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EXPLORING THE LANDSCAPE - A COMPREHENSIVE LITERATURE REVIEW ON APPLE PLANT LEAF DISEASE DETECTION APPROACHES USING DEEP LEARNING IN HIMACHAL PRADESH

Dr. Chandan Kumar [1], Vinod Sharma [2]

[1] Associate Professor, Department of CSE, CP University, Hamirpur, H.P, India
[2] Research Scholar, Department of CSE, CP University, Hamirpur, H.P, India

Corresponding Author
Dr. Chandan Kumar,
chandansharmahmr@gmail.com

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ABSTRACT

Himachal Pradesh is a beautiful hilly state in Northern India. It is known for its rich agriculture, especially apple farming, which is very important to its economy. Early detection of apple leaf diseases is crucial to prevent their spread and maintain the health of apple farms. Plant diseases can harm both the quantity and quality of crops. Recently, Convolutional Neural Networks (CNNs), a type of deep learning method, have been very useful in spotting leaf diseases and have helped farmers a lot. However, most studies conducted so far are general and do not focus on the special climate and farming style of Himachal Pradesh. This study presents a new method for detecting plant leaf diseases using deep learning. It focuses on how these methods can be useful in Himachal Pradesh. These new techniques can help prevent apple leaf diseases early, improve crop production, and improve disease control in the region. This study also aims to support local farmers by providing them with easy-to-use and affordable technology. By combining modern AI tools with traditional farming knowledge, the overall efficiency and sustainability of apple farming can be significantly improved.

Keywords: CNN, MobileNetV2, ResNet50, AI, Transfer Learning, SVM, PlantVillage

1. INTRODUCTION

Many countries consider farming to be the basis of their economic growth. It provides jobs in villages, provides food, and supports industries and medicine making. However, farmers face many problems, such as changing weather and environment, which affect crop growth (Ferentinos et al., 2018). A major challenge in farming is plant leaf diseases and pests, which are difficult to notice early (Abbas et al., 2021). These problems can cause heavy crop losses and lower yields for farmers. To address this, experts have studied machine learning, image tools, and deep learning to identify plant diseases. Recently, deep learning has become common for identifying and sorting plant diseases (Thapa et al., 2020; Khan et al., 2022; Sibiya et al., 2021). However, most of the work done is general and does not focuson the special climate and farming methods of Himachal Pradesh. The changing land and weather of this region require special models to detect diseases. This review examines the best deep learning methods for detecting leaf diseases, with a focus on apple farming in Himachal Pradesh. The aim is to fill the gap between general ways and local farming needs and help farmers grow crops in a better and lasting way. It also aims to guide future research in developing smart and low-cost tools for disease detection. These tools can help even small farmers use technology to protect their crops.

2. RELATED WORK

In recent years, new ideas in Artificial Intelligence (AI) and vision tools have brought significant changes in image work and computer vision tasks. These changes have helped in many fields, such as health, money, farming, and scene use (Chen et al., 2022; Yang et al., 2022; Hassan & Maji, 2022; Math et al., 2022). AI improves the speed, accuracy, and performance in these important fields.

Smart tools in farming have grown rapidly, helping farmers use modern methods (Barbedo, 2019; Zeng et al., 2020). Over the last 15 years, many experts have tested models to identify and group plant leaf diseases (Atole et al., 2018; Kuricheti & Supriya, 2019; Lv et al., 2024). Szegedy et al. (2015) demonstrated a strong CNN method for rice disease detection using deep learning.

Their results showed accuracies of 80% (TL), 85% (CNN+TL), 90% (ANN), and 95% (CNN+TL+ANN+GA). In ML, Random Forest gave 97.12% accuracy, CNN yielded a better result of 98.43%, demonstrating its great strength.

Bi et al. (2022) used MobileNet to find apple leaf disease with a smart model. MobileNet is a lightweight CNN that works quickly and efficiently on mobile phones. Their model identified apple leaf disease with 94.5% accuracy in real time.

It can distinguish between healthy and sick leaves while using fewer resources. The model is useful for farmers in the field using mobile devices. The authors stated that MobileNet is a good and simple tool for crop safety. They also suggested future work to improve the model's power in different weather and background settings in real-life fields.

Li et al. (2022) made a CNN model based on AlexNet for apple leaves. They used dilated filters and parallel layers to identify coarse features. This setup helped reduce the parameters while maintaining a wide view range. Shortcut links helped the network to learn better from complex images. The model achieved a final accuracy of 97.36 % %and had a size of 5.87 MB.

This shows that it works well without requiring heavy computing power. Kaur et al. used a MobileNet model for apple leaf disease detection. They tested 334 leaf images with Alternaria blotch and rust disease.

Although it runs well on phones, the accuracy is only 73.50%. This shows that the balance between size and quality remains a challenge. Models for low-power tools must be strong and sufficiently accurate.

Bi et al. (2022) again tested MobileNet for apple leaf identification. They were trained on apple images with scab, mildew, and rust diseases. This model showed 94.3% accuracy with fast and clear results. It worked well on mobile devices and assisted with real-time checks. Their results proved that MobileNet is suitable for smart farming practices. The study showed that it can be useful for field-based crop monitoring.

Yu et al. (2022) suggested an improved ResNet model for leaf disease detection. They improved it to solve problems such as overfitting and weak results. Their new model achieved 96.7% accuracy in apple leaf detection. It found good features and performed well under poor lighting conditions. The better ResNet also saved time and used a lower computing load. Their work showed that ResNet is suitable for real-time and smart farming applications.

Upadhyay and Kumar (2022) built a CNN for rice leaf disease detection. They used Otsu's method to remove noise before training their model. Their CNN achieved 99.7% accuracy on 4,000 healthy and sick samples. Anari (2022) used SVM and deep tools on 6 crop datasets together. His method achieved 98.5% accuracy for crops such as apples, corn, and grapes.

Chao et al. (2021) made a model using Xception and SE modules. Xception uses depthwise filters, and SE focuses on useful parts. Together, these factors made the model more focused and detail-sensitive. Their model achieved 97.4% accuracy with strong results on all tests. It handled noise, lighting, and angles better than the other models.

This method may help real-time applications in farming on smart devices. Many experts have attempted to improve apple leaf disease detection. Yong et al. used DenseNet-121 with 3 smart learning methods. They achieved 93.51%, 93.31%, and 93.71% accuracy, all of which were higher than those of previous studies. Their model performed better than the basic multi-class loss method. Qian et al. developed a new VGG16 model to detect leaf diseases.They reduced the model size and accelerated training using batch normalization. They used global average pooling to reduce the number of extra parameters. Their model achieved 99.01% accuracy and used only 11% of the size. It was 6.3% more accurate and 99.4% faster in training than the VGG16.

3. RESEARCH GAP IDENTIFIED

This review examines several studies on plant disease detection and diagnosis systems. This review highlights the limitations of old methods and helps improve clear research goals. After reading many works, it was observed that in past years, deep learning CNN methods have become a key tool used in farming studies. Although many deep learning models have been developed and used for apple leaf disease checking, this field still has more to explore and can be improved for better apple leaf disease checking.

From this literature review, we found that most existing studies rely on global datasets (e.g., PlantVillage), which may not represent the specific environmental and disease conditions of Himachal Pradesh. There is a lack of datasets curated specifically for apple orchards in Himachal Pradesh, capturing local disease variations influenced by the unique climate, soil, and altitude. These studies often focus on common diseases, such as apple scab and powdery mildew, ignoring rare diseases specific to this region. Therefore, there is a need to explore rare and region-specific diseases affecting apple crops in Himachal Pradesh. Most models are validated on laboratory-generated datasets and lack validation under field conditions. Extensive field tests must be conducted in apple orchards across Himachal Pradesh to evaluate the real-world performance of the proposed solutions.

To overcome the research gaps in apple leaf disease detection in Himachal Pradesh, a multifaceted approach is necessary. First, region-specific datasets should be developed that capture the unique climatic and soil conditions affecting disease prevalence in apple orchards. These datasets should focus on both common and rare diseases specific to Himachal Pradesh, which are often overlooked in global datasets. Extensive field testing is essential to evaluate the model performance under real-world conditions and address the discrepancies between laboratory datasets and field conditions. Additionally, hybrid deep learning models combining CNNs, Xception, and traditional machine learning techniques should be explored to enhance disease classification accuracy. Incorporating expert knowledge of regional disease patterns can further improve model precision. Real-time, mobile-based applications capable of disease detection in the field should be developed to make these technologies more accessible to farmers. Data augmentation and transfer learning can address the challenge of limited local data.

4. PROPOSED METHODOLOGY

This study aimed to investigate apple leaf diseases using deep learning and image recognition techniques. To obtain accurate outcomes, this study focused on image-oriented verification. This will clarify how deep learning assists in disease detection by analyzing images of leaves. This study will examine the issues, categories of illnesses, and methods for identifying beneficial characteristics from images. This study was conducted in three primary steps.

Phase I: In this stage, the research gathered and created an appropriate dataset of images of apple leaves. These images feature healthy foliage, foliage affected by diseases, and foliage infested with pests. These visuals are quite helpful for assessing the health of apple leaves during Phase II. Moreover, the results from this stage will be used in Phase III to determine the location of the disease or pest on the leaf.

Phase II: This phase, a model is constructed using a Convolutional Neural Network (CNN). It aids in determining and comprehending whether the leaf is healthy or diseased. This model employs deep learning to gain insights from numerous leaf images.

Phase III: At this stage, the model improves its ability to identify and indicate the precise location of diseases or pests on the leaf. It aids in identifying the kind of disease or pest observed in the leaf images.

The objective is to develop a system that enables farmers to quickly determine the health of their apple trees. This system can conserve time and facilitate prompt responses. This will also decrease crop harm and enhance yield. The model can additionally be utilized in mobile applications for convenient use in various fields. Future efforts might enhance the system's performance across various weather conditions. The complete design of the model for assessing apple leaf diseases is illustrated in Figure 1.1.

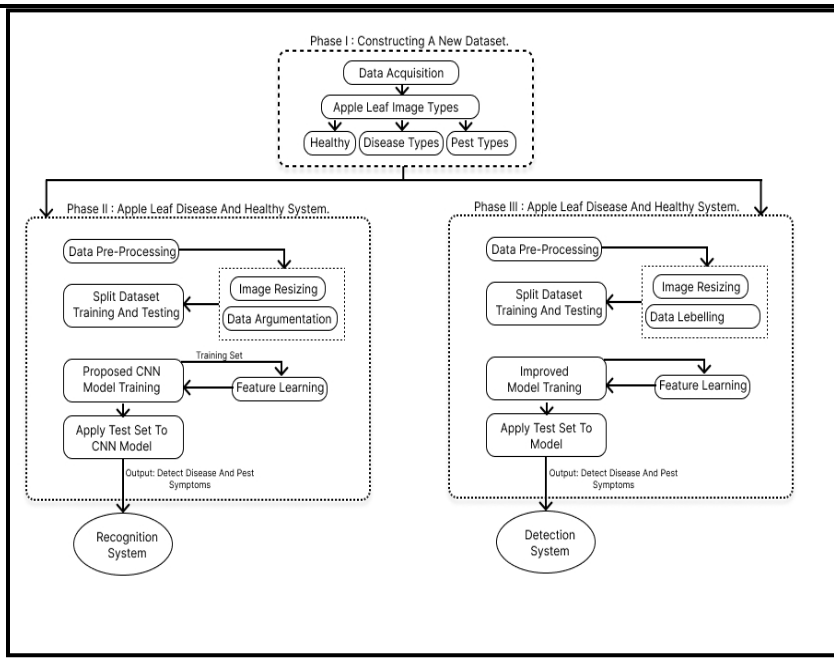

Figure 1.1 Proposed Methodology

5. PROPOSED APPLE LEAF DISEASE RECOGNITION CNN ARCHITECTURE

The suggested CNN model processes an input image measuring 227 × 227 × 3 pixels in size. It includes five convolutional layers, each featuring a unique filter count and varying window sizes. In the convolution layer, an input image is processed using various kernels, leading to the creation of convoluted images (feature maps) linked to each filter. The convolution process entails demanding calculations that become more intricate with larger image dimensions and an increased number of convolution layers. The weights that can be adjusted in the filter act as parameters. The suggested CNN structure includes two fully connected layers featuring 512 and 256 neurons in that order, followed by the final dense layer. A SoftMax function was employed in the last dense layer to determine the predicted probabilities for five distinct apple leaf diseases, along with one healthy leaf variety. The proposed CNN architecture is illustrated in Figure 1.2. The suggested CNN architecture comprises five blocks, with the initial two blocks containing convolution layers, BN, Activation, and Max pooling, whereas the final three blocks encompass convolution layers, BN, Activation, Max pooling, and dropout layers.

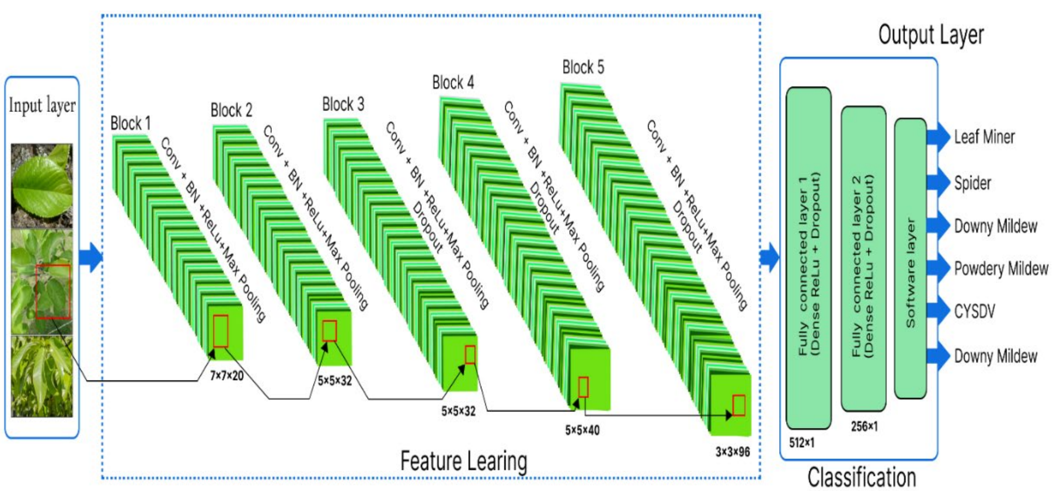

Figure 1.2 Proposed Apple Leaf Diseases Recognition CNN Architecture Apple leaf Disease Detection Model

Owing to the expansion of the agricultural sector, particularly in the area of leaf disease identification, numerous studies and initiatives have employed deep learning methods to recognize leaf diseases and pests. Motivated by recent developments in deep learning, this study proposes a novel method for identifying diseases and pests in apple leaves by enhancing the current model. In this study, we improved the foundational algorithm to develop a superior model. It is essential to address the difficulties in correctly identifying leaf symptoms and enhancing the initial algorithm. Consequently, the revised model will be enhanced to effectively identify even minor indicators of apple-leaf diseases and pests. The upgrades implemented in the new detection model will be designed to improve its capability to accurately recognize and categorize various disease and pest types on apple leaves. The primary objective was to deliver a robust and efficient solution that fosters improved farming methods and aids in the early detection and control of diseases in apple production.

6. CONCLUSION

In conclusion, this review emphasizes the critical role of deep learning in advancing plant leaf disease detection, particularly in the context of apple farming in the state of Himachal Pradesh. Despite the rapid growth in AI and machine vision algorithms for plant disease recognition, many existing studies have been generalized, often relying on global datasets that fail to reflect the unique environmental and agricultural conditions specific to Himachal Pradesh. This mismatch results in models that are not fully optimized for the region's distinctive climate, soil, and topographical factors. Furthermore, the focus of many studies on common diseases, such as apple scab and powdery mildew, overlooks rare diseases that are particularly prevalent in the region, thus limiting the comprehensiveness of disease identification and management in this region. To address these gaps, this study proposes a region-specific approach, calling for the development of localized datasets that capture both common and rare apple diseases unique to Himachal Pradesh. This would enable the creation of more precise models that account for local variation. Furthermore, this study highlights the importance of field validation to ensure that deep learning models perform effectively in real-world conditions, as most current research is based on controlled laboratory datasets. The integration of hybrid deep learning techniques, combining Convolutional Neural Networks (CNNs), Xception models, and traditional machine learning methods, could enhance classification accuracy and robustness. Additionally, mobile-based applications for real-time disease detection can empower farmers with timely information for improved crop management. Through data augmentation and transfer learning, challenges arising from limited local data can be addressed, ensuring that AI technologies can be successfully implemented to improve apple farming in the state. This comprehensive approach will help bridge the gap between theoretical models and practical on-the-ground agricultural needs, fostering sustainable farming practices in the region.

CONFLICT OF INTERESTS

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