International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Plant Disease Detection App Using Convolutional Neural Network

Shruti Patekar, Arvind Rana, Musareib Shaikh

Department of Electronics and Telecommunications Engineering

Thakur College of Engineering and Technology, Mumbai, Maharashtra, India

---***---

Abstract - Crop diseases pose significant challenges to the agricultural sector, resulting in substantial production losses and economic setbacks. The efficacy of conventional disease diagnosis techniques, such optical examination of plant leaves, is constrained. It is imperative to improve agricultural disease detection, monitoring, and prediction in order to address this problem. This work offers a mobile-based system that uses the plant-DOC Dataset to automate the diagnosis of plant leaf diseases. The system is powered by machine learning (ML) and computer vision. Deep learning algorithms, in particular Convolutional Neural Networks (CNNs), are used in the suggested model. CNNs are excellent at identifying diseases in plants and crops. Finding the plant's sickness is the aim of this application. Additionally, image processing can be used to detect the disease type, the appropriate pesticide, and to alert farmers so that prompt action can be performed. The whole process involves gathering plant images, preprocessing them by resizing, normalizing, and augmenting, segmenting if necessary, extracting features, selecting, and training a CNN model, evaluating its performance, and using it to detect plant diseases. In this paper, we have successfully developed both the frontend and backend components for integration into our proposed model, accompanied by corresponding screenshots showcased within the document.

Key Words: *plant leaf diseases, agriculture, mobile app, computer vision, machine learning, deep learning, Convolutional Neural Networks.*

1. INTRODUCTION

Unquestionably, technological advancements have helped to produce enough food to meet society's demands. But maintaining the security and safety of food and agriculture is still quite difficult [1]. Factors such as climate change, the decline in pollinators, and plant diseases pose considerable obstacles for farmers. It is imperative to establish a solid foundation for addressing these challenges promptly and effectively. The utilization of analysis and detection processes, leveraging current technologies, can offer valuable solutions to farmers, mitigating these problems [2]. Relying on cutting-edge technologies to prevent and solve key concerns has become increasingly important in light of the recent global pandemic, particularly the COVID-19 epidemic [3]. Because they can result in famines and droughts, plant diseases represent a serious threat to human survival. Because significant losses can happen in commercial farming, the repercussions are very dire.

Technologies like computer vision and machine learning (ML) become useful tools to tackle these problems [4]. In this study, we use machine learning approaches to offer a holistic remedy for plant illnesses. We break down the process into three separate phases in our approach: Identity, Analysis, and Verification. Each of these phases is backed by an accessible database [5].

Through the utilisation of machine learning, our goal is to provide farmers with precise and effective techniques for diagnosing, evaluating, and validating plant diseases. The goal of this study is to aid in the creation of workable solutions that will improve crop management and allow for prompt interventions. The literature survey delves into recent strides in machine learning applications for plant disease identification, drawing attention to the profound impact on agriculture. The integration of AI, specifically ML and deep learning, has revolutionized disease diagnosis, pest detection, and weed identification [6]. Notable methodologies include image processing techniques like k-Mean clustering [1] and SVM classification [7], coupled with diverse colour models such as RGH and HSI for efficient segmentation. Unsupervised learning, particularly through the k-Means clustering algorithm, emerges as a crucial tool for identifying infected regions in leaf images. Various studies showcase the effectiveness of GLCM [5] for feature extraction and the evaluation of models against both local and public datasets [8], underlining the potential for scalable and accurate disease identification in plants.

The table below encapsulates the database utilized, the features extracted, the technique employed for disease identification, and the outcomes obtained from the pertinent literature review. Section II furnishes detailed insights into the construction of the model, elucidating the methodologies and strategies harnessed for optimal performance. Furthermore, Section III delves into the practical implementation of the model, providing a comprehensive overview of the deployment process and its real-world applications. By assimilating and synthesizing findings from the literature review, this study endeavors to augment existing knowledge and contribute substantively to the domain of plant disease detection and classification using machine learning techniques.

Table 1. Literature Survey Analysis

Author names	**Year of Paper**	**Database used**	**Features Extracted**	**Technique used to identify disease**	**Results obtained**
Mr. Prasham Shah Et al. [2]	2023	87,848 photos showing a variety of plant combinations both healthy and diseased.	Color, shape and texture	Convolutional Neural Networks (CNNs), Directional Local Quinary Patterns (DLQP), Support Vector Machines (SVM), Transfer Learning.	Among 17 reviewed plant disease detection apps, 47.06% automatically identify plants from images, 41.18% allow manual plant selection, with notable variations in plant identification technologies.
Sreeya A ,Smita Unnikrishnan, Aliya Nazeer, Haneena , Niveditha [5]	2021	6167 images categorized into four classes: Bacteria, Virus, Sunburn, and Healthy.	The specific features extracted from the images are not detailed in the paper.	Image Processing Technique, Convolutional Neural Network (CNN),	The testing results indicate high accuracy in disease classification (88% for Bacteria, 90% for Virus, 85% for Sunburn, and 92% for Healthy).
Adedamola O. Adedoja, Pius A. Owolawi, Temitope Mapayi [9]	2022	54,309 photos featuring both good and unhealthy plants. 14 crops & 38 distinct healthy and unhealthy plants, including apples, cherries, blueberries, and others.	Modifications to specific plant elements (such as the leaf's hue)	NASNet-Mobile, Smartphone Application (Android and iOS), Web Service, Image Processing, Machine Learning (Deep Learning), CNN	99.31% accuracy was attained by the suggested NASNet-Mobile CNN model plant disease diagnostic system.
Sunil S. Harakannanavar , Jayashri M. Rudagi , Veena Puranikmath, Ayesha Siddiqua , R Pramodhini [10]	2022	Tomato leaf from the village database is taken into consideration, along with plants that are afflicted with various diseases.	Shape information, color space, texture-based	This article uses machine learning methods (SVM, KNN, and CNN) in conjunction with computer vision techniques	The proposed model exhibits an overall accuracy of 99.5% in distinguishing various tomato leaf diseases, with individual category accuracies ranging from 99% to 100% in the evaluation on a dataset.
Gyan Singh Sujawat, Dr. Jitendra Singh Chouhan [11]	2021	Plant diseases of various kinds are included in the DB, and JPEG photos are used for image storage.	Colour, texture edges, morphology are the features	Plant disease detection expert systems, image processing, machine learning, deep learning via convolutional neural networks	The paper underscores the vital role of agriculture in developing economies, highlights the potential of artificial intelligence in addressing crop diseases.

2. PROPOSED MODEL

This proposed model involves gathering plant images, preprocessing them, segmenting, extracting features, selecting and training a model, evaluating its performance, and using it to detect plant diseases and giving remedies.

Plant Dataset: A collection of pictures or information on plants is referred to as a plant dataset. Images of plants in good condition, plants with pest or disease problems, and different plant sections can all be found in these datasets. Plant diseases are identified and categorized using machine learning models that are trained and evaluated using plant datasets. The extensive PlantDoc dataset [9] was created especially for the purpose of visual plant disease identification. The collection includes 2,598 data points from 13 different plant species, representing up to 38 different disease classifications. After about 300 hours of labour, the dataset was produced by annotating images that were taken from the internet. Fig. 1 shows samples of leaf photographs from the database.

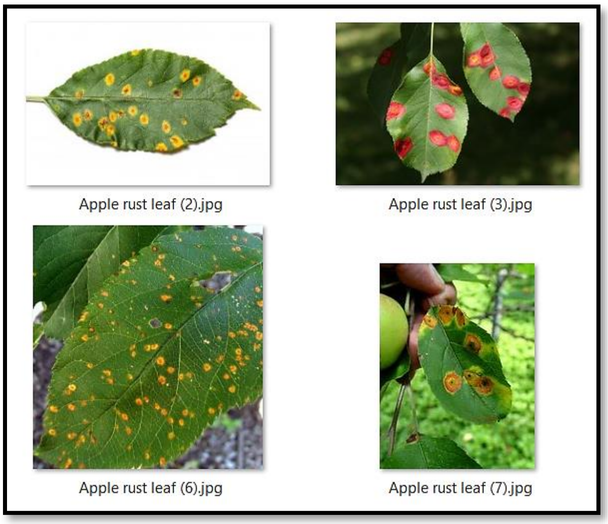

Fig-1: Sample of leaf having disorders

Data Preprocessing: Once we have the photos, we prepare them for the computer to understand. We make all the pictures the same size, improve their quality, and adjust them so they're easier to work with. We will be using Python libraries like OpenCV. To ensure that all your images have the same dimensions. Resizing images to a common size, such as 224x224 pixels also to Normalize the pixel values to a consistent scale. Usually, this entails scaling the pixel values so that they fall between 0 and 1. separating the dataset into sets for testing, validation, and training. An 80-10-10 or 70-15-15 split is typically employed. This aids in assessing the model's effectiveness and guarantees good generalization [10].

Image Segmentation: In this step we separate the plant parts (like leaves) from the background in our photos or we focus on the reason of plant where the chances of disease are more. This can help the computer focus on what's important in the picture. Converting the image to grayscale [10]. Grayscale simplifies the segmentation process. We will be using appropriate segmentation technique that is Thresholding which is a simple approach.

Feature Extraction: In this step, we're finding the most important clues in the pictures. We're looking for things like patterns, colours, and shapes that can help the computer figure out if a plant is healthy or sick.

Model selection: CNN stands for Convolutional Neural Network, it's excellent at understanding images. And commonly used for image classification tasks. In the context of plant disease identification, a CNN can be trained to classify images of plants into different categories such as healthy or diseased, or specific disease classes [13]. CNN, k-Nearest Neighbours (KNN), and Support Vector Machine (SVM) are some of the techniques used to classify the samples. The CNN is a specific type of artificial neural network (ANN) designed for data processing. The CNN architecture has multiple hidden layers (HL), an output layer (OL), and an input layer (IL). The HL consists of pooling, fully connected, normalization, convolutional, and the Rectified Linear Unit (RELU) layer, which implements the activation function. Its architecture is cross correlation, not convolution, which makes mathematical sense and is significant for the indexes of the matrix [14]. A typical three-layer network is shown in Fig. 2.

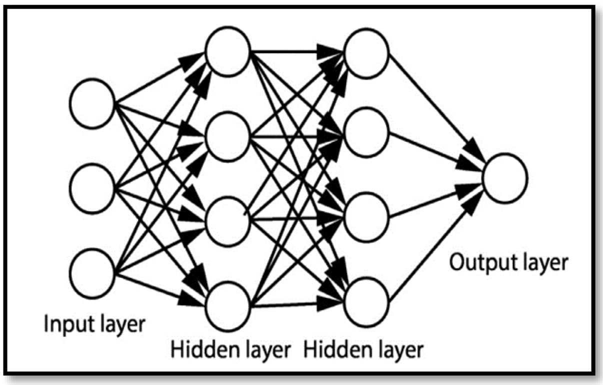

Fig 2: Convolutional Neural Network (CNN)

CNNs excel in plant disease detection, automatically learning crucial spatial features in images for efficient pattern recognition. Their adaptability, efficiency, and pre-trained models make CNNs a top choice for accurate and streamlined plant disease classification.

Model Training: In this crucial phase, our backend system undergoes intensive training to learn the intricate patterns distinguishing between healthy and diseased plants. Through exposure to a vast array of images, our model gains the ability to discern subtle visual cues indicative of plant health. This process is akin to imparting knowledge to a keen learner, empowering our system to accurately classify plants and identify potential diseases.

Model Evaluation: Similar to assessing a student's performance on an exam, we meticulously evaluate the effectiveness of our trained model. Utilizing various metrics, we gauge its proficiency in distinguishing between healthy and diseased plants. By comparing its predictions with ground truth labels, we ascertain the accuracy and reliability of our system in recognizing plant health conditions.

Diseases and Remedy: In a plant disease identification app, after classifying an input image as diseased, the app can provide information on the detected disease and offer guidance or remedies to the user on how to treat or manage the disease effectively.
Each of these steps plays a vital role in building a Plant Disease Detection application. It's all about getting the computer to understand plant images and help us identify any issues with the plants and suggest some remedies.

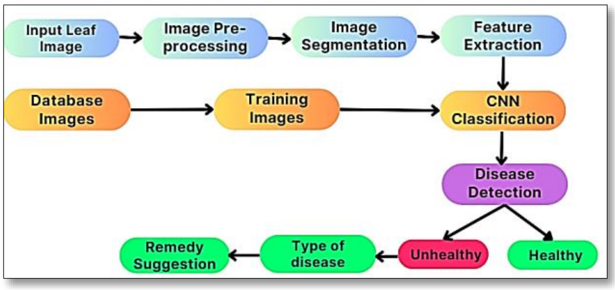

Fig 3: Flow chart

The comprehensive process as shown in Fig 3 of building a Plant Disease Detection and Remediation system encompasses several crucial steps. It commences with the collection of plant images, encompassing both healthy and diseased samples, followed by meticulous preprocessing that involves resizing, normalizing, and, optionally, augmenting the images to ensure uniformity and quality. Image segmentation techniques may be applied to isolate key plant parts from backgrounds, a step akin to carefully cutting shapes from a piece of paper to facilitate the computer's focus on the salient features. Subsequently, feature extraction techniques, including Convolutional Neural Networks (CNNs), are employed to capture discriminative information from the images [11]. Model selection and training, particularly with CNNs, empower the system to learn and recognize disease-related patterns. Next, a number of criteria, including accuracy and precision, are used to assess the model's effectiveness [4]. Finally, the trained model is leveraged to not only detect plant diseases but also provide remedies or recommendations for addressing the detected issues, offering a holistic solution for plant health management.

3. IMPLEMENTATION

In the front-end implementation of our application as shown in Fig 4, Fig 4 and Fig 6, we have designed an intuitive and user-friendly user interface using Android Studio, incorporating a tech stack that includes XML, JSON, Java, and related technologies. The front end comprises multiple pages, including an initial opening page, a starting display, and a dedicated image capture page. Users can seamlessly choose to capture images from either the device's camera or the gallery, enabling a smooth transition to the next stages of the application. These front-end components provide a visually engaging and responsive environment for users to interact with our forthcoming backend machine learning processes, fostering a holistic and efficient user experience.

Fig 4: Opening page

Fig 5: Starting display

Fig 6: Dedicated image capture page

Furthermore, significant progress has been made in the backend, particularly in model training and testing. Utilizing the TensorFlow and Keras libraries in Python, we developed and trained a Convolutional Neural Network (CNN) for plant disease classification. The training code involved preprocessing the training and validation datasets, followed by constructing and compiling the CNN model. Notably, the training process achieved a remarkable training accuracy of approximately 98.24% and a validation accuracy of 54.82%, as evidenced by Fig 7. Additionally, Figs 8 and 9 showcase the testing phase, where a sample image of a tomato plant was provided to the model for evaluation. Remarkably, the model accurately predicted the disease as 'Tomato___Tomato_Yellow_Leaf_Curl_Virus', demonstrating its efficacy in real-world scenarios
These backend advancements were achieved through rigorous experimentation on the Jupyter notebook platform using the Python programming language. The iterative training process involved initially training the model with a limited number of images and gradually increasing the dataset size, thereby enhancing the precision and reliability of our model. This comprehensive approach ensures the delivery of a sophisticated and efficient plant disease detection system, poised to make a significant impact in agricultural management.

Evaluating Model

```
#Training set Accuracy
train_loss, train_acc = cnn.evaluate(training_set)
print('Training accuracy:', train_acc)
```

```
29/29 [==============================] - 14s 458ms/step - loss: 0.0713 - accuracy: 0.9825
Training accuracy: 0.9824561476707458
```

```
#Validation set Accuracy
val_loss, val_acc = cnn.evaluate(validation_set)
print('Validation accuracy:', val_acc)
```

```
15/15 [==============================] - 7s 465ms/step - loss: 2.0591 - accuracy: 0.5482
Validation accuracy: 0.5482456088066101
```

Fig 7: Training and Validation Accuracy

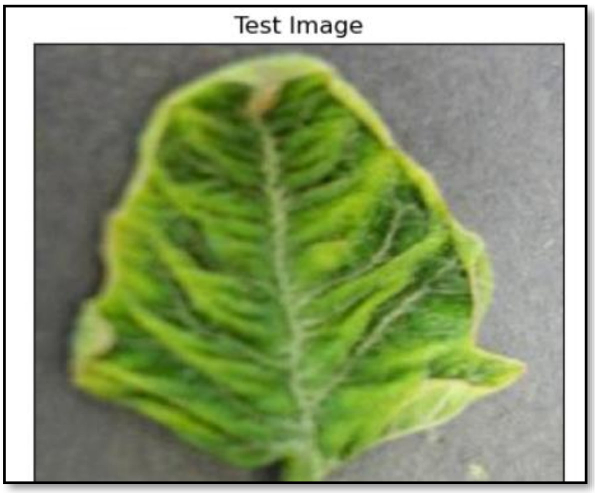

Fig 8: Uploading image of affected leaf

Fig 9: Prediction of the disease

4. CONCLUSION

In the process, we've solidified our expertise in both frontend and backend development, encompassing a wide array of technologies and methodologies. Our exploration of frontend development and user interface design culminated in the creation of a visually appealing and intuitive user interface, facilitated by platforms like Android Studio and frameworks like XML, Java, and JSON. Complementing this frontend accomplishment, we've delved into the intricacies of backend processes, focusing particularly on disease detection methodologies. Through meticulous study and implementation, we've mastered essential techniques such as image pre-processing, feature extraction, and segmentation. Moreover, our journey has led us to harness the power of machine learning, notably employing Convolutional Neural Networks (CNNs) for image classification tasks and exploring unsupervised learning techniques like k-means clustering for segmentation purposes. With the completion of our backend implementation, marked by the successful training and testing of our CNN model, we are now poised to seamlessly integrate our well-designed frontend with the advanced backend functionalities. Our vision is to empower users with a robust and efficient plant disease detection application, capable of accurately diagnosing and categorizing plant illnesses using images captured by the user. As we progress, our endeavour will continue to be defined by the seamless fusion of frontend sophistication and backend prowess, ultimately delivering a transformative solution that revolutionizes agricultural health management and enriches user experiences.

REFERENCES

[1] Ms. Kiran R. Gavhale, Prof. Ujwalla Gawande ,An Overview of the Research on Plant Leaves Disease detection using Image Processing Techniques, Ver. V (Jan. 2014).

[2]. Mr. Prasham Shah, Mr. Anshul Kherde , Mrs. Rasika Solav , Mrs. Megha Warghane , Mrs. Nafiya Khan5 , Dr. A. A. Khodaskar , S. W. Wasankar , Dr V. K. Shandilya, "Research Paper on App-Based Solution to Identify & Solve Disease in Plants", International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2321-9653, Volume-11 Issue-5, April 2023

[3]. https://www.tensorflow.org/datasets/catalog/plant-DOC.

[4] Gyan Singh Sujawata, Dr. Jitendra Singh Chouhan, " Application of Artificial Intelligence in detection of diseases in plants ", 2121.

[5] Smita Unnikrishnan, Aliya Nazeer, Haneena Najeeb, Niveditha T G,Sreeya A Y, plant disease identification using ml, Volume 9, Issue 5 May 2021

[6] Intelligent Mobile Plant Disease Diagnostic System Using NASNet-Mobile Deep Learning, Adedamola O. Adedoja, Pius A. Owolawi, Temitope Mapayi, Member, IAENG, and Chunling Tu, Volume 49, Issue 1: March 2022

[7] Aliyu M. Abdu, Musa M. Mokji, Usman U. Sheikh, Vol. 9, No. 4, December 2020Machine learning for plant disease detection: an investigative comparison between support vector machine and deep learning, Vol. 9, No. 4, December 2020.

[8] Ayesha Siddiqua , Muhammad Ashad Kabir , Tanzina Ferdous , Israt Bintea Ali and Leslie A. Weston , Evaluating Plant Disease Detection Mobile Applications: Quality and Limitations, . Agronomy 2022.

[9] Adedamola O. Adedoja, Pius A. Owolawi, Temitope Mapayi, Intelligent Mobile Plant Disease Diagnostic System Using NASNet-Mobile Deep Learning, Volume 49, Issue 1: March 2022.

[10]. Sunil S. Harakannanavar a,∗ , Jayashri M. Rudagi b , Veena I Puranikmathb , Ayesha Siddiquaa , R Pramodhini a, "Plant leaf disease detection using computer vision and machine learning algorithms ", September 2022

[11] Gyan Singh Sujawata, Dr. Jitendra Singh Chouhan ,Application of Artificial Intelligence in detection of diseases in plants, Vol.12 No.3(2021), 3301-3305

[12] Ahmed, A.A.; Reddy, G.H. A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning. Agri Engineering 2021, 3, 478–493.

[13] C Jackulin, S. MurugavalliA, comprehensive review on detection of plant disease using machine learning and deep learning approaches,2022.

[14] L. R. Priya, G.Ignisha Rajathi, R. Vedhapriyavadhana, Crop Disease Detection and Monitoring System, ISSN: 2277-3878, Volume-8 Issue-4, November 2019