International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2024.0183

e ISSN: 2584-2854
Volume: 02
Issue: 05 May 2024
Page No: 1338-1344

A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Convolutional Neural Network

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Abstract
Plant diseases pose a significant challenge to agriculture in India, causing substantial losses in crop production each year. Limited-resource farmers often struggle with diagnosing these diseases accurately, especially when relying on visual observation of leaf symptoms. Hence, there is an urgent need to enhance the detection, monitoring, and prediction of crop diseases to mitigate agricultural losses effectively. To address this challenge, we propose a mobile-based system empowered by Machine Learning (ML) and computer vision tailored for the Indian context. Our system utilizes Convolutional Neural Networks (CNNs) as the core deep learning engine to classify 37 disease categories commonly found in Indian crops. We have curated a comprehensive dataset comprising 96,206 images of plant leaves, encompassing both healthy and infected, for training, validation, and testing purposes. The user interface of our system is designed as an Android mobile application, enabling farmers to capture images of diseased plant leaves effortlessly. Upon image capture, the system swiftly identifies the disease category and presents it to the user along with a confidence percentage. This functionality empowers farmers to take timely action to protect their crops, thereby reducing reliance on incorrect fertilizers that may exacerbate plant stress. Furthermore, we evaluated the performance of our system using various metrics, including classification accuracy and processing time. Our results indicate an impressive overall classification accuracy of 94% across the 37 disease classes prevalent in 14 different crop species commonly cultivated in India. In essence, our ML-powered mobile-based solution offers Indian farmers a robust tool for efficient crop disease diagnosis and management, ultimately contributing to the enhancement of agricultural productivity and sustainability in the country.
Keywords: *Agriculture; Convolutional Neural Networks (CNN); Deep Learning; Mobile App; Plant Diseases*

1. Introduction
Plant diseases, pest infestation, weed pressure, and nutrient deficiencies stand as formidable challenges for agricultural producers across diverse operational scales and geographical locations in India. The timely identification and management of these threats are crucial for sustaining crop productivity and operational profitability. However, accessing readily available technological solutions capable of guiding farmers in addressing these challenges is paramount. In the context of India, where agricultural activities form a cornerstone of the economy, it is imperative to acknowledge the substantial impact of plant diseases on crop production. Annual losses ranging between 20 and 40 percent of agricultural crop yields due to plant diseases underscore the urgency for farmers to swiftly diagnose and mitigate such threats within their fields. Traditionally, Indian farmers, particularly those with limited access to resources, rely on optical observation of plant leaf symptoms for disease diagnosis, a method fraught with complexity. Misdiagnosis not only exacerbates crop losses but also increases the risk of inadvertently applying incorrect fertilizers, thereby inducing plant stress and nutrient deficiencies in agricultural fields. The integration of Machine Learning (ML) with

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computer vision technologies has already revolutionized precision agriculture practices globally. By optimizing farm returns, conserving natural resources, reducing fertilizer misuse, and enabling disease identification in crops, these advancements offer promising avenues for enhancing agricultural productivity in India. Imagining a scenario where farmers can utilize a smart, mobile-based system for accurate identification of plant diseases underscores the transformative potential of such technological innovations for both smallholder and large-scale agricultural operations in India. The subsequent sections of the paper delve into a comprehensive exploration of Section 1. Related Literature and Studied, Sec 2. CNN algorithm, Sec 3. Existing System, followed by detailed discussions on the Sec 4. system design, Sec 5. prototype implementation, Sec 6. experimental evaluations, and Sec 7. concluding remarks summarizing the key findings and contributions of this research endeavor.

2. Related Literature and Studie

Related Literature and Studie The literature review aims to contrast various methodologies previously suggested for the detection of plant diseases utilizing deep learning and image processing techniques. Numerous research endeavors have put forth diverse approaches to identify diseases within plants. Research has explored the use of IoT systems for plant disease detection, achieving high accuracy rates exceeding 90% (Thorat & Nikam, 2017) [1]. These systems often employ a combination of image processing, clustering algorithms, and artificial neural networks for disease classification. In their work, Sharath et al. (2019) introduced a system aimed at identifying diseased areas on plants or fruits utilizing an edge detection methodology. Initially, the process involves capturing images of the fruit, followed by image segmentation using a specific technique. Subsequently, the edges of the diseased areas are determined in terms of pixels. The degree of contamination within the plant or fruit is then quantified based on the number of pixels identified. Based on the specific disease affecting the fruit, control and treatment strategies are recommended. [2] In their study, Valdoria et al. (2019) conducted an investigation into a deep learning neural network algorithm for detecting plant diseases. Tensor Flow was utilized to preprocess the data, preparing it for training purposes. Through the application of deep learning techniques and neural network algorithms, a model was developed for the identification of plant diseases, with its performance evaluated using the F1 score. An Android-based mobile application, named iDahon, was developed to embody this model and underwent assessment by field specialists. The reported accuracy of the developed model reached 80%.[3] In the study by Ferentinos (2018), various deep learning model architectures, particularly based on Convolutional Neural Network (CNN) structures, were instantiated to distinguish plant diseases using leaf images from healthy and diseased plants. Among these architectures, the VGG CNN model emerged as the most effective, exhibiting an impressive accuracy rate of approximately 99% in the classification task. This performance was achieved while handling a substantial dataset comprising 17,548 plant leaf images. [4] In their study, Mahalakshmi and Shanthakumari (2017) focused on detecting a disease affecting paddy plants through image processing techniques. The system initiates by taking a paddy leaf image and converting it from RGB format to grayscale. Subsequently, a morphological opening operation is applied to reduce noise, followed by image segmentation. These procedures collectively facilitate the identification of the infected region on the paddy leaf. In their study outlined in reference [5], Thakre et al. (2017) developed a mobile application for recognizing plant diseases using image processing techniques. The application assesses the color patterns of diseased marks on plant leaves and bodies. Training data for the model were images captured under controlled laboratory conditions with a digital camera. To gauge the similarity between different species, a distance matrix was computed to measure the distance between each pair. Image segmentation techniques were applied to partition plant images into distinct regions , with each pixel sharing similar attributes. The primary method

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utilized for disease identification within segmented regions was the k-means clustering algorithm. The authors reported a commendable accuracy rate of 90% for their model, achieved with a relatively small training set. [7] In their work documented, Raut and Fulsunge (2017) presented effective techniques for detecting and identifying plant diseases through image processing methods implemented in MATLAB. They employed the K-means clustering algorithm and multisupport vector machine (SVM) methods, tailored for disease identification in both plants and fruits. Image segmentation and feature extraction were utilized to preprocess the images, preparing them for training the models. Singh and Misra (2017)], presented a study on diverse disease identification methods employed in detecting plant diseases, alongside a method for image segmentation crucial for disease detection and identification. The accuracy of the system they presented is reported to be approximately 95%. However, it's noteworthy that the number of sample images utilized in the system amounted to only 60, covering four different plant species. [8] Mohanty et al. (2016) developed a model trained on images of plant leaves using deep Convolutional Neural Networks (CNN) to classify crop species and identify diseases. Their proposed model showcases rapid classification, rendering it suitable for integration into applications. However, it's noted that the accuracy achieved on images not included in the dataset is just slightly above 31%. [9] In reference, Khirade and Patil (2015) elucidated various techniques for segmenting diseased areas of plants. They explored different procedures for feature extraction and identification, particularly focusing on methods employed to extract features from diseased leaves and subsequently identify plant diseases. Additionally, the authors delved into the utilization of artificial neural network methods for plant disease detection, including discussions on the backpropagation algorithm and Support Vector Machines (SVM).[10]

3. CNN Algorithm

Convolutional Neural Networks (CNNs) are a powerful tool for machine learning, especially in tasks related to computer vision. Convolutional Neural Networks, or CNNs, are a specialized class of neural networks designed to effectively process grid like data, such as images. A Convolution Neural Network (CNN) is a type of Deep Learning Algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, Pooling Layer, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain, and they are well-suited for capturing hierarchical patterns and spatial dependencies within images.

3.1 Initialization

The Convolutional Neural Network (CNN) architecture comprises two primary types of layers: convolution and pooling. Each layer consists of specialized neurons tasked with specific operations. Convolution entails detecting visual features within input images, such as edges, lines, and color gradients. On the other hand, pooling aids the CNN in focusing solely on relevant features by down sampling generated feature maps through summarization into patches. Two prevalent pooling methods are employed: average-pooling and max-pooling. In this instance, the maxpooling method is utilized, determining the maximum value within each patch as the dominant feature. Upon completion of Conv2D and MaxPooling2D layers, the output assumes a 3D tensor form (height, width, channels), figure 1 with the width and height dimensions typically diminishing as the network progresses deeper. The third argument (e.g., 16, 32, or 64) governs the number of output channels for each Conv2D layer. During the training phase, the CNN model encompasses around 4 million trainable parameters. Before deploying the trained CNN model to a mobile device, it undergoes conversion into an optimized Intermediate Representation (IR) model. This conversion process entails transforming the trained network topology, weights, and biases values. The Intel Open VINO toolkit is employed for generating the IR model, which is the sole format compatible with and comprehensible by the inference engine on the Android platform. Throughout the conversion, irrelevant convolution

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and pooling layers are removed to align with the capabilities of the mobile device's inference engine. Specifically, Open VINO splits the trained model into two distinct file types: XML, housing the network topology, and BIN, containing the weights and biases binary data. To replicate this CNN implementation in a mobile application utilizing a different toolkit with similar functionalities, the conversion process would involve adhering to the specific requirements and file formats compatible with the chosen toolkit, ensuring seamless integration with the mobile platform.

4. Existing Systems

There are already several existing apps that use DL for plant disease detection. One such example is Plant. id, which uses a deep learning-powered algorithm to identify plant species from photos. It can recognize over 20,000 species of plants with an accuracy rate of over 95%. The app allows users to take a photo of the plant and receive a diagnosis within seconds, along with information on how to treat the disease. Another example is the Plant Doctor app, which uses machine-learning algorithms to diagnose plant diseases based on images and symptoms. The app is trained on a large dataset of plant images and disease descriptions, and it can identify over 30 common plant diseases.

Agro.AI: This app uses computer vision and deep learning algorithms to identify and diagnose plant diseases in real time. It can identify over 50 different types of plant diseases and provide recommendations for treatment.

Plant.AI: This app uses DL to analyze images of plants and diagnose diseases based on visual symptoms. It provides detailed information on how to treat the disease and how to prevent it from happening again in the future.

Crop.AI: This app uses computer vision and DL to identify plant diseases and pests in real time. It can be used by farmers to quickly diagnose problems and take action to prevent crop losses.

4.1 Disadvantages of Existing Systems

- The process is Extremely slow
- Trained on old Dataset
- Not much compatible with Indian diseases
- UI is not many user's friendlies

5. Systems Design

The schematic depiction of the proposed system is delineated in Figure 2. In the application, the user initiates the process by capturing an image of a leaf from the target plant utilizing the phone's camera. Subsequently, the captured image undergoes processing via the embedded trained model within the Mobile application. Following processing, the application furnishes outcomes predicated on the image's accuracy, discerning whether the plant is in a healthy state or afflicted by disease. The resulting output delineates the specific disease name along with suggested remedies for its mitigation. Additionally, the application offers a functionality enabling users to promptly contact community to ask own doubts and resolve other farmers query and Plant, Bug and weather information. As depicted in Figure 2, the distributed operational framework for the plant disease detection system is structured with components operating on mobile devices at the user end, alongside centralized servers at the cloud end. Tier 1 delineates the deep learning model employed within the system (namely, CNN) and the Intermediate Representation (IR) model operational on the mobile device. Tier 2 showcases the user interface, designed as an Android application to facilitate convenient interaction between system users (as depicted in tier 3) and the system

6. Prototype Implementation

The proposed system deployment methodology begins with loading the relevant image dataset that will serve as the foundation for training the machine learning model. Subsequently, the images undergo preprocessing to ensure their compatibility with the model's input requirements. This involves operations such as resizing, normalization, and other necessary transformations. Figure 3 The Tensor Flow libraries and a pre-trained transfer learning model are then imported, leveraging the power of transfer learning to expedite the training process. The training model is meticulously configured using Python, a versatile programming language renowned for its applications in machine learning and data science. This configuration process establishes the architectural

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and parametric specifications of the neural network training model. Upon completion of the configuration, the neural network commences its training phase, ingesting the preprocessed image data and iteratively optimizing its internal parameters to learn the intricate patterns and representations inherent within the dataset. Periodic evaluations are conducted to assess the model's accuracy on a holdout validation set, enabling quantitative monitoring of its performance and guiding potential refinements. Once the training process achieves satisfactory results, the trained model is converted to the Tensor Flow Lite format, a lightweight and optimized variant tailored for deployment on mobile and embedded devices. This Tensor Flow Lite model is subsequently integrated into an Android application through the Android Studio Integrated Development Environment (IDE). Following successful integration, the Android application, now encapsulating the machine learning model, is installed and executed on an Android smartphone or tablet, table 1 enabling on-device inference and leveraging the model's capabilities for tasks such as image recognition or detection.

Table 1 Experimental Accuracy of Models

S.No	Model	Best Score
1	SVM	0.611
2	Random Forest	0.294
3	Logistic Regression	0.366
4	CNN	0.94

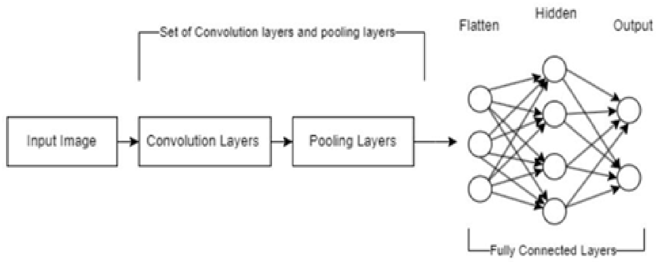

Figure 1 Convolutional Neural Network

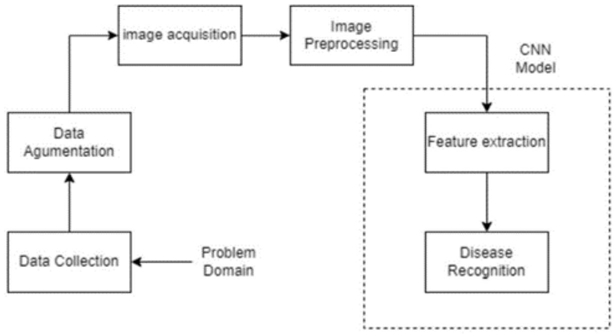

Figure 2 System Architecture

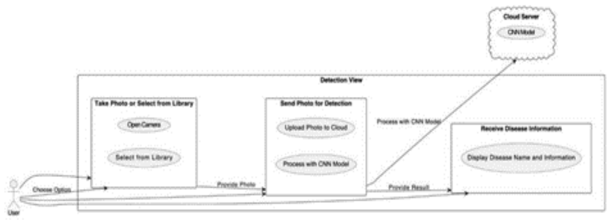

Figure 3 Prototype Use Case Diagram

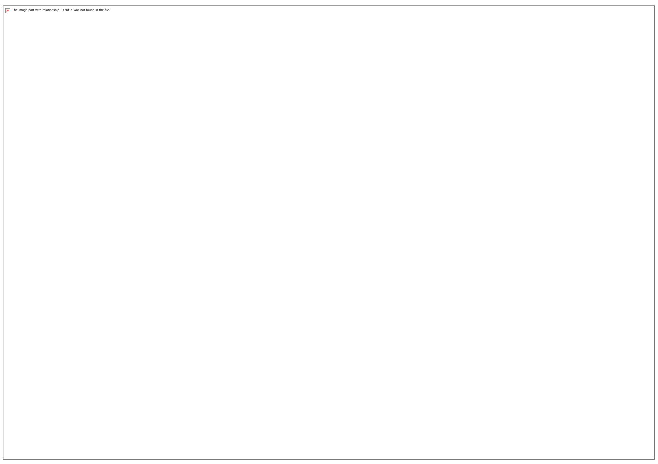

Figure 4 Executed Example of Prototype

e ISSN: 2584-2854
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7. Results and Discussion

Our prototype implementation underwent rigorous experimental evaluation concerning both classification accuracy and performance metrics. Within the mobile application running on a smartphone, we integrated instrumentation to meticulously measure the processor time required for various tasks, encompassing photo capturing, image preprocessing, and disease recognition processes. Each experiment detailed in this section was conducted across ten trials, following which we computed the average results. In assessing classification accuracy, we observed commendable outcomes under natural conditions, even when plant images were captured from varying distances, orientations, and illumination settings. The confusion matrix for the CNN model offers a comprehensive analysis, illustrating how the model's performance varies across distinct disease classes. Within the matrix, rows represent the actual (true) disease classes, while columns denote the predicted classes. Figure 4 The diagonal cells highlight the proportion of correct predictions, while off-diagonal cells delineate the model's error rate. The analysis of the confusion matrix underscores the model's efficacy, particularly in distinguishing between disease classes and achieving notable prediction accuracy levels. Notably, for prevalent crop diseases like blight, scab, and rot, the model attained accuracies exceeding 96%, 98%, and 97% for corn blight, apple scab, and grape black rot, respectively. Additionally, we observed that diseases instigated by fungi (e.g., rust and rot) were generally easier to identify compared to those caused by bacteria (e.g., blight and scab) and viruses (e.g., mosaic and leaf curl). This disparity is logical as fungal infections often manifest conspicuous symptoms on plant leaves, simplifying identification compared to bacterial and viral infections with milder symptoms. The accompanying table delineates classification accuracy and prediction time metrics across disease classes. Notably, the CNN model achieved an impressive overall average classification accuracy of 94%, with an average prediction time of 0.88 seconds. These findings underscore the feasibility of farmers diagnosing plant diseases in agricultural fields swiftly using a convenient mobile application, with inference occurring in less than one second. Furthermore, noteworthy instances of 100% prediction accuracy across multiple classes attest to the robustness and real-time inference capabilities of our model in agricultural settings.

Conclusion

This paper presented the design and implementation of an ML-powered plant disease detector that enables farmers to diagnosis the most common 38 diseases in 14 species. We trained a CNN model using an imagery dataset consisting of 96,206 photos of healthy and diseased plant leaves, where crowded backgrounds, low contrast, and diverse illumination condition images are taken into consideration. To increase the system usability, we developed a mobile app that would create a better opportunity for limited-resources farmers to detect plant diseases in their early stages and eliminate the use of incorrect fertilizers that can hurt the health of both the plants and soil. We carried out several sets of experiments for evaluating the performance and classification accuracy of our system, paying particular attention to the classification and processing time. After analyzing different techniques, it shows the following results while approaching this with the traditional algorithmic way analyzed various algorithms which are namely SVM random forest, and logistic regression. Out of all these three models SVM gave an accuracy of up to 84% where random forest gave an accuracy of 69% and logistic regression gave an accuracy of 76% this overall concludes that while going through the traditional algorithm way the best-suited model is SVM. Thereafter while focusing to solve this thing using a convolution neural network gave an accuracy of 94%. The application interface is very easy to understand. So, it is quite practical for the farmers to be able to use the application. Farmer in rural areas can use it to detect plant disease accurately and take action accordingly. It will help to avoid disaster in food production, thus increasing gross food production.

Acknowledgements

Prof. A.W. Bhade, Head of Department of Information Technology, Government College of Engineering, Amravati, has been a tremendous source of support and guidance to the authors throughout this project

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