Machine Learning Model to identify and detect Grape Disease: Literature Survey

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Abstract

This research work explores the landscape of automated crop disease identification techniques, focusing on grape leaf disease detection. The study highlights the prevalent use of publicly available crop leaf image datasets in existing research, which often lack the complexity of real-time datasets, leading to challenges in accurate disease identification and generalization. With a significant portion of research contributions relying on such datasets, there is a critical need for advanced techniques, particularly utilizing Convolutional Neural Networks (CNN), to process real-time images effectively. To address these limitations, this survey emphasizes the necessity for a more comprehensive and precise automated system for grape leaf disease recognition. The proposed approach involves leveraging CNN models on a newly curated grape leaf image dataset and implementing tailored hyperparameter tuning to enhance system performance and generalizability.

Keywords: Convolutional Neural Networks Deep Learning Disease Classification Machine Learning Transfer Learning

1. Introduction

Image Processing, as detailed in [1], focuses on enhancing images captured from cameras or sensors for various purposes. This process includes several stages such as image acquisition, pre-processing, segmentation, feature extraction, and classification, as explained in [2]. This scientific field primarily employs classification and clustering techniques, as mentioned in [2]. Grapes, which are among the most vital fruits, are prone to diseases that can lead to yield losses of 10% to 30%. Thus, early detection of these diseases is essential to offer solutions to farmers, helping to minimize damage and boost productivity. Farmers typically rely on visual inspection with the naked eye to identify these diseases. However, this method can be unreliable. Frequently, farmers need to consult experts for disease detection, which can be time-consuming, particularly on large farms. Grape cultivation is vulnerable to substantial losses due to leaf diseases that damage the leaves and create adverse conditions for optimal growth. These plant diseases impact various parts of the grapevine, including the leaves, fruits, and stems. Early detection of leaf diseases remains a significant challenge in agricultural practices. Advanced image processing techniques are utilized in various fields, including industrial inspection, medical imaging, remote sensing, and agricultural processing. In agriculture, these digital image processing methods have proven to be effective tools for applications like plant recognition, soil quality assessment, and crop yield estimation. In agriculture, computerized image processing techniques are used to identify plant diseases. These diseases can be bacterial, viral, fungal, and more. In India, common fungal diseases on grape leave include Downy Mildew, Powdery Mildew, and Anthracnose. Traditionally, the detection and identification of plant diseases relied on manual inspection by farmers, scientists, and breeders. This method required significant expertise and understanding for accurate results. However, as the volume of plants increased, manual inspection became cumbersome and time-consuming, making it less efficient overall.

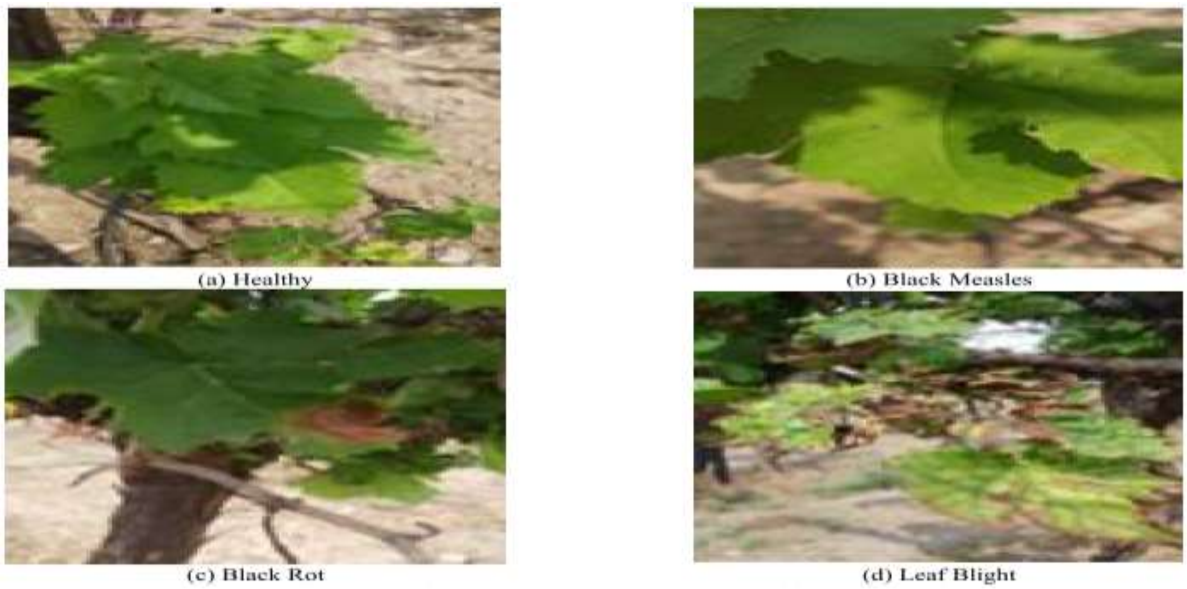


Figure 1: Categorization of Grape Leaf Images (Healthy & Diseased)

2. Literature Survey

Many research studies have delved into the detection of plant diseases due to the critical importance of identifying and classifying diseases for the effective treatment of affected plants. The agricultural sector is increasingly utilizing these methods, driven by technological advancements. The continuous development of machine learning (ML) and deep learning (DL) techniques has significantly enhanced the identification and classification of plant diseases. Here, we review five specific studies in this field.

In the literature, the application of Convolutional Neural Networks (CNN) for the detection of grape leaf diseases was explored. Liu et al. [3] introduced the DR-IACNN model, which efficiently detects grape leaf diseases by utilizing modules such as Inception-v1, Inception-ResNet-v2, and SE-blocks to identify multiscale and minor diseased areas. Xie et al.[4] focused on enhancing the classification accuracy of grape leaf diseases using a specialized CNN technique called Dense Inceptional CNN (DICNN). To address the issue of overfitting, data augmentation techniques were applied to grape leaf images. Shantkumari and Uma [5] utilized machine learning methods to identify grape leaf diseases, leveraging various features extracted from leaf images and employing multiple classifiers to achieve high categorization accuracy. Additionally, transfer learning methods were implemented to improve model performance and achieve comparable accuracy in disease classification. Ansari et al[6]. proposed an advanced approach based on support vector machine (SVM) and image processing for the identification and categorization of grape leaf diseases.

Their research demonstrates superior results compared to other methodologies. Lin et al.[7] introduced GrapeNet, a compact CNN model specifically designed for detecting grape leaf diseases, with enhanced accuracy achieved through the use of transfer learning techniques. Phukhronghin et al. [8] developed a diagnostic system for grape leaf diseases utilizing CNNs and Support Vector Machines (SVM). Various contributions extensively reviewed the latest techniques in automating agricultural processes, detailing the methods used, their applications, and the challenges faced. The utilization of deep learning to tackle complex issues in various fields has been highlighted by Hinton et al. [9]Fuentes et al.[10 focused on creating an optimized CNN model for precise disease detection in tomato plants, incorporating algorithms such as Faster R-CNN, Region-based Fully CN (R-FCN), and Single Shot Multibox Detector (SSD), along with VGG net and ResNet feature extractors. Their results showed improved performance indicated by an increase in average precision. Joshi et al. [11] proposed a method for identifying virus-induced diseases in a specific crop species, Vigna Mungo, by evaluating the condition of plant leaves and categorizing them into three groups: healthy, mildly diseased, and substantially sick Data obtained from fields of Vigna Mungo was used in the study by Fenu and Malloci,[12] where they introduced a multioutput approach for detecting plant diseases and evaluating their severity in pear leaves. This method involves a multioutput convolutional neural network (CNN) that aims to predict multiple outputs from a single input. The proposed model is designed to detect and assess the presence of stress (disease) and its severity level in a pear leaf. By incorporating Global Average Pooling (GAP) and Batch Normalization (BN) after extracting features from pre-trained CNNs, the model's robustness, stability, and learning capabilities are enhanced. Vashisht et al. [13] introduced a prognostic measure by utilizing a Gaussian filter in the data preprocessing stage with pre-existing CNN models. Their research also focused on identifying various disorders. Hybrid models, combining different methodologies, have proven to be more effective in improving the accuracy of symptom identification in damaged crops, while also reducing the training time significantly. Ahmad et al.[14] investigated the optimization of pre-trained models like VGG16, VGG19, ResNet, and Inception V3 by fine-tuning hyperparameters. Training most CNN models typically requires a considerable amount of time, and for the classification of new diseases, retraining of the models is necessary.

Moreover, mobile devices lack the computational capacity required for Convolutional Neural Networks (CNN). To address this limitation in crop disease identification, Morbekar and Ponnusamy introduced the You Only Look Once (YOLO) algorithm. YOLO offers faster processing speeds compared to traditional CNN models by utilizing a single CNN to estimate both bounding boxes and class probabilities in a single iteration, enabling effective recognition of multiple diseases on a single leaf with increased confidence. Huayhongthong explored the use of Ensemble Modeling and Deep Transfer Learning for incremental object detection, employing YOLO and Transfer Learning models for disease class detection. The decision model utilizes a bagging approach to select the class label with the highest probability score. Evaluation metrics in the studies primarily include accuracy, precision, recall, F1-score, and mean average precision, with the latter providing valuable insights into the overall performance of crop disease diagnosis and classification models, surpassing sole reliance on accuracy. Research publications analyzed show classification accuracies ranging from 80% to 95% when the number of classes is limited. However, as the number of disease categories increases, models require significant time for training and evaluation. While CNN models have shown potential to enhance performance in crop disease recognition tasks, it is noted that many existing contributions rely on publicly available crop leaf image datasets for model training and evaluation. These datasets typically consist of single plant leaf images captured in controlled or simple background environments, posing challenges in accurately identifying and distinguishing diseases in real-time datasets and limiting the generalizability and accuracy of results on unforeseen images.

While previous studies suggest that CNN models can enhance performance in crop disease recognition tasks, our research indicates that many existing contributions rely heavily on publicly available crop leaf image datasets for model training and evaluation. These datasets, as documented in literature, typically consist of single plant leaf images captured in controlled or simple background settings. However, utilizing such models on real-time datasets may lead to inaccuracies in disease identification and discrimination, limiting their ability to generalize effectively and provide precise results on unfamiliar images. Approximately 60% of research contributions in plant leaf disease identification utilize public datasets, highlighting the necessity for a technique capable of accurately processing real-time images using CNN and advanced techniques. Addressing these challenges underscores the critical need to develop a more comprehensive and precise automated system for crop disease identification and classification that can effectively handle real-time data. Our study introduces a novel approach that leverages CNN models on a newly curated grape leaf image dataset to enhance system generalizability. Additionally, we propose tailored and efficient hyperparameter tuning to improve the overall performance of grape leaf disease recognition.

3. Problem statement

The problem statement revolves around the limitations of existing crop disease recognition systems, particularly in the context of grape leaf disease detection. Current approaches heavily rely on publicly available crop leaf image datasets, which often consist of single plant leaf images captured in controlled environments. When applied to real-time datasets, these models struggle to accurately identify and differentiate diseases, leading to challenges in generalization and providing precise results on unfamiliar images. With around 60% of research contributions in plant leaf disease identification utilizing public datasets, there is a clear need for a more effective technique that can process real-time images accurately using advanced methods like CNN. Therefore, there is a pressing requirement to design a more generalized and accurate automated system for grape leaf disease identification and classification that can handle real-time data efficiently. This study aims to address these challenges by introducing a novel approach that utilizes CNN models on a newly curated grape leaf image dataset to enhance system generalizability. Additionally, the study proposes customized hyperparameter tuning to boost the overall performance of grape leaf disease recognition.

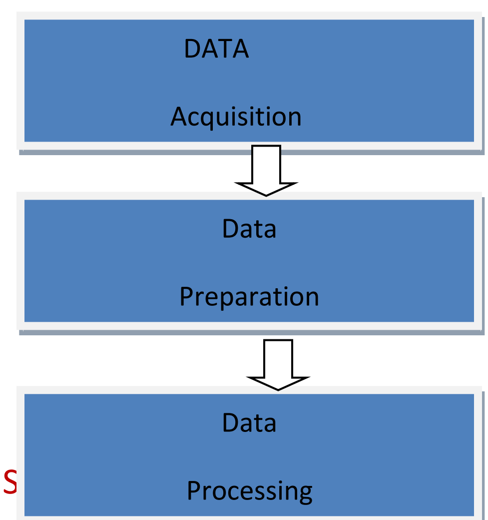
4. Objectives

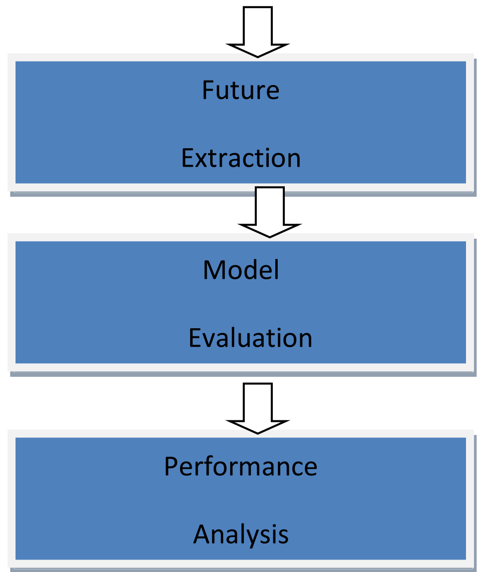
The major objectives of the study can be outlined as follows:

1. Evaluate the limitations of existing crop disease identification techniques that heavily rely on publicly available crop leaf image datasets, which may not accurately generalize to real-time datasets.
2. Address the challenges associated with accurately identifying and discriminating grape leaf diseases in real-time datasets by proposing a novel approach that leverages Convolutional Neural Networks (CNN) on a newly curated grape leaf image dataset.
3. Enhance the generalizability and accuracy of automated crop disease identification and classification systems, particularly focusing on grape leaf disease detection.
4. Develop customized hyperparameter tuning strategies to optimize the performance of grape leaf disease recognition models, thereby improving the overall efficiency and effectiveness of the system.
5. Provide insights into the importance of utilizing advanced techniques, such as CNN models, for processing real-time images in crop disease identification, emphasizing the need for more comprehensive and precise automated systems in this domain.

5. Proposed Methodology

The proposed methodology of the work can be outlined as follows





Data Acquisition: Collect high-resolution images of grape leaves from grape fields in specific regions, ensuring a balance between healthy and diseased leaf samples. Capture images from various perspectives and at different time intervals to create a diverse dataset.

Dataset Preparation: Categorize the collected images into two main groups: Healthy and Diseased. Pay attention to optimal lighting conditions during image capture to ensure quality data.

Data Pre-processing: Conduct pre-processing and segmentation of the acquired images to enhance the quality and prepare them for feature extraction and model training.

Feature Extraction: Utilize pre-existing models to extract relevant features from the grape leaf images. Fine-tune these features using a neural network to enhance disease type prediction accuracy.

Model Training: Implement deep learning techniques, particularly Convolutional Neural Networks (CNN), to analyze multi-scale information of the grape leaf images and identify disease patterns. Utilize transfer learning with pre-trained models to improve training efficiency.

Hyperparameter Tuning: Fine-tune the hyperparameters of the CNN models, such as batch size, number of epochs, and activation functions, through iterative experimentation to optimize model performance.

Model Evaluation: Rigorously evaluate the trained CNN models against a comprehensive test dataset to assess accuracy, validation loss metrics, and generalizability on real-time grape leaf images.

Performance Analysis: Compare the performance of the proposed approach with existing techniques, showcasing superior accuracy and lower loss values. Demonstrate the effectiveness of the model in real-time applications, particularly in the agricultural sector, to assist farmers in precise grape leaf disease identification and classification.

By following this methodology, the study aims to develop a robust and accurate automated system for grape leaf disease detection, leveraging advanced techniques to enhance performance and generalizability.

6. Conclusion

The survey highlights the critical challenges faced by existing automated crop disease identification techniques, particularly in the context of grape leaf disease detection. The reliance on publicly available crop leaf image datasets, which may not accurately represent real-time scenarios, poses significant limitations in generalization and precise disease identification. The study emphasizes the necessity for advanced techniques, such as Convolutional Neural Networks (CNN), to process real-time images effectively and improve the accuracy of disease recognition systems.

By proposing a novel approach that leverages CNN models on a curated grape leaf image dataset and implementing customized hyperparameter tuning, the study aims to enhance the generalizability and accuracy of automated crop disease identification systems, specifically focusing on grape leaf diseases. The results demonstrate superior accuracy and lower loss values compared to existing approaches, showcasing the potential of the proposed methodology in assisting farmers with precise grape leaf disease identification and classification.

Overall, the survey underscores the importance of developing more comprehensive and precise automated systems for crop disease identification, particularly in the agricultural sector. By addressing the limitations of existing techniques and leveraging advanced methodologies, the study contributes to the advancement of efficient and effective grape leaf disease detection systems, ultimately benefiting farmers and enhancing crop productivity.

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