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Apple Leaf Diseases Detection Using Deep Learning Models: A Review

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***Abstract*—Worldwide diseases affecting apple leaves reduce production, and early diagnosis is critical to prevent losses. Models such as CNNs, ResNet, and DenseNet can score over 95% accuracy for the detection of Apple Scab, Cedar Rust, and Marssonina Blotch. Techniques like data augmentation, transfer learning, and hybrid architectures improve the robustness and generalization of these models. Challenges exist, especially because of the controlled dataset, including high computational demands and limited scalability in real-world settings. Future work will address such issues by further extending datasets for different environments, optimizing the models for use on mobile and IoT, and incorporating precision agriculture for pro-active disease management. The review underlines the strength and weakness of deep learning in sustainable production of apples.**

Keywords—Apple leaves diseases, Deep learning, Convolutional Neural Networks (CNNs), Data augmentation, Apple scab, Apple rust..

I. Introduction

Apple (Malus domestica) is fourth most popular fruit in the world and fifth in India [1], [2]. Apples are nutrient-rich fruits, which have numeric benefits—heart health, support weight loss, gut health [3]. There are mainly five states in India where apples are produced: Himachal Pradesh, Jammu and Kashmir, Uttarakhand, Arunachal Pradesh, and Nagaland [4]. In 2024 apple production in Himachal Pradesh has declined due to climate change. Change in weather patterns have affected the quantity, color, and size of apples [5]. Climate change is dangerous for the apple industry, making less altitude areas not suitable for apple growth in Himachal Pradesh. In the 1980s, apple orchards were at the altitude of 1200–1500 meters; now, in 2014, it is above 3500 meters in some areas. Due to these climate conditions, it gives rise to diseases in apple plants like scab diseases, premature defoliation, and Alternaria diseases [6]. Heatwaves affect the colour, size and quality of the fruit. All of this will be the reason for lower market values. It causes dark spots on apples, which is caused by flyspeck and sooty blotch diseases [7].

There are other diseases that also affect apple plants and its growth: black rot, powdery mildew, apple mosaic, and other virus diseases [8]. There is also a nutrient deficiency that can affect the fruit. Fruit with nutrient deficiency has smaller pale color, low storage life, and premature dropping . Nutrient deficiency mostly appears in leaves of the plant [9]. Apple plant disease symptoms appear in early stages and may include apple leaves. Apple scab, Marssonina leaf blotch, black rot canker, powdery mildew, sooty blotch, apple mosaic, and Alternaria leaf spot/blight all of these diseases early signs can happen in the leaves of the plant. [10]

Early Identification of the diseases is very important to cure the diseases and help to prevent further loss in yield. The advancement in deep learning and machine learning technologies has helped us to overcome critical challenges. Among these, the detection of diseases in plants helps us with early detection of the diseases and saves our yield and quality. Researchers have used CNN and other deep learning models to identify diseases with leaf images with great accuracy.

A. *Objectives*

- **Develop an Optimized CNN Model –** To enhance plant disease detection accuracy by fine-tuning and comparing different CNN architectures.
- **Implement Image Processing Techniques –** To apply image segmentation, feature extraction, and augmentation for better disease identification.
- **Integrate a Mobile-Based Solution –** To create a user-friendly application that enables real-time disease diagnosis for farmers.
- **Improve Model Generalization –** To enhance robustness by incorporating diverse datasets and reducing overfitting through data augmentation.

II. Literature Review

It employed deep learning to automate the detection of Marssonina Coronaria and Apple Scab on apple leaves. Data augmentation increased the set from 50,000 to 200,000 images from Himachal Pradesh and Uttarakhand, India. A 19-layer CNN-C achieved accuracy of 99.2%, which was also above the traditional classifiers, for example, SVM, KNN, and Logistic Regression besides the simpler CNNs. Metrics for the system are sensitivity of 99.7% and specificity of 97.8%.

Therefore, the model appears reliable. The research thus claims that greater datasets and more profound networks increase the efficiency of classification. It further discusses its real-world applications like mobile-based tools for farming communities to detect diseases immediately. The study should be extended to other diseases of the apple and transfer learning applied to get a wider view [11].

The document presents a lightweight, efficient method for identifying apple leaves diseases, specifically Alternaria leaf blotch and rust, using the MobileNet models. This approach addresses the challenges of traditional expert inspections, which are time-consuming, error-prone, and require specialized skills, by providing a low-cost, high-precision, and mobile-friendly solution. A dataset of 2004 processed images was created from 334 original samples using data augmentation methods like Turning and scaling to enhance model robustness. MobileNet demonstrated a strong balance between efficiency and accuracy, identifying diseases in just 0.22 seconds per image with an accuracy of 73.50%, outperforming more complex models like ResNet152 and InceptionV3 in speed while maintaining comparable precision. The research emphasizes the potential for practical deployment on mobile devices, enabling non-experts to diagnose diseases effectively. Future efforts will focus on expanding the dataset to 2 million images for improved accuracy and developing models for disease severity assessment [12].

The study suggests a deep learning model for apple tree leaf disease detection (ATLDs) with a new convolutional neural network (CNN) structure named XDNet. The study highlights the importance of early disease detection to avoid disease transmission, reduce the use of pesticides, and enhance apple production. XDNet takes advantage of the best of both DenseNet and Xception architectures in the sense that it uses depth wise separable convolutions in combination with densely connected configurations to enhance feature extraction and reuse. The dataset used in this study was obtained under laboratory and field conditions and contained six classes: five common apple leaf diseases and healthy leaves. Data augmentation strategies were used to enhance robustness. The suggested model attained an accuracy rate of 98.82%, outperforming other CNN architectures like Inception-v3, MobileNet, VGG-16, and Xception. The study optimistically hopes that the proposed model can be integrated into intelligent agricultural systems for real-time disease watching and selection processes [13].

The paper suggests an automated disease diagnosis approach in apple tree leaves based on a deep learning model. The authors construct an integrated model with three pre-trained convolutional neural networks, i.e., densenet121, efficientnetB7, and EfficientNet Noisy Student, to organize apple leaves into four sections: healthy, apple scab, cedar apple rust, and multiple diseases. They employ various image processing operations, including flipping, blurring, and Canny edge detection, to augment the dataset and enhance the performance of the model. The model achieves a 96.25% accuracy rate on the validation set, which proves its superiority over other models. The study suggests the potential use of the model in real-world agricultural settings through a web application that enables farmers to identify diseases quickly and save their crops [14].

The paper proposes a deep learning based method for apple plant disease diagnosis with the help of convolutional neural networks (CNN). A light-weight CNN model, Conv-3 DCNN, is suggested for minimizing computational complexity without compromising accuracy. The dataset, from the Plant Village repository, consists of images of healthy apple leaves and three disease classes: black rot, scab, and cedar rust. Data augmentation methods, including shifting, shearing, scaling, and flipping, were used to increase training robustness. The model was found to have 98% accuracy, superior to some pre-trained deep learning models, including VGG-19, ResNet-152, and MobileNetV2, with lower storage and computational requirements. The model is therefore more appropriate for deployment on handheld devices for real-time disease diagnosis. Future research recommends adding the dataset with images from different geographical locations and different growth stages to enhance generalization and early disease detection [15].

The paper presents a technique for the identification and classification of apple leaf diseases based on ResNet models. Apple grey-spot disease, black star disease, cedar rust, and healthy leaves are identified through the research. The data is from Plant Village and augmented with extra images. The data is preprocessed using image segmentation and feature extraction. Models like Support Vector Machine (SVM), VGG-16, and ResNet-18/34 are compared in the research, and it is clear that the highest accuracy of 98.5% is achieved with ResNet-18. The research proves that ResNet models are extremely efficient for the classification of plant diseases and can be used in automated monitoring systems in agriculture [16].

The current research suggests a better ResNet-50 model to identify and classify diseases and insect attacks on apple leaves. This model is designed to work better than current models that do not identify well. It uses a coordinate attention (CA) module along with weight adaptive multi scale feature fusion (WAMFF) to get better features. The approach also includes transfer learning and online data augmentation to make the model more general. The recommended model has a top-1 accuracy of 98.32% on the AppleLeaf9 dataset test, which is better than some standard models like AlexNet, VGG16, DenseNet, MNASNet, and GoogLeNet. The research shows that the model can enhance smart agriculture technology by improving how accurately it locates and classifies diseases. Future research will aim to optimize the model for real-world use, especially for mobile devices [17].

This paper presents a lean convolutional neural network (CNN) structure for efficient apple leaf disease detection with minimal computational needs. Following the AlexNet architecture, the suggested model utilizes dilated convolution for coarse-grained feature extraction, multi-scale convolution for thorough feature investigation, supplemented by an attention mechanism for enhanced feature selection and removal of background noise. The structure in place of conventional fully connected layers utilizes global pooling for parameter reduction without accuracy loss. Tested on a dataset of five apple leaf diseases, the model had a recognition accuracy of 97.36% with an incredibly small footprint of just 5.87 MB, which makes it a candidate for real-time agricultural use. This paper demonstrates the efficiency of light-weight deep learning architectures in plant disease detection under real-world environmental conditions [18].

The paper introduces a CNN-based model for detect apple leaf diseases using Inception-v3, combined with image segmentation techniques like canny edge detection and watershed transformation. The dataset consists of real-world apple leaf images divided into four classes: healthy, rust, scab, and multiple diseases. The proposed method enhances feature extraction by segmenting diseased regions, improving classification accuracy. Stratified 5 fold cross-validation was applied to evaluate the models, achieving 94.76% accuracy, 84.6% precision, 87.4% recall, and an 85% F1-score. The study highlights the model's superiority over previous methods and suggests its potential for practical agricultural applications, with future improvements focusing on real-world deployment and expanded datasets [19].

The paper suggests a diagnostic method for apple diseases using deep learning methods via a Multi-Scale Dense Classification Network. Data augmentation via Cycle-GAN was used to stabilize training, and synthetic images of anthracnose and ring rot were generated. Two network architectures were implemented: Multi Scale Dense Inception-V4 and Multi-Scale Dense Inception-ResNet-V2, using DenseNet along with multi-scale connections for facilitating feature reuse. The models' performance was validated via an 11-category dataset of healthy and diseased apple fruits and leaves and attained state-of-the-art classification accuracies of 94.31% and 94.74%. A cloud-based diagnosis system was also implemented to facilitate real-time diagnosis in agriculture. Future work involves increasing the dataset and improving the model's performance [20].

The paper presents deep learning method for canker disease detection in citrus and apple plant leaves through image embedding and machine learning techniques. The process entails leaf image preprocessing, feature extraction through deep learning models (Inception V3 and VGG16), and disease classification through different machine learning models such as Support Vector Machine (SVM), Gradient Boosting, Neural Network, and K-Nearest Neighbor (KNN). The study concludes that the combination of Inception V3 and a neural network has the maximum accuracy rate of 95.6%. This system prevents the need for manual identification of the disease, thus improving efficiency for farmers as well as agricultural practitioners. The paper also suggests a mobile app for real-time disease diagnosis, which would lead to timely intervention and minimize losses to crops [21].

This paper presents an enhanced Convolutional Neural Network (E-CNN) model for early disease detection and classification of Apple, Corn, and Potato crop diseases. The paper optimizes hyperparameters with care and tests different pre-trained CNN models, demonstrating the superior performance of the proposed E-CNN model, which achieves a 98.17% accuracy rate in fungal disease classification. Data augmentation techniques improve the generalization ability of the model, and it is integrated into a mobile app that supports real-time disease detection. The app allows farmers to take or upload a picture, receive instant disease classification, and receive treatment suggestions. This paper highlights the contribution of deep learning to precision agriculture and suggests further model efficiency improvements as well as increasing dataset diversity to support wider real-world applications [22].

III. Research Methodology

This study Implements a deep learning method for identifying and organizing plant diseases using Convolutional Neural Networks (CNNs) and other machine learning methods. The methodology research framework is categorized into three subsections: Research Design, Data Collection, and Data Analysis. These are collaborating in an effort to implement a systematic process for improving the accuracy and effectiveness of plant disease diagnosis.

A. Research Design

The research employs an experimental design approach where different deep learning models are created, experimented, and tested depending on how they perform in plant disease classification. The research focuses on fine-tuning convolutional neural network (CNN) architectures like ResNet, VGG16, MobileNet, and the Enhanced CNN (E-CNN) to improve classification accuracy. Image processing methods like segmentation and feature extraction are utilized before feeding data into the models. Hyperparameter tuning is also conducted to fine-tune activation functions, optimizers, dropout rates, and learning rates to improve model performance.

B. Data Collection

The dataset operated in this research is collected from publicly accessible repositories such as Plant Village and supplemented with additional real-world images of infected and healthy leaves. The collected dataset consists of images from crops such as apples, potatoes, and corn, categorized into different disease types. Image augmentation techniques, including flipping, rotation, contrast adjustments, and edge detection, are applied to enhance dataset diversity and improve model robustness.

C. Data Analysis

The research utilizes a number of data analysis and processing techniques to conclude the effectiveness of the deep learning models. Image preprocessing amid this stage entails the utilization of techniques such as resizing, noise removal, and normalization to ensure consistency of image input. Feature extraction is done by Convolutional Neural Network (CNN) image embedding models, for example, Inception V3 and VGG16, that enable the conversion of leaf images to component vectors to improve the accuracy of classification. Machine Learning Classification: SVM, Neural Networks, and Gradient Boosting are among the machine learning methods compared with CNN models to determine the best classifier. Performance Measure Evaluation: The models are compared based on important performance measures such as accuracy, precision, recall, F1-score, and confusion matrices to determine the capability of the classification process.

IV. Significance of the Research

The current study is highly relevant since it enhances precision agriculture by offering a automated and highly precise method for early identification of plant diseases. By utilizing machine learning and deep learning technique, the current study minimizes the use of manual inspection, which is often time-consuming and subject to human mistakes. The software developed with the current study enables farmers to take a picture or upload an image of diseased leaves, thus availing instant disease classification and treatment advice. This ability not only enables quick action but also avoids crop loss, maximizes yields, and ensures optimal use of pesticides. The findings of the current study have the potential to guide the development of more advanced intelligent agricultural systems and consequentially benefit large-scale agribusiness companies and small-scale farmers.

V. Conclusion

A detailed study on techniques implementing deep learning domains to the experience of apple leaf infection and outstanding performance regarding both accuracy and efficiency seem to be practically achievable. As shown in the above review, all of them perform significantly well achieving a very high accuracy (> 95%) to beat conventional machine learning-based methods such as SVM, k-NN and Random Forest on similar databases. Approaches focused on transfer learning, data augmentation and ensemble modeling seem to have come in leaps and bounds at achieving robustness and generalization. These allow for different image datasets, the ability to simulate real-world conditions, class imbalances, etc. Several other works combine deeper architectures like XDNet and attention mechanisms and increase accuracy on salient features in significantly more complex settings. These systems have been embedded in mobile applications and IoT technologies as stepping stones toward the future vision of bringing the products of scientific research from the laboratory to the field for real-time disease detection. They further provide scalable building blocks in achieving successful experimentation in controlled conditions en route to precision agriculture, with significant potential to intervene at timely points in reducing crop loss and enhancing yield. It mentions recurring issues: limited disease classes under investigation, reliance on curated datasets, and susceptibility to confounding variables. These studies emphasize such specific challenges that must be addressed for AI to achieve its full potential in agriculture as a whole. When taken in conjunction, the findings point to an exciting potential of AI tools to revolutionize disease management and consequently promote sustainability in agriculture.

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