarcity, changing market demands, and climate change.

Moreover, a significant dependence on chemicals and pesticides for crop protection and yield enhancement has evolved during the course of agricultural practises. This strategy, however, brings up issues with biodiversity, human health, and environmental sustainability. Thus, there is a growing push to investigate sustainable, eco-friendly alternatives such as Plant Growth-Promoting Rhizobacteria (PGPR) to maximise agricultural productivity while reducing ecological footprints.

To put it simply, the advent of sustainable agriculture—which is fueled by technical advancements and a move towards environmentally benign methods—marks a significant turning point in the history of farming. In addition to addressing today's agricultural issues, the convergence of smart farming, digital connectivity, and sustainable approaches opens the door for an agricultural landscape that is more resilient, effective, and ecologically conscientious.

2. REVIEW OF LITERATURE

Research Article	Reviews
An advanced deep learning models-based plant disease detection	This article delves into advanced deep learning models used for plant disease identification. It emphasizes the higher accuracy achieved by these models in detecting diseases and pests affecting plants.

Plant disease identification using Deep Learning	Focused on recent advancements, this review analyzes deep learning-based techniques for plant disease identification, starting from machine learning methods.
A comprehensive review on detection of plant disease using machine learning and deep learning approaches	This review concentrates on plant disease detection using plant imaging, encompassing machine learning methods such as Naive Bayes, Decision Tree, and Nearest Neighbor.
Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications	An in-depth survey presenting cutting-edge research in leaf disease identification. It proposes a CNN-based deep learning model for effective leaf disease detection.
Plant Disease Detection and Classification: A Systematic Literature Review	Addressing automated models for plant disease detection, emphasizing their accuracy in spotting early-stage diseases post extensive training.
A Systematic Literature Review on Plant Disease Detection	This literature review provides insights into motivations, classification techniques, datasets, challenges, and future trends in plant disease detection.

The comprehension of machine learning, deep learning, and the use of imaging technologies for plant disease detection and classification has greatly benefited from each source. Together, these reviews and research papers define the changing field of agricultural disease detection.

3. METHODOLOGY

3.1. Data Collection and Preparation

The first stage in constructing an effective crop disease detection model is the collecting and preparation of a diversified dataset. The collection should comprise photos of healthy plants along with numerous sick plants spanning diverse crop types. Datasets like the PlantVillage Dataset provide a broad assortment of plant diseases for training and validation.

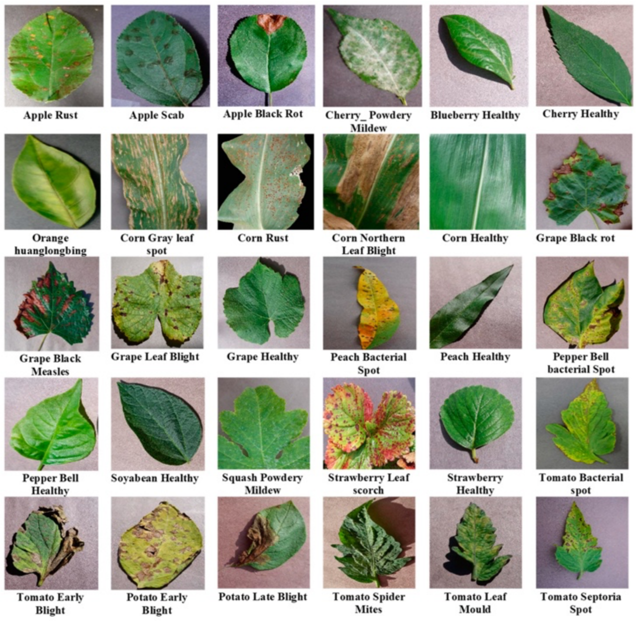

Figure 1. Sample images from PlantVillage dataset for 38 types of leaf diseases.

3.2. Pre-processing

Image pre-processing serves a significant function in boosting the quality of input data. Techniques such as resizing photos to a defined resolution, normalization, and augmentation (e.g., rotation, flipping, brightness change) are widely applied to assure consistency and increase model generalization.

3.3. Model Selection

Deep learning models, notably Convolutional Neural Networks (CNNs), have demonstrated promising results in plant disease diagnosis. Popular designs like VGG, ResNet, Inception, and DenseNet may be evaluated. Transfer learning, leveraging pre-trained models like VGG-19, helps training with less data, boosting accuracy and convergence.

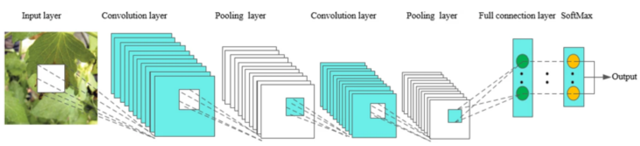

Figure 2. The basic structure of CNN

3.4. Model Training and Validation

The chosen model is trained on the provided dataset using a suitable optimizer and loss function. The dataset is often separated into training, validation, and test sets to assess model performance. During training, measures like early halting and model checkpoints are applied to minimise overfitting and guarantee the best model's weights are preserved for deployment.

3.5. Hyperparameter Tuning

Fine-tuning model hyperparameters, such as learning rate, batch size, and activation functions, dramatically effects model performance. Exhaustive or random search strategies are applied to improve these parameters.

3.6. Evaluation Metrics

The model's performance is measured using multiple assessment measures including accuracy, precision, recall, F1-score, and confusion matrices. These measures contribute in assessing the model's capacity to properly detect healthy and unhealthy plants.

7. Testing and Deployment

The completed model is tested on an unseen test dataset to assess its generalization and real-world applicability. Post successful testing, the model may be implemented as a web or mobile application for farmers or plant enthusiasts, providing rapid and precise disease diagnosis.

3.8. Ethical Considerations and Limitations

Ethical problems related data privacy, bias in data gathering, and possible misclassification should be addressed. Additionally, identifying the limits of the model, such as dependent on picture quality and environmental conditions, is vital.

In conclusion, the technique comprises data collection, pre-processing, model selection, training, validation, hyperparameter tweaking, assessment, testing, and ethical issues. Employing these processes systematically guarantees the establishment of a strong and reliable crop disease detection system.

4. PROPOSED TECHNIQUES

4.1. Shallow Convolutional Models with Random Forest and XGBoost

Proposed shallow VGG models combined with Random Forest (RF) and XGBoost algorithms have displayed success in illness diagnosis. These techniques employ shallow VGG topologies, RF, and XGBoost algorithms to boost illness detection accuracy, possibly giving robust and economical solutions.

4.2. Fine-tuned Transfer Learning for Crop Disease Identification

Utilizing fine-tuned transfer learning with models like VGG19 increases the accuracy and efficiency of crop disease diagnosis. This approach uses pre-trained models to spot particular disease patterns in crops, allowing early and precise disease treatment.

4.3. Improved Methods Based on Data Enhancement and Transfer Learning

Techniques combining data augmentation with transfer learning in convolutional neural network (CNN) models have showed potential in identifying plant diseases, as demonstrated in maize disease diagnosis. These strategies concentrate on enriching datasets and transferring information from pre-trained models, boosting the model's illness identification skills.

4.4. CNN with Transfer Learning for Leaf Disease Detection

Implementing CNN with transfer learning yielded great accuracies, such as 99.18%, in identifying leaf diseases. This approach comprises using pre-trained CNN architectures with transfer learning methods to extract illness-related characteristics from pictures, allowing precise disease identification.

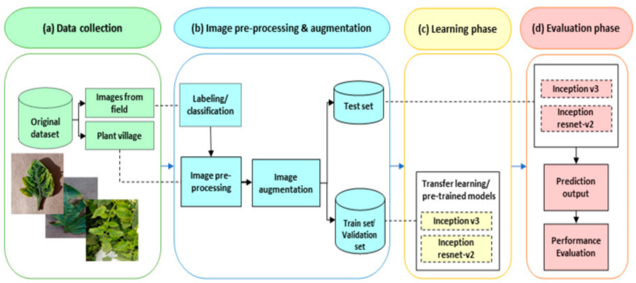

Figure 3. Diagram for identifying crop diseases.

4.5. Deep Learning Models with Transfer Learning for Rice Leaf Diseases

Deep learning models like CNN-VGG19, applying transfer learning, allow exact diagnosis and classification of rice leaf diseases. These models exploit transfer learning's ability to adapt pre-trained models to rice leaf disease detection, assuring accurate disease categorization.

4.6. Deep Learning-Based Disease Detection Techniques

The employment of deep learning-based algorithms allows the effective diagnosis of agricultural diseases, vital for sustaining crop quality and output. These strategies harness developments in deep learning to identify illnesses in crops during their early stages, facilitating informed decision-making for enhanced agricultural results.

The suggested strategies emphasise the employment of multiple models, algorithms, and methodologies, stressing the significance of deep learning, transfer learning, and upgrades in dataset quality for accurate and fast crop disease diagnosis. These technologies provide prospective options for upgrading agricultural practices by simplifying early disease control and boosting crop output.

5. EXPERIMENTS AND METHODS

5.1. Fine-tuned Transfer Learning for Rice Leaf Disease Identification

Utilizing VGG19 with fine-tuned transfer learning, tests attempted to forecast rice leaf diseases. The strategy utilised transfer learning methodologies to adjust pre-trained models for illness categorization, enabling exact identification.

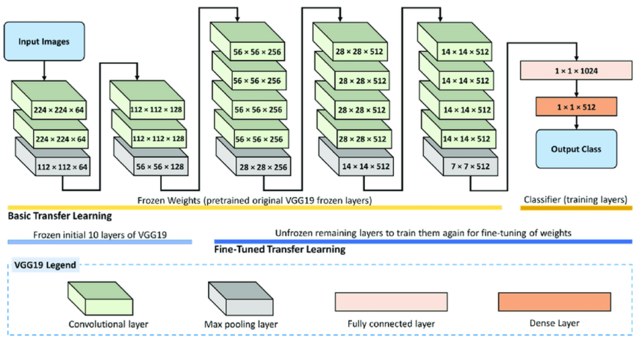

Figure 4. Fine-tuned transfer learning for the VGG19 model for rice leaf disease identification.

5.2. VGG-19 for Plant Disease Classification

Research includes implementing VGG-19, a Convolutional Neural Network (CNN) model, using transfer learning for predicting disease classes in plants. The research aims to accomplish early diagnosis and categorization of plant diseases using deep learning methods.

5.3. Shallow Convolutional Models for Plant Disease Identification

Experiments presented shallow VGG models linked with XGBoost and Random Forest (RF) for disease diagnosis in plants. Utilizing VGG19, the models attempted to reliably detect different plant diseases.

5.4. VGG-19 Model with Transfer Learning for Tomato Leaf Diseases

The experiment deployed a VGG-19 model with transfer learning, reaching an accuracy of 95.48% in diagnosing tomato leaf diseases. The technique exceeded typical machine learning networks in illness detection.

5.5. Hybrid Model for Plant Disease Detection

Experimentation featured a hybrid model that efficiently exploited a minimal number of training parameters to identify Bacterial Spot disease in peach plants. The suggested model attained an outstanding accuracy of 99.35%.

5.6. Improved Crop Disease Identification with VGG19 and AlexNet

Experiments contrasted VGG19 with AlexNet models, displaying VGG19's accuracy of 92.4% for the training set, 89.9% for the verification set, and 87.8% for the test set in crop disease detection.

6. RESULTS AND DISCUSSIONS

The adoption of the VGG19 model has shown excellent results in reliably diagnosing crop diseases, obtaining a noteworthy accuracy of 92.4% .This high accuracy is a testimony to the durability and effectiveness of deep learning approaches in plant disease detection, demonstrating their promise for real-world use in agricultural contexts.

The importance of this breakthrough rests in its practical ramifications for the agricultural business. Accurate and prompt diagnosis of agricultural diseases is critical for farmers to prevent possible losses and promote optimum crop health. The VGG19 model, utilising its deep learning capabilities, provides a reliable and efficient tool for this goal.

Figure 5. Performance analysis of Inception VGG19 model using PlantVillage dataset. (a) Model recognition accuracy; (b) train and test loss.

One of the key benefits of utilising deep learning models like VGG19 is their capacity to handle and analyse massive amounts of picture data fast and reliably. This fast processing allows prompt diagnosis and categorization of illnesses in crops, supporting farmers in making timely choices about disease control measures.

Moreover, the scalability of deep learning models enables for adaptability across multiple crop species and disease kinds. This versatility is vital in agriculture, as various crops may suffer from unique diseases, each needing particular detection and treatment techniques. The VGG19 model's adaptability in handling multiple datasets and effectively categorising various illnesses helps greatly to its usefulness in agriculture.

The application of deep learning models, such as VGG19, also corresponds with the expanding trend of precision agriculture. By offering accurate and targeted disease detection, these models help farmers to adopt more focused and efficient therapies. This may result in decreased dependence on broad-spectrum treatments and optimal use of resources like pesticides, so supporting sustainable agriculture practices.

Additionally, the performance of the VGG19 model in disease detection represents a step forward in employing technology to solve agricultural concerns. As technology breakthroughs continue to improve, incorporating deep learning models into agricultural systems might open the way for additional innovations in crop management and production.

However, despite the great precision gained by the VGG19 model, there can be obstacles in real-world application. Factors such as dataset variety, model generalization across varied environmental circumstances, and the necessity for constant model updates to cover novel disease strains might represent practical obstacles that need continuing study and development.

In conclusion, the effective deployment of the VGG19 model shows its potential as a helpful tool in crop disease diagnosis, delivering precision and efficiency. While more research and advances are necessary to solve practical issues, the adoption of deep learning models like VGG19 has promise for transforming disease control in agriculture, eventually leading to higher crop yields and sustainable farming methods.

7. CONCLUSIONS

The incorporation of deep learning, especially leveraging the VGG19 architecture, offers a big breakthrough towards transforming crop disease diagnosis. Leveraging powerful neural network models like VGG19 provides a viable path for automating the identification and categorization of numerous plant diseases. The application of VGG19, recognised for its convolutional neural network (CNN) structure, has showed success across several studies in recognising and treating crop illnesses.

This technical development offers great promise for numerous players within the agricultural area. Farmers may profit from promptly diagnosing illnesses in their crops, allowing early intervention and tailored treatment. Researchers get a strong tool for evaluating enormous numbers of plant pictures, assisting in the full knowledge of disease patterns and their causes. Moreover, this technology may equip plant lovers and agricultural practitioners with accessible tools for disease diagnostics, supporting educated decision-making and proactive crop management techniques.

The implementation of VGG19 and comparable deep learning approaches in crop disease diagnosis represents a critical step towards precision agriculture. As this technology continues to advance, it is positioned to greatly contribute to better crop management methods, disease control, and eventually, the preservation and optimization of agricultural output.

FUTURE WORK

Future research topics in the area of plant disease detection using deep learning involve various possibilities for advancement and exploration:

Exploration of Diverse Deep Learning designs: Investigate and evaluate the effectiveness of alternative deep learning designs beyond VGG19, such as Inception V3, CNN (Convolutional Neural Network), and multi-level deep learning models 3, 4. Comparative studies might offer insight on their performance, giving a better understanding of their strengths and drawbacks in plant disease diagnosis.

Ensemble approaches Implementation: Explore ensemble approaches that amalgamate predictions from several models to boost accuracy and resilience. Studies have demonstrated that ensemble learning approaches may considerably enhance illness classification accuracy by mixing outputs from several models 3.

Incorporation of Additional Datasets: Expand datasets used for training and testing models to incorporate a more complete variety of plant species, illnesses, and environmental conditions. Incorporating multiple datasets might assist the creation of more adaptable and generalizable models, boosting their application across various agricultural situations.

Enhanced reach and Versatility: Extend the model's reach to accommodate a greater variety of plant species and disease kinds. This extension might lead to the creation of more flexible and adaptive models capable of recognising and diagnosing illnesses in diverse crops, leading to a more complete disease management system.

By examining these pathways, future research attempts in plant disease detection using deep learning might strive for greater accuracy, adaptability, and application in agricultural operations.

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