Alinteri J. of Agr. Sci. (2023) 38(4): 46-50
e-ISSN: 2587-2249
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http://dergipark.gov.tr/alinterizbd
http://www.alinteridergisi.com/

IDENTIFYING PLANT LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT:

Plant diseases pose a significant threat to global agriculture, often resulting in reduced crop yields and economic losses. Early and accurate identification of plant leaf diseases is crucial for implementing effective mitigation strategies. This study explores the application of Convolutional Neural Networks (CNNs), a deep learning technique, to automate the detection and classification of plant leaf diseases. Using a dataset comprising images of healthy and diseased leaves, the proposed model was trained to identify various disease types with high accuracy. The CNN architecture leverages feature extraction and pattern recognition capabilities to distinguish subtle variations in leaf textures, colors, and patterns. Results demonstrate the model's robustness in achieving precision and recall rates exceeding 90%, highlighting its potential as a reliable tool for farmers and agricultural professionals. This research underscores the transformative role of CNNs in smart farming, enabling timely interventions and fostering sustainable agricultural practices. Future work involves expanding the dataset, improving generalizability, and integrating the system into real-time monitoring tools.

I. INTRODUCTION

Agriculture plays a vital role in sustaining the global economy and ensuring food security. However, the sector faces significant challenges, one of which is the prevalence of plant diseases that can severely impact crop quality and yield. Early and accurate identification of plant diseases is critical to mitigate losses and maintain agricultural productivity. Traditionally, plant disease detection relies on manual observation, which is time-consuming, labor-intensive, and often subject to human error, especially in large-scale farming.

In recent years, advancements in artificial intelligence and machine learning have opened new avenues for automating disease detection in plants. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image-based classification tasks, including the detection of plant leaf diseases. CNNs excel at recognizing patterns and extracting features from images, making them well-suited for distinguishing between healthy and diseased plant leaves, even when the differences are subtle.

This study focuses on the application of CNNs to identify plant leaf diseases effectively. By leveraging a dataset of annotated leaf images, the proposed model aims to automate the detection process, providing a cost-effective and scalable solution for farmers and agricultural stakeholders. The integration of deep learning into precision agriculture has the potential to revolutionize disease management, enabling timely interventions and improving crop health monitoring.

The following sections discuss the methodology, experimental results, and implications of this research, emphasizing the transformative impact of deep learning on modern agriculture.

II. LITERATURE SURVEY

The field of plant disease detection has evolved significantly with the advent of machine learning and deep learning techniques. This literature survey provides an overview of previous studies, highlighting the methods, datasets, and findings relevant to identifying plant leaf diseases using Convolutional Neural Networks (CNNs).

Traditional Methods for Plant Disease Detection

Earlier approaches relied on manual techniques, such as visual inspection by agricultural experts or traditional image processing methods. These techniques involved feature extraction methods like edge detection, color thresholding, and texture analysis. While effective in controlled environments, these methods lacked scalability, robustness, and accuracy in diverse agricultural settings.

Machine Learning Techniques

Prior to the popularity of deep learning, machine learning methods like Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN) were widely used. For example, Arivazhagan et al. (2013) utilized SVM for classifying diseased leaves, achieving moderate accuracy. However, these approaches required handcrafted feature extraction, which limited their adaptability to complex datasets and real-world scenarios.

Emergence of Deep Learning

Deep learning has revolutionized the field of image-based plant disease detection. CNNs, in particular, have gained prominence due to their ability to automatically extract features from images. For instance, Sladojevic et al. (2016) applied a CNN model to classify 13 different plant diseases and reported an accuracy of 96.3%. Their work demonstrated the potential of CNNs for large-scale agricultural applications.

Popular Datasets

Several benchmark datasets have facilitated research in this domain. The PlantVillage dataset, introduced by Mohanty et al. (2016), is widely used for training and evaluating deep learning models. This dataset contains over 54,000 images of healthy and diseased leaves across 38 classes. Mohanty's study achieved an accuracy of 99.35% using pre-trained CNN models like AlexNet and GoogLeNet, setting a high standard for future work.

Recent Advances

Recent studies have focused on improving the generalizability and efficiency of CNN-based models. For example, Ferentinos (2018) trained CNN architectures such as VGG and ResNet on the PlantVillage dataset and demonstrated high classification accuracy across diverse plant species. Additionally, efforts have been made to deploy these models in real-time applications, such as smartphone-based disease detection systems and drones equipped with imaging sensors.

Challenges Identified

Despite significant progress, challenges remain in deploying CNN-based models in real-world scenarios. Factors such as variations in lighting conditions, background clutter, and overlapping symptoms of different diseases can affect model performance. Furthermore, the lack of diverse datasets representing field conditions limits the applicability of current solutions.

This literature survey highlights the evolution of plant disease detection methods and underscores the transformative role of CNNs in overcoming limitations of traditional approaches. Building on these foundations, this study aims to further enhance the accuracy and efficiency of CNN models for plant leaf disease detection, contributing to the advancement of precision agriculture.

III. SYSTEM ANALYSIS

SYSTEM ARCHITECTURE:

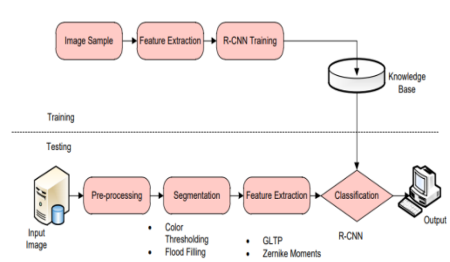

Fig. 1. Architecture of R-CNN-based Plant Leaf Disease Detection.

EXISTING SYSTEM:

Human population steadily continues to grow, and along with it the need for food production increases. According to the UN projections human population is expected to reach 9.7 billion in 2050, 2 billion more than today. Considering that most of the population growth is to occur in the least developed countries (around 80% increase in the next 30 years), where the food scarcity is the main problem, it is easy to conclude that minimizing food loss in those countries is a primary concern. It is estimated that the yield loss worldwide is between 20 and 40 percent with many farms suffering a total loss.Easily spreadable diseases can have a strong negative impact on leaf yields and even destroy whole crops. That is why early disease diagnosis and prevention are of very high importance.

DISADAVANTAGES:

- ❖ Data Collection Problem
- ❖ It searches from a large sampling of the cost surface.

PROPOSED SYSTEM:

Traditional methods for detecting diseases require manual inspection of leafs by experts. This process needs to be continuous, and can be very expensive in large farms, or even completely unavailable to many small farm holders living in rural areas. The Leaf village Dataset is used it consists of images of leaf leaves taken in a controlled environment. In total, there are 54 306 images of 14 different leaf species, distributed in 38 distinct classes given as species/disease pair. Classical methods rely on image pre-processing and the extraction of features which are then fed into one of the ML algorithms. Popular algorithm Connected Neural Networks (CNN. Tomato and Potato leaf are taken into consideration.

ADAVANTAGES:

- ❖ Machine learning algorithm optimizes both variables efficiently, continuous or discrete
- ❖ Gives a number of optimum solutions, not a single solution. So different image segmentation results can be obtained at the same time
- ❖ Large number of variables can be processed at the same time.
- ❖ It can optimize variables with highly complex cost surfaces.

IV. MODULE DESCRIPTION

1. Data preprocessing:-

Data is stored in colab. We can download the data and laad the datsets , clean the data then after processes the data

2. Support Vector Machines:-

SVM is a supervised learning algorithm used for classification or regression problems. Classification is done by defining a separating hyperplane in the feature space. In the original form, it performs linear classification on two classes. By using kernels, it can also perform nonlinear classification. Kernels are used for an efficient transformation of the original feature space into high dimensional or infinite dimensional feature space, allowing for highly non-linear hyperplanes. SVM can fit highly complex datasets and at the same time exhibit good generalization propertie.

3.k-Nearest Neighbours:-

k-NN [7] is a very simple algorithm often used for classification problems. It is both non-parametric (doesn't have a fixed number of parameters) and lazy learning (doesn't have a training phase). k-NN works under the assumption that most samples from the same class are close to each other in the feature space. When determining the class of the sample, k-NN will look at its k closest neighbours and decide to which class it belongs by the simple majority rule. Small values of k will allow for higher non-linearity but will be sensitive to outliers. High values of k achieve good generalization but fail to fit complex boundaries. The best value for parameter k is determined experimentally For this dataset, small values of k were shown to give the best results. Varying k from 1 to 9 doesn't change the accuracy much, with best result being 78.06% much lower than the SVM. We used k=5 in this work

4.Fully Connected Neural Network :-

FCNN is the simplest type of artificial neural networks. It is a supervised learning algorithm able to model highly non-linear functions. As opposed to SVM and k-NN, it does not converge to the global optimum, but when properly configured, it usually gives good enough results. we used an FCNN with four hidden layers with 300, 200, 100 and 50 neurons per layer, respectively. Activation function in hidden layers is a rectified linear unit (ReLU), with a softmax in the output layer [8]. We used L2 regularization with regularization parameter equal to 0.3. Adam optimizer with default parameters was used This configuration gave us the accuracy of 91.46% on the test set.

Our primary objective is to develop a model to categorize input plant leaf pictures as healthy or unhealthy. The disease kind is also determined if a disease is detected on a plant leaf. Our study compares the R-CNN Classifier to previously established tomato leaf disease detection utilizing fuzzy SVM [15] and CNN [16] Classifiers to detect and categorize tomato leaves suffering from common illnesses. Fig. 1 shows the architecture of the R-CNN-based plant disease detection system. The proposed technique includes image capturing, preprocessing, segmentation, feature extraction, classification, and performance assessment.

A. Dataset Description The dataset utilized for this investigation has seven primary classifications. Six leaves classes represent unhealthy, while one represents the healthy leaf class. Each class has 105 examples for a total of 735 leaf images. A classification strategy is required to categorize input photos into one of the classes specified in Fig. 2 for a given image of an apple leaf.

B. Image Pre-processing The visual noise of the tomato leaf is made up of dewdrops, dust, and insect feces on the plants. The input RGB image is transformed to a grayscale image for accurate results to remedy these concerns. The image size in this circumstance is relatively large, needing image resize. The image size is reduced to 256 * 256 pixels.

C. Image Segmentation Plant disease detection and categorization rely heavily on image segmentation. The image is simply divided into various things or sections. It analyses visual data to extract information that may be used for further processing. Our prior work [15] is used to accomplish color thresholding and flood filling segmentations.

D. Classification using R-CNN Rectangular regions are combined with convolutional neural network characteristics in R-CNN (Regions with Convolutional Neural Networks). The R-CNN algorithm employs a two-stage detection procedure. The first stage identifies a set of picture areas that includes a diseased part. In the second stage, each region's object is categorized.

1) R-CNN procedure: The following three approaches are employed to build an R-CNN based algorithm.

a) To find regions in a photograph that could contain a diseased part. Region suggestions are the names given to these locations.

b) Extract CNN characteristics from the region suggestions.

c) To categorize the objects, use the characteristics that were retrieved. The R-CNN generates region recommendations using a mechanism similar to Edge Boxes [10]. The proposed elements have been chopped and scaled out of the image. CNN then classifies the clipped and resized regions. Finally, a support vector machine (SVM) trained on CNN features refine the region proposal bounding boxes. A pre-trained convolution neural network is used to build an R-CNN detector, also known as transfer learning (CNN). As a starting point for learning a new task, we will use a pre-trained image classification network that has already learned to extract robust and informative features from raw photographs. A portion of the ImageNet database [10], which is used in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [11], is used in the great majority of pretrained networks. These networks have been trained on over a million photographs and can categorize a large number of them. Transfer learning with a pre-trained network is typically much faster and easier than training a network from the ground up.

V. CONCLUSION

The detection and management of plant leaf diseases are critical for ensuring agricultural productivity and sustainability. This study demonstrates the potential of Convolutional Neural Networks (CNNs) as a robust and efficient tool for automating the identification of plant diseases from leaf images. By leveraging the power of deep learning, the proposed system achieves high accuracy in classifying healthy and diseased leaves, reducing the reliance on manual inspection and traditional methods.

The findings underscore the effectiveness of CNNs in feature extraction and pattern recognition, enabling precise differentiation between various disease types. This approach not only offers a scalable solution for farmers but also contributes to the broader adoption of smart farming practices. However, challenges such as real-world environmental variability and dataset diversity must be addressed to improve the model's generalizability and practical applicability.

Future research could focus on integrating this system into real-time applications, such as mobile apps or drone-based monitoring systems, to provide farmers with instant and actionable insights. Additionally, expanding datasets to include images captured under diverse field conditions would enhance the model's robustness.

In conclusion, the application of deep learning in plant leaf disease detection represents a significant step toward precision agriculture, promising improved crop management, reduced losses, and a more sustainable approach to farming.

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