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Prediction of Sick Leaf with its Sickness Percentage by Using Deep Learning Methods

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Abstract

Background / Objectives: Any cultivation health depends on its crop's health, and a crop health totally depends on various factors such as soil moisture, pesticides, weather condition etc. from these factors some are out of the control of a farmer so if we have information of crop health 24X7 than we can utilized this information to take precautionary steps to control the degradation of crop and with this we can also be able to decide further steps in that cultivation.
Methods / Statistical Analysis: So here in this paper deep learning methodology is used where leaf's sickness is predicted and on the basis of percentage of leaf sickness further steps can be planned for particular crops, like now it is feasible to go with this crop or not etc.
Findings / Applications: Disease can be detected by using CNN techniques of deep learning.
Improvements: The better prediction can be used for better outcomes in future.
Keywords: Deep Learning, CNN, Disease Detection.

1. Introduction

Prediction of Leaf Sickness using deep learning is a pivotal area of research in agriculture, offering innovative solutions to address the challenges posed by plant diseases. In the realm of precision agriculture, where technology intersects with farming practices, this terminology to identify and diagnosis of leaf sickness in early stages plays a crucial part in crop management and yield optimization. This research work focuses on employing state-of-the-art deep learning models to revolutionize the detection of leaf sickness, providing a more efficient and accurate means of diagnosis compared to conventional methods. The introduction delves into the significance of early sickness detection of leaves to ensure early diagnosis of problems and root causes do that precautionary step can be taken. This work signifies the impact of plant health for crop yield and quality, emphasizing the economic implications for farmers. Furthermore, this paper discusses the limitations of conventional methods for disease identification and emphasizes the potential of deep learning algorithms in overcoming these challenges.

In addition to highlighting only agricultural implications, the introduction also underscores the technological landscape that underpins the research, emphasizing the role of deep learning as a transformative force in image recognition and pattern analysis. By leveraging convolutional neural networks (CNNs) and other updated deep learning architectures, this work aims to enhance the accuracy and speed of leaf sickness identification. The section also touches upon the increasing availability of high-quality image datasets, facilitating the training of robust models capable of discerning subtle nuances in leaf health. As the introduction unfolds, it elucidates the methodology that will be employed, highlighting the integration of cutting-edge technologies to create a robust and reliable leaf disease/sickness detection system. This endeavour is not merely about addressing current challenges but also positioning agriculture at the forefront of technological innovation, ensuring a sustainable and resilient future for global food production.

2. Literature Review

Various techniques are proposed by the researchers in the recent past. Chowdhury, Muhammad EH, et al. proposed a system that is used to detect leaf disease using deep learning architecture based on a recent CNN called Efficient Net on 18,161 plain and segmented tomato leaf images to classify tomato diseases. In this paper the comparison study of performance of the models is based on binary classification that includes healthy and unhealthy leaves, the six-class classification includes healthy and various groups of diseased leaves, and ten-class classification includes healthy and various types of unhealthy leaves. The modified U-net segmentation model showed better accuracy but the Efficient Net-B7 showed superior performance for the binary classification and six-class classification using segmented images with an accuracy of 99.95% and 99.12%, respectively [1].

Jasim, Marwan, et al. proposed in his paper that some plants that are infected by diseases will have adverse impacts on the country's agricultural production and its economic resources. This paper presents a system that is used to classify and find plant leaf diseases using deep learning models. The training images were obtained from Plant Village dataset website. In this work, the authors have taken specific types of plants that include tomatoes, pepper, and potatoes, as they are the most common types of plants in Iraq. This Data Set contains 20636 images of plants and their diseases. As a outcome, they obtained excellent accuracy in training and testing, they have got an accuracy of 98 for training, and 98% for testing for all data set that were used [2].

Dhaka, Vijaypal Singh, et al. presented a system in their paper that used powerful tools for image recognition. Convolutional Neural Networks are one of the best deep learning tools that have attained an impressive outcome in this area. Identifying objects, faces, bones, handwritten digits, and traffic signs signify the importance of Convolutional Neural Networks in this world. The accuracy of Convolutional Neural Networks in image recognition motivates the researchers to explore its applications in the area of agriculture for recognition of plant species, yield management, weed detection, soil, and water management, fruit counting, diseases, and pest detection, evaluating the nutrient status of plants, and much more useful [3].

Ozguven, Mehmet Metin, et al. proposed that disease symptoms should be detected as early it can be so that proper precaution or measures should be taken in that real time to prevent future spread of the disease. In this paper, they have developed updated Faster R-CNN architecture by manipulating the parameters of a CNN model and a Faster R-CNN architecture for automatic detection of leaf spot disease. The method that is proposed for the detection of disease severity was trained and tested with 155 images and according to the test results, the overall correct classification rate was found to be 95.48% [4].

Panchal, Adesh V., et al. they have proposed a methodology that includes infected leaves of crops and they have labeled them as per the disease pattern. The images of infected leaves are processed by pixel-based operations to gather improved information from the images and then feature extraction is done that was followed by image segmentation and at the last classification of crop diseases is performed that is based on the patterns extracted from the diseased leaves. The CNN (Convolutional Neural Network) is used for the classification of diseases, for the demonstration purpose the public dataset is used consisting of around 87 K images (RGB type images) including healthy as well as diseased leaves [5].

3. Methodology

The main focus here is to develop a system which is capable of predicting leave sickness with the percentage of damage. For this purpose, two phases have been designed: 1st is the training phase and 2nd is the testing phase. In 1st phase a number of tasks is performed such as Image acquisition, Image Pre-processing and CNN based training. In 2nd phase Image acquisition, Image Pre-processing, Classification and disease identification have been performed. Below we have mentioned the step wise step methodology as per technique that has been used.

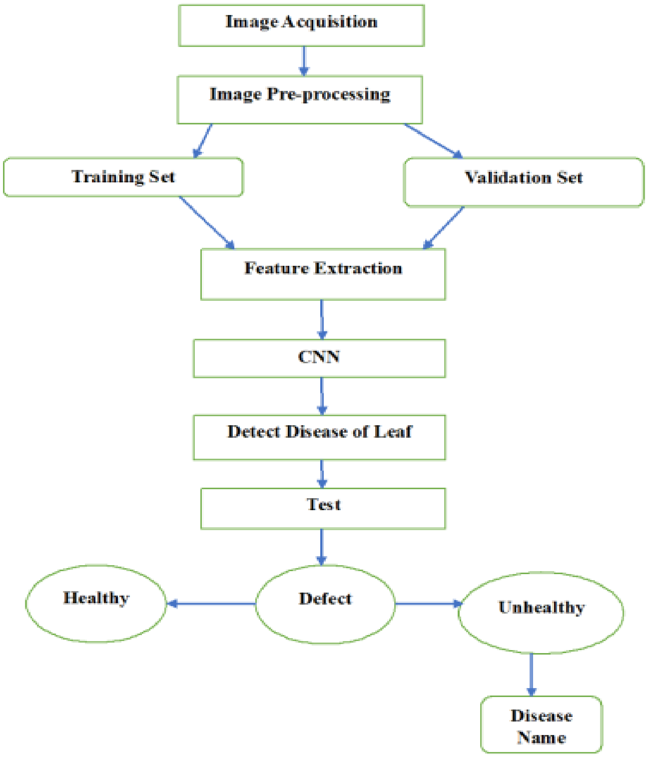


Figure 1. Flow Diagram of Sickness Detection Model

1. Image Dataset Preparation: This is a collection of images representing leaves and their associated disease status. These images serve as the foundation for training and evaluating the deep learning model.
2. Data Annotation: Annotation involves labelling images to provide the model with ground truth information. For leaf disease detection, this typically means marking regions of an image where diseases are present, aiding the model in learning relevant patterns.
3. Data Augmentation: Data augmentation entails creating variations in the dataset by applying transformations like rotation, scaling, and flipping. This diversifies the training data, enhancing the model's ability to generalize to new, unseen examples.
4. Testing, Training, Validation: These subsets serve distinct purposes:

- Training Set: Used to train the model.
- Validation Set: Employed for fine-tuning model hyperparameters and preventing overfitting.
- Testing Set: Utilized to assess the final performance of the trained model on previously unseen data.

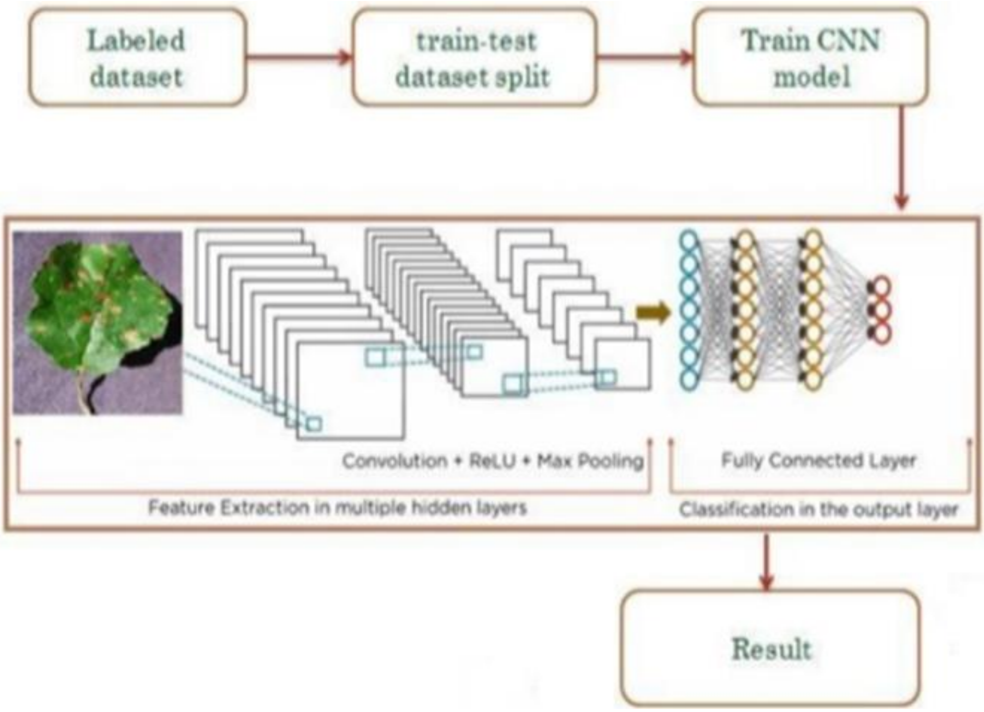


Figure 2. Procedural Diagram of Training and Learning Through CNN Model

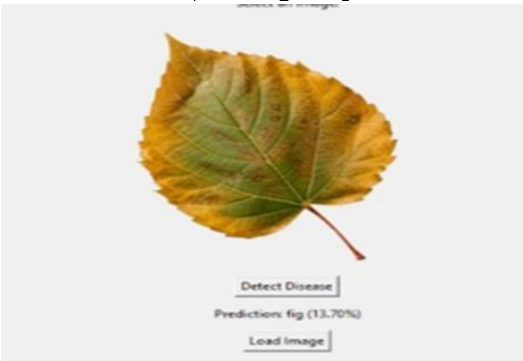
5. Disease Detection: In this phase, the trained model is applied to new images to classify leaves as healthy or diseased. The model leverages the learned patterns during training and validation to make predictions.
6. Disease Training: This involves training the deep learning model on the annotated dataset, typically employing algorithms like convolutional neural networks (CNNs). The model learns to recognize patterns and features associated with healthy and diseased leaves.
7. Performance Verification: After training, the model's performance is evaluated using metrics such as accuracy, precision, recall, and F1 score. This assessment gauges how effectively the model identifies diseases and its generalization to new, unseen data.

4. Result and Discussion

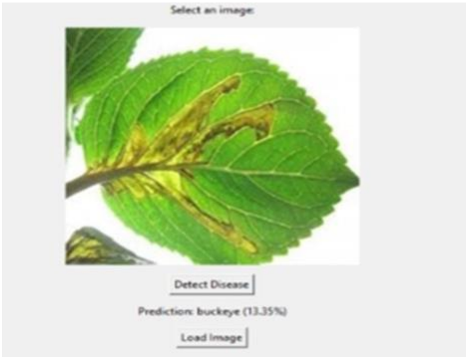
Here CNN is used to find the sickness of the leaf or we can say that we can classify if the leave is healthy or unhealthy. If the leaf is unhealthy then this method displays the name of disease or the reason behind the leaf sickness. Using Kaggle data can be obtain for different types of problem domain and we can apply CNN, Tensor Flow and Deep learning methods and enabled the model to learn hierarchical representations for differentiation between sicked and healthy leaves. This work is totally based on the adaptability and learning capacity of these deep neural networks, providing a robust foundation for image classification tasks.

a) Image Inputs

b) Leaf Sickness Percentage



c) Leaf Sickness Percentage



d) Leaf Sickness Percentage

Figure 3. Prediction of Sickness of Uploaded Images

5. Conclusion

Detecting leaf sickness using deep learning systems represents a significant advancement in agriculture, revolutionizing crop management and ensuring global food security. The application of deep learning models in disease identification offers an efficient, accurate, and scalable solution to address the challenges faced by farmers and agronomists. This technology not only aids in the early detection of diseases but also enables prompt intervention, potentially preventing widespread crop damage and economic loss.

The paper explored the implementation of various deep learning architectures, such as Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in disease Classification and detection. By training these models on vast datasets containing diverse leaf Images, the system has exhibited commendable accuracy in distinguishing between healthy and diseased leaves, as well as identifying specific diseases.

The implications of deploying a deep learning-based disease detection system extend beyond the realms of agriculture, contributing to sustainable farming practices, reduced chemical usage through precise disease management, and overall environmental conservation. The integration of such systems into smart farming technologies holds the promise of optimizing resource Allocation, crop yield, and ultimately, global food production.

A thorough investigation exposes the capabilities and limitations of the model. The achieved accuracy depends on a number of factors including the stage of disease, disease type, background data and object composition. Due to this, a set of user guidelines would be required for commercial use, to ensure the stated accuracy is delivered. As the model will be trained using a plain background and singular leaf, imitation of these features is best.

In conclusion, the synthesis of deep learning in leaf disease detection underscores its pivotal Role in modernizing agricultural practices, empowering farmers with early, accurate, and cost-Effective disease diagnosis. This technology not only mitigates agricultural risks but also paves the way for a more sustainable, productive, and resilient farming ecosystem essential for Meeting the growing demands of an ever-expanding global population. The potential for further Research and development in this field is vast, promising continued enhancements in accuracy, Speed, and adaptability, ultimately fostering a more robust and efficient agricultural landscape.

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