

Image Based Plant Disease Detection using CNN: An Experimental Research

Disha Wankhede¹, Aman Narnaware², Abhaykumar Baral³, Akash Gawade⁴ and Atharva Valsange⁵

¹⁻⁵Department of Computer Engineering, Vishwakarma Institute of Information Technology

Email: disha.wankhede@viit.ac.in, {amannarnaware8, abhaybaral03, akashgawade162, atharvavalsange}@gmail.com

Abstract— The first step in preventing losses in agricultural product output and quantity is the identification of plant diseases. The study of patterns that are visible to the human eye on plants is referred to as plant disease research. Plant disease identification and health monitoring are essential for sustainable agriculture. Manually keeping an eye on plant diseases is really challenging. It necessitates an enormous amount of processing time, a great deal of labor, and knowledge of plant diseases. Therefore, plant disease detection uses image processing. A number of processes are involved in disease detection, including feature extraction, classification, segmentation, pre-processing, and image acquisition. This study examined techniques for identifying plant illnesses using photos of their leaves. A few segmentation and feature extraction techniques for plant disease identification were also covered in this work.

Index Terms— Plant disease detection, Convolution Neural Network, CNN Architecture, Deep learning.

I. INTRODUCTION

Approximately 70% of people in India are employed in agriculture. It's critical to identify plant diseases in order to minimize yield losses. Manually observing plant diseases is very tough. It requires a significant amount of labor, knowledge of plant diseases, and a lengthy period of time. Therefore, plant disease detection can be accomplished through the use of image processing and machine learning models. In this project, we have outlined the method for using photos of the plants' leaves to identify plant illnesses. A subfield of signal processing called image processing is responsible for extracting valuable information or attributes from images.

Plant diseases can be found in several methods. Certain illnesses exhibit no outward signs at all, or if they do, they do so when it is too late to treat them. In these situations, in-depth analysis is required, typically using potent microscopes. In certain situations, the symptoms are limited to areas of the electromagnetic spectrum that are invisible to humans.

Nonetheless, the majority of illnesses manifest in some way in the visual range. The signs of the illnesses might appear on the leaves, stem, fruits, seeds, and other sections of the plant. This study aims to identify and categorize illnesses of plants according to the symptoms that manifest on the plant's leaves. The majority of the time, a visual diagnosis—or at least an initial estimation of the illness—is made by people. Skilled professionals might be effective in identifying the illness. Regretfully, most of the time there aren't any subject matter specialists available to provide farmers with data-driven analysis and advice. Thus, it is critical to find a quick, automated, low-cost, and precise way to identify plant diseases.

Agricultural research has made use of machine learning techniques and DL Convolutional neural networks, or CNNs, have been utilized recently to classify images and recognize objects. An example of a deep neural network (DNN) that processes images is a convolutional neural network, which was inspired by the human visual system. For object recognition, a number of CNN architectures were suggested. Keras and Tensorflow are two of them that have been used as standards for different kinds of work.

The study is structured as follows: part II covers earlier research in a related field. Convolutional Network Architecture is covered in Part III. Part IV presents the proposed methodology while Part V presents the results obtained and finishes with discussions of the result.

II. LITERATURE SURVEY

K. Muthusan and colleagues used a range of machine learning algorithms to detect spot infections in leaves and categorized them based on the diseased leaf classifications. Diseased plant leaves were identified by assessing form and texture data gathered from the afflicted leaf shot using FFNN, RBFN and LVQ (Learning Vector Quantization). The efficiency of the recommended system was shown by the simulation. The creation of a machine learning-based plan to improve crop quality has been made possible by this study, benefiting India's economy. [1] Malvika Ranjan and associates' work on the detection of plant leaf disease begins with image capturing. The results of the segmentation process are utilized to extract color data, such as HSV characteristics, and these feature values are then used to train an artificial neural network (ANN) to discriminate between samples that are healthy and those that are sick. The current study provides a method for reliably and promptly identifying illnesses of cotton leaves by combining image data processing techniques and an. [2] Walleign, Serawork, Crop Disease Detection Through CNS, and Soybeans all state The viability of using CNN to identify crop diseases in images of leaves captured in their natural habitat is demonstrated in this work. The model's creation makes use of the LeNet architecture in order to classify plant diseases in soybeans. The PlantVillage collection yielded 12,673 samples of tested green photos of four different kinds, including pictures of healthy leaves. The photos were taken in an impromptu setting. The created model demonstrates that convolutional neural networks can extract relevant information and identify plant ailments from field photos with a 99.32% classification accuracy. [3] This study describes a method for accurately diagnosing illnesses of apple leaves. It is necessary to construct a deep CNN with a unique architecture based on AlexNet and enough unhealthy images to diagnose apple leaf ailments. Using a dataset of 13,689 photos of diseased apple leaves, the proposed deep CNN model aims to detect four common diseases of apple leaves. The overall accuracy of the suggested illness detection model is 97.62 percent. The suggested model produced pathological images that increased the accuracy of the model by 10.83%, and its parameters were 51,206,928 less than those of the AlexNet model. According to this study, a deep learning model for disease management could lead to better disease control because it would be more accurate and would converge more quickly. [4]. The use of deep learning (DL) to the identification of plant leaf diseases, including a thorough rundown of current developments and obstacles. The paper highlights the need of different datasets with substantial variability and highlights how DL approaches can achieve high accuracy in disease detection when sufficient training data is available. Methods for increasing classification accuracy are presented, including data augmentation, transfer learning, and visualisation of CNN activation maps. Problems are noted, such as the prevailing dependence on the PlantVillage dataset and the inadequacy of current DL models in terms of robustness. This calls for the development of more flexible models and larger datasets that are collected in real-world scenarios. The survey acknowledges the difficulties in acquiring labelled datasets and also looks at the potential of hyperspectral imaging for early disease identification. [5] Alzubaidi, L., Zhang, J., Humaidi, A.J. research delves into the main issues and potential paths in deep learning (DL), especially as they relate to multimodal DL, dataset needs, and shared frameworks. It draws attention to the challenges of modelling many data modalities at once and stresses the need for large labelled datasets in real-time applications. The analysis emphasises how important data augmentation and transfer learning are in reducing dataset constraints. Discussed are issues with hardware resources, hyper-parameter tuning, and the shift in DL towards unsupervised and semi-supervised learning. The survey provides insightful information for academics studying the dynamic field of deep learning by projecting future trends in cloud-based platforms, mobile applications, and creative DL architectures. [6]. The review of the literature explores the ongoing development of convolutional neural networks (CNNs) and their essential function in vision and image processing applications. It offers a taxonomy for current architectures based on processing unit design patterns in addition to reviewing CNN developments. The paper highlights a noteworthy advancement in learning ability with the switch from traditional layer structures to creative block designs. By acting as auxiliary learners, these blocks improve CNN performance by utilising spatial or feature-map

information. Block-based architecture's modular design makes networks easier to grasp and fosters innovation. Trends to be expected are further emphasis on block creation, attention mechanisms, and more effective use of channel and spatial information to increase CNN efficacy. [7] The literature study highlights the unique features that set Convolutional Neural Networks (CNNs) apart from other types of Artificial Neural Networks. It places a strong emphasis on utilising particular input knowledge, which simplifies network structures. The paper offers a basic grasp of CNN principles, clarifying necessary layers and providing the best possible organisation for image analysis tasks. Notably, it dispels the myth about the alleged difficulty and knowledge requirements of utilising neural networks for image processing. By demystifying this notion, the authors hope to increase the field's accessibility for novices and encourage further investigation and study into CNN image analysis. [8]. An extensive review of deep learning, a crucial element of artificial intelligence and data science, is given in this paper. It starts with an overview of artificial neural networks in the past and go on to discuss deep learning techniques and advancements in a variety of industries now. The investigation includes key methods, multi-dimensional deep neural network modelling, and a taxonomy covering different deep learning applications and tasks. The study presents hybrid learning for solving problems in the real world and covers supervised and unsupervised learning, including generative learning. Convolutional neural networks (CNNs) are the subject of important topics in the conclusion, which emphasises the importance of the convolution layer and the effect that layer count has on network performance in the training and testing stages. [9]. This study highlights deep learning's primary benefit above traditional machine learning by highlighting its capacity to independently identify pertinent characteristics in high-dimensional data. With a focus on Convolutional Neural Networks (CNN), the study clarifies the fundamental concepts of CNN, including its general model, several topologies, and important learning methods. CNN has shown to be quite helpful in resolving challenging issues, especially those involving contextually-based classification. Applications such as traffic sign identification, ocean front recognition, high-resolution data analysis, audio scene understanding, remote sensing, and MR brain image segmentation are noteworthy. The study offers insights on CNN's capabilities and uses, making it a useful tool for learners and starting out in the deep learning sector. [10] Six common grape leaf pests and diseases—anthracnose, brown spot, mites, black rot, downy mildew, and leaf blight—cause significant financial losses for the grape sector. For the disease to be contained and the grape industry to grow healthily, early diagnosis and precise identification of grape leaf diseases are essential. In order to diagnose grape leaf diseases, this research suggests a unique recognition method based on enhanced convolutional neural networks. First, using image enhancement techniques, a data set of 107,366 grape leaf photos is created, based on 4,023 images taken in the field and 3,646 images taken from public data sets. The performance of multi-dimensional feature extraction is then improved by applying the Inception framework. [11] Identifying plant diseases early and accurately is essential to the crop protection process. In conventional methods, identification is accomplished through laboratory testing or visual inspection. While the laboratory test takes time and might not be able to deliver results quickly, the visual observation requires experience and can vary depending on the individual, which could result in an error. A literature-presented image-based machine learning technique to plant disease detection and classification has been proposed as a solution to these problems. In this work, we have concentrated exclusively on rice plant (*Oryza sativa*) illness. The rice field provided the photos showing the sick indications on the leaves and stems. [12]. Deep Convolutional Neural network Supported Identification of Crop Diseases by Plant Image Classification is a novel approach for building a crop diseases recognition model based on plant image classification and deep convolutional networks, as presented by Srdjan Sladojevic and colleagues. The unique training technique combined with the methodology used makes it possible to quickly and easily set up the system in practice. This constructed model can distinguish thirteen forms of plant diseases from healthy leaves, and it can identify crops from their environment. The paper goes into depth about every step required to deploy this disease recognition algorithm, starting with taking pictures to create a database that is assessed by specialists in agriculture. The deep CNN training was carried out using Caffe, a deep learning framework created by Berkley Vision and Learning Center. For independent class testing, the experimental findings on the created model yielded an average precision of 96.3%, falling between 91% and 98%. [13]. To increase the quality and quantity of agricultural production, disease control techniques must be implemented when plant diseases have been identified. Plant disease automation is highly helpful because it lessens the amount of effort that large farms must do for monitoring. Since leaves are a plant's primary food supply, it's critical to identify leaf diseases as soon as possible. This article contains an automated method based on deep learning for identifying leaf diseases in Mango plant species. Anthracnose, Alternaria leaf spots, Leaf Gall, Leaf Webber, and Mango leaf burn are among the five leaf diseases that have been detected from a dataset that includes 1200 photos of both healthy and defective mango leaves. The accuracy of the suggested CNN model in identifying the leaf is 96.67% [14] An In-the-Moment Identification of Tomato Plant Pests and Illnesses Using Deep Learning Three types of detectors are examined by

Alvaro Fuentes and colleagues; they are called "deep learning meta-architectures" in this research and include the Area Convolutional Neural Network (R-FCN), the Single Action Multibox Detector (SSD), and the Faster Region-based CNNs (Faster R-CNN). We combine each of these meta-architectures using "deep feature extractors" such as Residual Network and VGG net (ResNet). We demonstrate the performance of deep morpho and feature extractors, and we propose a method for both locally and globally achieving better accuracy and fewer false positives during training through feature extraction and category labeling. Our extensive Tomato illnesses and Pests Dataset, which includes difficult photos of pests and illnesses together with multiple inter- and extra-class variables like infection status and plant location, is used to train and test our systems end-to-end.[15] Author had done plant disease prediction using Machine Learning and Deep Learning algorithms also they had done detailed survey on agriculture Soil Nutrients for Crop (pH, N, P, K)Using Machine Learning Classifier [16][17][18][19]

III. DATASET AND PROPOSED METHODOLOGY

In the development of our proposed model, we leveraged the power and flexibility of the tensorflow.keras library. TensorFlow, an open-source machine learning framework, provides a good foundation, and Keras, as its high-level API, facilitated seamless access to neural network layers.

In this research we used the data from New Plant Disease dataset which provided us with 38 classes of plant diseases and 70295 RBG images for testing and 17572 RBG images for validation. The dataset provided is already augmented for more diverse and better model performance. The default dimensions of images in our dataset are (256x256x3). The dataset images are clear RBG with a little noise for better generalization of the model.



Fig. 1. Apple Scab sample image

Our model is designed to effectively capture intricate patterns and hierarchical features within the image data. The architecture comprises of multiple convolution layers with increasing filter complexity followed by strategically placed pooling layers to extract spatial hierarchies. Batch normalization layer is also employed to enhance the network convergence and generalization.

The fully connected layers at the end of the network interpret learned features for precise classification. A distinctive aspect of our proposed methodology lies in the integration of Batch Normalization, strategically applied after a significant convolutional layer, contributing to improved training stability and convergence.

The proposed methodology is trained and fine-tuned using an Adam optimizer with a carefully selected learning rate. The model is configured to minimize the sparse categorical cross entropy loss, while accuracy metrics are employed to assess the model's performance.

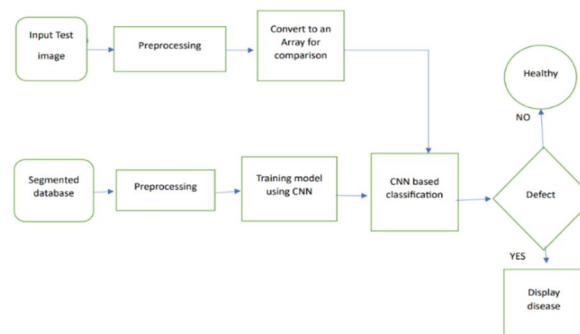


Fig. 2. Flowchart of our model.

Generally explanation of the flowchart :

1. In the following step, the input test image is obtained, pre-processed, and then arrayed for comparison.
2. The chosen database is appropriately pre-processed, divided, and renamed into the appropriate directories.
3. After the model has been appropriately trained with CNN, categorization occurs.
4. The result is displayed after a comparison between the trained model and the test image.
5. The program shows the disease if there is a flaw or illness in the plant.

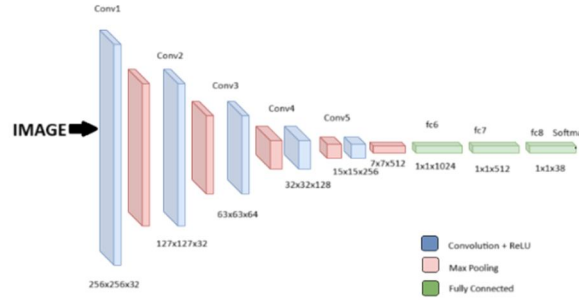


Fig. 3. Model Architecture

TABLE I. MODEL SUMMARY

	Layer	Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	256 x 256 x 3	-	-	-
1	Convolution	32	256 x 256 x 32	3x3	1	relu
2	Max Pooling	32	127x 127x32	3x3	2	relu
3	Convolution	64	127x 127x64	3x3	1	relu
4	Max Pooling	64	63 x 63 x64	3x3	2	relu
5	Convolution	128	63 x 63 x128	3x3	1	relu
6	Max Pooling	128	31 x 31 x 128	3x3	2	relu
7	Convolution	256	31 x 31 x 256	3x3	1	relu
8	Max Pooling	256	15 x 15 x 256	3x3	2	relu
9	Convolution	512	15 x 15 x 512	3x3	1	relu
10	Max Pooling	512	7 x 7 x 512	3x3	2	relu
11	FC	-	1024	-	-	relu
12	FC	-	512	-	-	relu
Output	FC	-	38	-	-	Softmax

Fig. 3. Displays the layers and the output dimensions of the image after each convolution layer. The Activation function used in every convolution and max pooling layer is ReLU (Rectified Linear Unit) which is most used in artificial neural networks and deep learning models. The last fully connected layer has the size 38 for our total number of classes in our dataset, with softmax activation function to essentially normalize the input vector into a probability distribution. The output then can be interpreted as the probabilities of the input belonging to each class in a multi-class classification problem.

The first Conv2D layer utilizes 32 filters with a kernel size of (3, 3), creating feature maps of size (256, 256, 32). Subsequent max-pooling layers with a pool size of (3, 3) and strides of (2, 2) progressively down sample the feature maps, capturing increasingly complex patterns. The network incorporates Conv2D layers with 64, 128, 256, and 512 filters, each followed by max-pooling, contributing to a deep and expressive feature hierarchy. The final architecture is completed with three dense layers, comprising 1024, 512, and 38 neurons, respectively. The Flatten layer transforms the spatial dimensions of the feature maps into a flat vector, serving as input to the fully connected dense layers. The model, with a total of 29,903,206 parameters, undergoes training to adapt the weights and biases, ultimately yielding a trainable parameter count of 29,902,182. These parameters collectively define the convolutional filters and dense layers, enabling the model to learn intricate patterns for accurate image classification.

IV. EXPERIMENTAL RESULTS

The high training accuracy indicates that the model has effectively captured the underlying relationships within the training data, achieving a substantial level of accuracy during the learning process and test accuracy implies that the model has successfully extracted relevant features and patterns, enabling accurate predictions on real-

world, diverse image. Fig 4. And Fig 5. Displays the accuracy vs epoch metric which indicates that the model is generalizing well and is less prone to overfitting. The achieved low model loss in our research underscores the efficacy of our training strategy and model architecture. The low model loss values attest to the stability of the training process and suggest an optimal level of model complexity suited to the intricacies of our classification task. This increases our confidence in the model's ability to make accurate predictions on diverse datasets and highlights its potential for real-world applications in image classification.

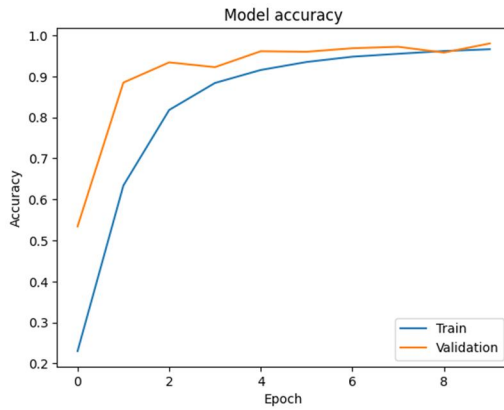


Fig. 4. Model Accuracy

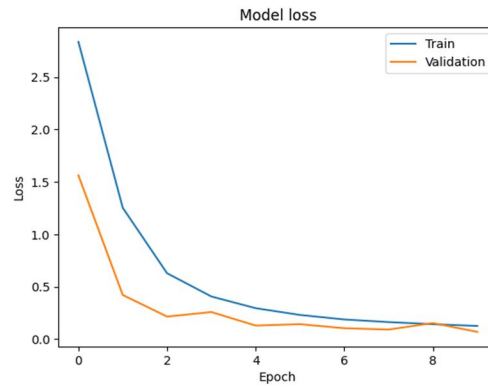


Fig. 5. Model Loss

The observed pattern of a concentrated diagonal in our confusion matrix, particularly in the context of a multi-class classification task with 38 classes, signifies a good level of accuracy and precision achieved by our model. The diagonal elements represent instances where the model correctly predicts the class labels, indicating robust performance across the majority of classes. Our model achieved Training accuracy of 96.61 %, Testing accuracy of 99.15 % and Validation accuracy of 98.02 %, with other important metrics such as Precision score of 99.15 %, Recall score of 99.15 % and F1 score of 99.14 %. Our model performed exceptionally well for the dataset and high testing and validation accuracy implies that it is well suited for external unseen data and the precision, recall, and F1 scores emphasize its effectiveness in minimizing false positives and false negatives. The following are some sample predictions our model performed:

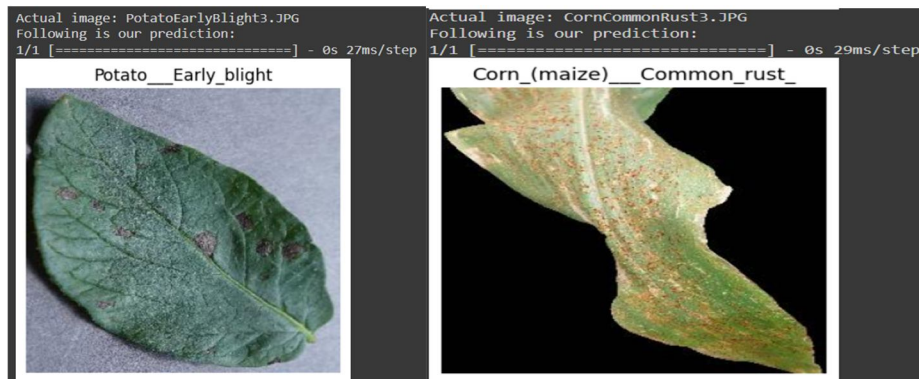


Fig. 6. Sample predictions performed by our model.

TABLE II. SIMULATION SYSTEM CONFIGURATION

Python	Version 3.8.0
OS	Windows 11 Home
Memory	16 GB DDR3 RAM
CPU	Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz 1.80 GHz
GPU	T4 GPU

V. CONCLUSION

In conclusion, the utilization of CNNs for image-based plant disease detection in the context of crop health has revolutionized agricultural practices. The accuracy, spatial precision, and adaptability of these networks contribute significantly to advancing precision agriculture, paving the way for sustainable and efficient crop management. As technology continues to evolve, the marriage of CNNs with agriculture holds immense potential for addressing global food security challenges. The fusion of artificial intelligence with agriculture opens new possibilities for addressing the complexities of modern farming. As we embrace the challenges and opportunities that lie ahead, we envision a future where technology continues to be an ally in nurturing our crops, ensuring global food security, and fostering agricultural sustainability. In the future, a number of interesting directions could influence CNN-based image-based plant disease diagnosis. One notable possibility is the integration of data across several modalities. Plant disease detection models can be made far more accurate and robust by include data from a variety of sources, including soil, climate, and satellite imaging. With the use of this multi-modal approach, crop health may be understood holistically, facilitating more thorough and knowledgeable agricultural decision-making. There is a lot of promise for developing explainable artificial intelligence (XAI) in agriculture. Creating methods that offer clear insights into the decision-making process of CNN models can enable farmers and other stakeholders to make well-informed decisions. In addition to inspiring confidence, transparent AI models guarantee that end users can comprehend and take action on the CNNs' recommendations.

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