International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Enhancing Plant Disease Recognition on Mobile Devices: A Hybrid Approach with CNNs, Rule-Based Systems, and Machine Learning

Prem Bhandari[1], Ujwal Chaudhari[1], Ekta Kapase[1], Atharva Bodake[1]

[1] Final Year Student, Department of Computer Engineering, Zeal College of Engineering and Research, Pune, Maharashtra, India

ABSTRACT

The food industry has significantly boosted the agricultural economy of India, historically known as the largest producing nation with a strong agricultural identity. The primary crops include grains, fruits (such as potatoes, oranges, tomatoes), sugarcane, and specially cultivated grains and cotton. Maharashtra, a state in India, has experienced substantial economic growth, particularly attributed to citrus and cotton industries. This growth has generated employment opportunities and holds significant potential for the state's economic advancement. To sustain the prosperity of these industries, the government is actively addressing concerns related to disease control, Labor costs, and global market dynamics.

In recent times, citrus canker, citrus greening, and black spots on cotton have emerged as severe threats to citrus crops in Maharashtra. Farmers are troubled by the costs associated with tree loss, scouting efforts, and the use of chemicals to control diseases. An automated detection system could play a crucial role in preventing and minimizing these losses, thereby safeguarding the industries, farmers, and the overall economy.

This research focuses on developing disease detection through pattern recognition methods for various crops. The image detection process has some main categories which are image acquisition, image processing, and pattern recognition. Image preprocessing is used to process the image in a clear and clean format. Pattern recognition methods are then utilized to classify samples into different crop conditions.

To assess classification approaches, results will be compared across different crops for disease detection. The goal is to demonstrate a classification accuracy surpassing existing models, reaching the highest. The research primarily aims to showcase the feasibility of disease detection based on visible symptoms on fruits or leaves. Data collection and initial knowledge acquisition are planned through offline and online approaches. The overall motive is to have accurate detection of the fruits and leaves thereafter using those results for diseases detection.

Keywords: Machine Learning Algorithms, Plant disease detection, Image Recognition, Rule-Based mechanism, CNN, Detection technologies, Color Grading

I. INTRODUCTION

Crop stress, caused by factors like viral infections or environmental issues such as air pollution, can significantly impact crop growth, development, and yield. The visible symptoms of stress, like disruptions in water balance control leading to reduced photosynthesis and increased leaf surface temperature, are observable by humans. However, the scale of modern farms and the decline in farm labour make it challenging to assess entire fields. Additionally, some diseases may not manifest visible symptoms within the human eye's sensitivity range.

A research approach employing pattern recognition and the colour co-occurrence texture method is proposed for the detection. Digitized RGB images representing various disease conditions are captured using an image acquisition system. To address the detection of diseases, a novel research methodology is put forth, integrating pattern recognition and the colour co-occurrence texture technique. The process involves the acquisition of digitized RGB images representing diverse disease conditions through a specialized image acquisition system. For each HSI (hue, saturation, intensity) image, three spatial grey-level dependence matrices (SGDMs) are systematically generated. From each sample, essential texture features are extracted, forming the basis for subsequent analysis.

A crucial element in this methodology is the incorporation of stepwise discriminant analysis, aimed at identifying valuable texture features across three distinct colour combinations. These combinations include 1) HSI, 2) hue and saturation (HS), and 3) intensity (This strategic approach enables a comprehensive examination of texture features within various colour contexts,

enhancing the accuracy and efficacy of disease detection processes. The method's adaptability to diverse colour combinations ensures a robust and versatile framework for addressing the complexities of disease recognition in agricultural settings.
In general, the back-propagation neural network method demonstrates high performance with accuracy exceeding 93%. While the support vector machine yields good classification results, its accuracy is comparatively lower. The back-propagation method is recommended for disease detection due to its superior performance and straightforward implementation, making it suitable for a detection system. Hence, we would use rule-based system for the above algorithms to work efficiently.

II. LITERATURE SURVEY

Plant diseases represent a significant threat to global food security, often resulting in substantial crop losses, diminished yields, and economic hardship for farmers worldwide. Timely detection and proactive management of these diseases are pivotal for sustaining agricultural productivity and ensuring food sufficiency. Recent advancements in technology, particularly in the domains of computer vision and machine learning, have sparked innovation in the realm of plant disease detection and management. Among these innovations, mobile applications have emerged as promising tools for delivering real-time disease recognition and prevention guidance to farmers, capitalizing on the widespread availability of smartphones and the accessibility of digital technologies in agricultural settings.

This literature survey endeavours to explore the landscape of existing research and developments pertaining to mobile applications designed for plant disease recognition and prevention. By scrutinizing past studies and projects, we aim to elucidate the methodologies, technologies, and outcomes that characterize this evolving field. Through a comprehensive review of the literature, we seek to discern prevalent trends, challenges, and opportunities, thereby shedding light on the efficacy, scalability, and practical implications of employing mobile applications as aids in agricultural disease management.

From our review of the literature, we have identified several gaps and opportunities for research in this field.

1. Farmers express concerns about the expenses associated with tree loss, scouting activities, and the use of chemicals to manage diseases. Implementing an automated detection system could aid in preventive measures, thereby reducing substantial losses for industries, farmers, and the overall national economy.
2. The sheer size of contemporary farms, coupled with a decline in available farm labour, poses challenges in conducting comprehensive field assessments. Additionally, certain diseases exhibit symptoms beyond the visible range (400 - 700 nm), which is beyond the sensitivity of the human eye.
3. Our survey underscores the close correlation between soil health and plant productivity.
4. There is a lack of awareness among farmers regarding the adverse effects of excessive chemical use on plant productivity.

Table 1: Study of existing methodology being used: -

Paper	Method	Observation
Aanis Ahmad et al. Toward Generalization of Deep Learning-Based Plant Disease Identification Under Controlled and Field Conditions	***Transfer Learning***	***Improved DL model generalization***
Khalid M. Hosny et al. Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern	***CNN and Local Binary Pattern***	*Solution for early control of diseases*
SK Mahmudul Hassan Plant Disease Identification Using a Novel Convolutional Neural Network	*CNN*	*Only few parameters included*
Muhammad Hammad Saleem et. Al A Performance-Optimized Deep Learning-Based Plant Disease	*RFCN*	*Mean average precision of 93.0%*

Detection Approach for Horticultural Crops of New Zealand		
Y. Harshavardhan Reddy Plant Leaf Disease Detection using IoT, DL and ML	*Random Forest and CNN*	*Opportunity for improvement in the supplied models' predictions*
Mitali V. Shewale High performance deep learning architecture for early detection and classification of plant leaf disease	*CNN*	*High-precision disease classification*
Zhiyong Xiao Leaf Disease Detection Based on Lightweight Deep Residual Network and Attention Mechanism	*SE-VRNet*	Effective and suitable for identifying leaf diseases using mobile devices.
Emre Özb˙ilge Tomato Disease Recognition Using a Compact Convolutional Neural Network	*Compact six-layer CNN*	Accuracy, F1 score, Matthews correlation coefficient, true positive rate, and true negative rate of 99.70%, 98.49%, 98.31%, 98.49%, and 99.81%, respectively, on 9,077 unseen test images

III. EXISTING DISEASE DETECTION METHODS

A. Manual Inspection

One of the conventional methods historically utilized in plant disease detection involves visual inspection by agricultural experts. Trained professionals would visually examine plants for symptoms such as discoloration, lesions, or abnormal growth patterns indicative of diseases. While this method has been relied upon for years, its subjectivity and dependency on human expertise can lead to inconsistencies and inaccuracies in disease identification, particularly when dealing with subtle or early-stage symptoms. Moreover, visual inspection is time-consuming and labour-intensive, making it impractical for large-scale or real-time monitoring efforts.

B. Laboratory Based Technique

Another traditional approach to plant disease detection involves laboratory-based techniques, such as microscopic examination and culturing of plant samples. Microscopic examination allows researchers to observe pathogens or characteristic structures associated with diseases, aiding in their identification. Similarly, culturing involves isolating and growing pathogens from plant samples on nutrient media to facilitate their characterization.

While laboratory-based techniques offer high specificity and accuracy, they are resource-intensive, requiring specialized equipment, trained personnel, and time-consuming procedures. As a result, these methods are often reserved for research purposes or cases where detailed pathogen identification is necessary rather than for routine field monitoring.

C. Digital Image Analysis

In recent years, technological advancements have led to the development of automated imaging systems for plant disease detection. These systems utilize digital cameras or sensors to capture images of plants, which are then analysed using computer vision and machine learning algorithms. Image analysis techniques, such as pixel classification, texture analysis, and pattern recognition, are employed to identify diseased regions based on visual cues.

While automated imaging systems offer the potential for rapid and non-destructive disease detection, their effectiveness may vary depending on factors such as lighting conditions, image quality, and the diversity of plant species and diseases. Additionally, the accuracy of automated systems relies on the quality and diversity of training data used to develop the underlying algorithms, emphasizing the importance of robust dataset collection and annotation processes.

IV. PROPOSED DISEASES DETECTION METHOD

The mobile application for plant disease recognition and prevention encompasses several intricate modules and materials, each crucial to its functionality and efficacy. Firstly, the Image Acquisition Module serves as the gateway to capturing images of plant leaves or affected areas, utilizing the smartphone's camera or a connected camera module, and accessing it through software development kits (SDKs). Subsequently, the pre-processed images undergo enhancement and normalization in the Image Preprocessing Module, leveraging image processing libraries like OpenCV for noise reduction and overall quality enhancement. Following this, the Feature Extraction Module extracts pertinent features from the pre-processed images, employing machine learning or computer vision algorithms to analyse colour histograms, texture patterns, and shape descriptors, facilitating accurate disease identification.

The heart of the application lies in the Disease Recognition Module, which employs sophisticated machine learning models such as Convolutional Neural Networks and Support Vector Machines. These models are trained on datasets comprising labelled images of diseased plants, employing rigorous training and validation procedures to ensure accuracy and reliability in disease diagnosis. Complementing this module is the Database Integration Module, responsible for storing and retrieving comprehensive information on plant diseases, including symptoms, preventive measures, and treatment options. Integration with external databases or online resources related to plant pathology enriches the application's knowledge base.

Real-time notifications play a pivotal role in alerting users about detected diseases and recommended preventive measures, facilitated by the Real-Time Notification Module. Leveraging push notification services and seamless integration with the mobile operating system, timely alerts are delivered to users, enabling proactive disease management. The User Interface (UI) Module ensures an intuitive and user-friendly interaction with the application, employing design tools and mobile app development frameworks to craft visually appealing interfaces. Additionally, the backend infrastructure provides the necessary support for data storage, processing, and communication with external services, leveraging cloud computing platforms and server-side programming languages.

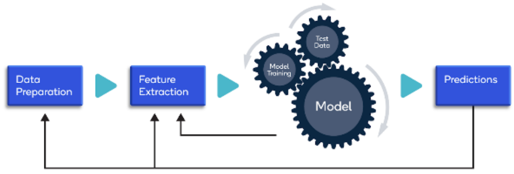

Fig.1: Image Recognition Flow

Testing and validation tools are imperative in ensuring the reliability, accuracy, and performance of the application. Utilizing testing frameworks and simulation tools, comprehensive testing is conducted under various environmental conditions to validate the application's functionality. Lastly, deployment materials facilitate the packaging and distribution of the application to end-users through app distribution platforms and packaging tools. This meticulous infrastructure underscores the application's robustness and reliability in effectively combating plant diseases, providing users with a powerful tool for real-time disease recognition and preventive guidance.

V. SYSTEM ARCHITECHTURE AND ALGORITHMS

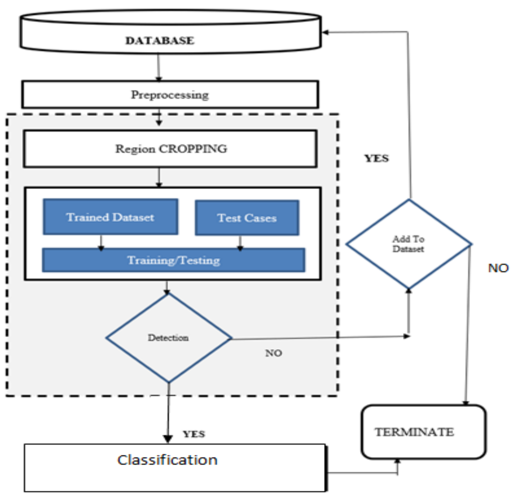

Fig.2: Layout of Proposed System

A. Database Access:

The system initiates by accessing a database presumed to contain a variety of images depicting different plant diseases.

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B. Image Preprocessing:

After database access, images undergo preprocessing procedures, which may encompass:

Resizing: Standardizing all images to a uniform dimension to ensure consistency for subsequent processing by the model.
Normalization: Adjusting pixel values within the images to a specified range, potentially enhancing the efficiency of the model training process.
Colour Conversion: Potentially converting images to a designated colour space, such as grayscale, to streamline the computational requirements of the model.
Region Cropping: Following preprocessing, a determination is made regarding the necessity of region cropping. This step aims to isolate the region of interest within the image, typically the afflicted area of the plant. In instances where the model is engineered to detect diseases across the entire image, this step may be omitted.

C. Data Splitting:

The pre-processed data is then partitioned into two subsets: a training set and a testing set. The training set, constituting the larger portion of the data, is utilized to train the machine learning model, while the testing set is employed to assess the model's performance on unseen data.

D. Model Training:

Training of the machine learning model is conducted utilizing the training set. This iterative process involves presenting the model with pre-processed images along with their corresponding disease labels, enabling the model to discern the distinguishing features of various plant diseases.

E. Disease Detection:

Upon completion of training, the model is deployed to identify diseases in new, unseen images. These images may either belong to the testing set utilized for evaluating the model's accuracy or be real-time images captured directly from live plants. The model analyses the pre-processed images and generates predictions regarding the presence or absence of disease.

F. Disease Classification:

In instances where a disease is detected within the unseen image, the model proceeds to classify the specific type of disease present. This classification task entails determining the disease depicted in the image based on the learned features acquired during training.

G. Test Case Incorporation:

The classification outcome, whether a disease is detected or not, is subsequently compared to the actual disease status of the image. Any discrepancies are addressed by appending incorrectly classified images and their corresponding true labels to the test case set.

H. Iteration Termination:

The system iteratively progresses through the training, testing, and classification phases until meeting predetermined termination criteria. These criteria may include reaching a specified number of iterations or achieving a desired level of accuracy on the testing set.

I. Real-Time Dataset Integration:

The accumulated test case set, comprising misclassified images, can be utilized to retrain the model, potentially enhancing its accuracy on real-time data. Real-time data encompasses images captured live from plants, with the model expected to furnish classifications for these unseen images with notable accuracy.

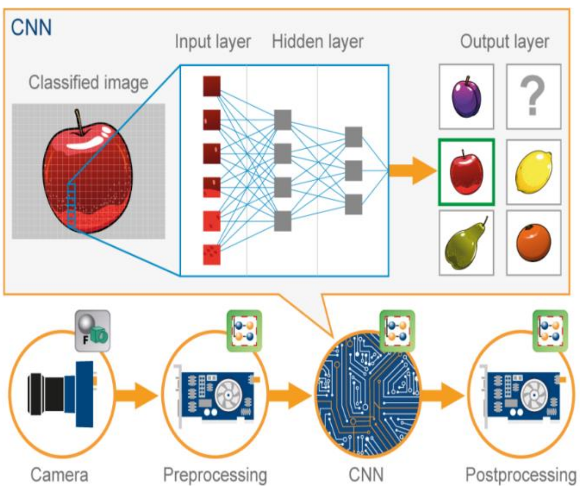

Fig.3: CNN Image Recognition Process

VI. APPLICATIONS

1. Crop Disease Management:

Utilizes cutting-edge image recognition to swiftly identify diseases from leaf images, aiding prompt action for disease control.
Provides comprehensive insights into disease symptoms, causes, and effective treatment strategies, empowering farmers with actionable information.

2. Educational Tool:

Curates a rich repository of articles, tutorials, and guides covering diverse agricultural topics, catering to users of varying expertise levels.
Empowers users with practical knowledge on sustainable farming practices, pest management techniques, and soil conservation methods, fostering informed decision-making.

3. Community Resource:
Establishes a vibrant online community platform where users can share experiences, seek advice, and collaborate on resolving agricultural challenges.
Facilitates expert consultations and peer-to-peer knowledge exchange, promoting a culture of learning, support, and collaboration among farmers and enthusiasts.

4. Sustainability Promotion:
Advocates for sustainable agricultural practices such as organic farming and water-efficient irrigation, promoting environmental stewardship.
Raises awareness about the importance of biodiversity conservation and soil health management in ensuring the long-term sustainability of agricultural systems.

5. Global Relevance:
Adapts to diverse agricultural landscapes and climatic conditions, making it accessible and beneficial for farmers worldwide.
Addresses region-specific agricultural challenges and needs, fostering inclusivity and relevance across different farming communities and geographical regions.

6. Food Security:
Empowers farmers with tools and knowledge to mitigate crop losses, enhance productivity, and contribute to stable food supplies for communities.
Supports efforts to strengthen food systems through sustainable intensification, resource optimization, and resilience-building measures against climate change and other threats.

VII. RESULTS AND DISCUSSION

Our evaluation aimed to determine the effectiveness of the mobile application in achieving maximum accuracy for plant disease recognition. Critically, we compared these results to a model trained solely on pre-existing datasets to isolate the impact of incorporating live user-generated data. The analysis focused on whether live data improved the model's ability to recognize diseases not well-represented in the original datasets.

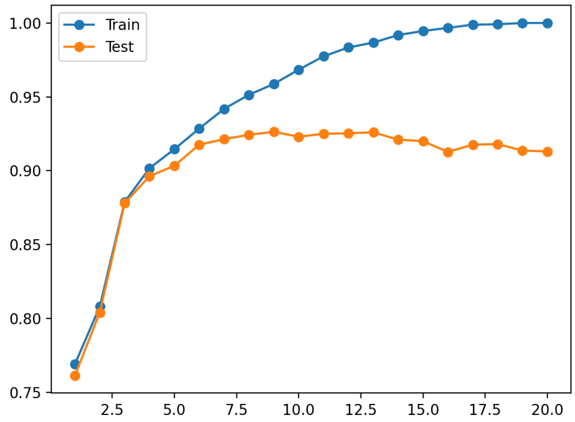

Fig.4: Graph of Training and Testing Datasets

The discussion section will delve deeper into these findings. We'll explore the effectiveness of live data integration and its impact on accuracy, particularly for under-represented diseases. This might involve visualizing how accuracy for specific diseases changed after incorporating live data. We will also address the challenges of incorporating live data, such as potential inconsistencies in user-generated images (blurry photos, incorrect plant parts captured) and the possibility of mislabelled data (user mistakenly identifies a healthy plant as diseased). Strategies to mitigate these challenges, such as implementing data cleaning techniques or user training on image capture best practices, will be explored.

Finally, the discussion will outline future directions for the application. This could involve exploring techniques for real-time disease severity estimation, allowing users to not only identify the disease but also understand its potential impact on the plant. Additionally, integrating functionalities like treatment recommendations based on the identified disease would empower users to take informed action and potentially improve plant health outcomes. By continuously learning from live data and adapting the model, the mobile application has the potential to become a valuable tool for both individual plant enthusiasts and large-scale agricultural operations.

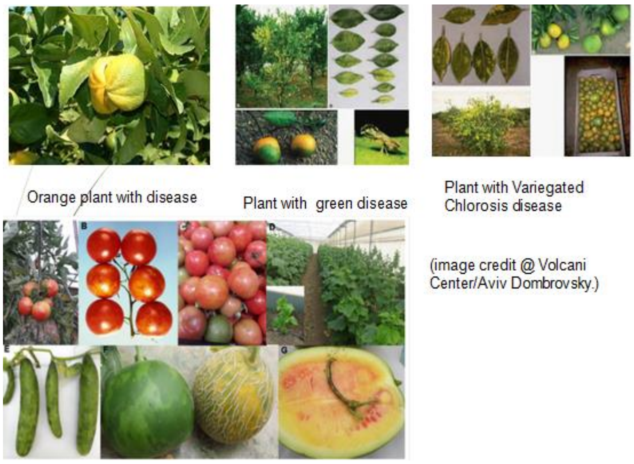

Fig.5: Crop Diseases Samples

VIII. CONCLUSION

This research has conducted a comprehensive review of existing algorithms for plant disease recognition. This in-depth analysis establishes a strong foundation for the development of a mobile application for plant disease detection utilizing a rule-based system. The reviewed algorithms showcase promising potential for accurately identifying a wide variety of plant diseases. However, translating these algorithms into a mobile application necessitates careful consideration of certain challenges.

Rule-based systems offer a practical and adaptable approach. They translate expert knowledge into actionable decision-making algorithms specifically designed for mobile platforms. By leveraging the insights gleaned from this extensive research, we can now embark on building a mobile application that empowers farmers and agricultural professionals with a novel tool for prompt and accurate plant disease diagnosis.

The envisioned mobile application will prioritize key features to enhance its user experience and effectiveness. First, the application will encompass a diverse range of plant diseases affecting a multitude of crops, ensuring comprehensive diagnostic capabilities for users. Second, a meticulously designed, user-friendly interface will foster intuitive navigation and effortless disease identification, even for those without extensive technological expertise. Finally, offline functionality will enable farmers to diagnose diseases seamlessly even in remote areas with no internet connectivity, fostering accessibility across diverse agricultural settings.

Our future research endeavors will focus on several key areas to ensure the success of the mobile application in real-world scenarios. First, we will conduct meticulous real-world validation to assess the application's efficacy and robustness under genuine agricultural conditions. This evaluation process will ensure the application's adaptability to the dynamic complexities of real-world farming scenarios. Second, we will continuously refine the rule-based algorithms to augment diagnostic precision and encompass a broader range of diseases. This ongoing optimization will propel enhancements in application performance. Finally, we will integrate valuable insights gleaned from user experiences to drive iterative application improvements. This user feedback will ensure the application remains aligned with the evolving needs of the agricultural community.

By addressing these aspects, we strive to deliver a powerful tool capable of catalyzing a paradigm shift in plant disease management. Ultimately, this will foster bountiful harvests, safeguard food security, and nurture the prosperity of agricultural communities worldwide.

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