Vol.15, Issue No 2, 2025

Harnessing Deep Learning for Real Time Apple Leaf Disease Detection and Classification

[1]MANGINA GANESH, [2]GANGULA VENKATA MANIKANTA, [3]PALA LAKSHMAN, [4]TAMMINENI RAMBABU, [5]Mr. CH. VENKATA REDDY,

[1234]Student, Department of CSE, DNR College of Engineering & Technology, Balusumudi, Bhimavaram, India.

[5]Assistant Professor, Department of CSE, DNR College of Engineering & Technology, Balusumudi, Bhimavaram, India.

Abstract:

When it comes to India's economy, agriculture is king. The production of crops is impacted by a variety of diseases that impact plant leaves. Aside from dealing with pests and illnesses, apple growers are also faced with the ongoing problem of increasing crop yields. Diseases and pests are common, which greatly reduce apple yields and causes the sector to lose a lot of money every year. Predicting leaf diseases could be a challenging task for farmers. In order to manage and control apple leaf diseases (ALD) in orchards, rapid and precise detection is essential. In particular, new opportunities for early illness detection and comprehension on leaves have arisen because to developments in computer vision algorithms using Deep Learning (DL). An issue-solving web application built on DL models is suggested to forecast the presence of Healthy and Alternaria, Leaf Spot, Marssonina Blotch, and Powdery mildew on the afflicted leaf. The computer science and engineering department of Chandigarh University in Punjab, India, is headed by Meenu Gupta. information and resources to make educated decisions, send an email to meenu.e9406@cumail.in. The "web App" revolutionizes plant disease detection and prevention via the use of AI and picture recognition, leading to increased yields and more environmentally friendly farming practices. The goal of this project is to develop a web application that uses expert knowledge to diagnose apple leaf diseases (ALDs) using deep learning (DL). This application will assist farmers detect apple diseases more accurately. Once a disease has been identified, the farmer will ensure that the appropriate treatment is administered quickly and on schedule. As a consequence, crop yields are increased. Farmers and customers alike may benefit from this online app's emphasis on disease prevention, which in turn reduces the need of toxic pesticides. Disease prediction in leaves using DL, ALD-4C, and Convolutional Neural Networks (CNNs).

Introduction

Agriculture is a major contributor to India's economy. An estimated 70% of the population works in agriculture in some capacity, and the country grows a wide variety of crops. Manual labor is becoming the primary method of production for many Indian farmers [1]. Consequently, making ensuring the right cultivation methods are in place is crucial. Plant diseases are a major problem in farming since they reduce harvest yields and cost farmers a lot of money. As a result, fixing this problem is really necessary. Due to a dearth of technological understanding, the majority of Indian farmers are turning to manual farming methods. To increase crop yields and speed up plant development, leaves are essential. Researchers and farmers have challenges when trying to detect illnesses in plant leaves [2]. A "web App" is created to simplify farming by predicting three different types of ALD. All farmers have to do is snap a picture of the impacted leaf and send it to the app; it will then tell them whether the leaf is harmed or not. This breakthrough gives farmers the ability to better predict and deal with illnesses, which in turn increases their profitability and decreases their losses. Agribusinesses benefit from the use of technology since it streamlines agricultural processes and gives farmers access to The parts of this work are well defined. In Section II, we review the previous work of several researchers who have attempted to identify and categorize ALD. In part III, we cover the process of web applications. Section IV focuses on our suggested model, including its formulation and discussion. In Section V, we cover the process of finding the results. In conclusion. Section VI concludes the study by outlining its future ramifications.

Background Study

In the field of agriculture, automating the process of disease detection is of utmost worldwide significance. Many scientists have been researching various methods for detecting diseases. What follows is a compilation of research on plant diseases and the methods used to study them. L. Li et al. identified lesion sites and segments using three semantic segmentation network models: PSPNet, DeepLabV3+, and GCNet. There were two separate groups of diseased and healthy apple leaves in the picture collection. The parameters of the model were fine-tuned using Transfer Learning (TL) since the dataset was restricted. The segmentation model attained a MIoU of 83.85% and an MPA of 97.26%. Y. Gao et al. developed BAM-Net, a network that can identify ALD in difficult environments, in [4]. For the complicated backdrop, BAM-Networks validates BAM-Net's performance using a five-fold cross-validation procedure. Impressively, this model was able to distinguish between six distinct types of apple leaves with an F1-score of 95.25% and an accuracy of 95.64%. To further improve object recognition, X. Gong and S. Zhang presented an improved variant of the Faster Region-Based CNN (Faster R-CNN) technique in [5]. To enhance feature extraction, it used the advanced Res2Net and feature pyramid network architecture. Instead of RoIPool, RoIAlign was used to generate precise candidate areas for object localization. Additionally, in order to enhance the accuracy of ALD detection, it used soft non-maximum suppression during inference. On average, the suggested model was 63.1% accurate. For ALD detection in real-time, Y. Wang et al. presented the MGA-YOLO lightweight model in [6]. To boost its potential for ALD detection, the ALDOD dataset was manually annotated and enriched using several augmentation approaches. It was created by using four public dataset categories in the study. By including the Ghost module, CBAM, and other valuable tactics, MGA YOLO achieved better results than other state-of-the-art (SOTA) methods on the ALDOD testing set. Its model size was the smallest, its detection speed was the quickest, and its average accuracy was the greatest. A mean average accuracy (mAP) of 94.0% was achieved using this approach. S. Liu et al. presented YOLOX-ASSANano, a detector for ALD identification based on DL, in [7]. Here, the asymmetric Shuffle Block improves the network's feature extraction capabilities while keeping the model lightweight, which is a unique method. To further assist the network in zeroing in on important disease-related characteristics, the CSP-SA module was designed to include attention mechanisms. Convergence speed and overall performance are further enhanced by using BSConv and CIoU loss. On the MSALDD dataset, it achieves a mAP of 91.08%, but on the public dataset, it reaches 58.85% mAP. An EfficientNet MG model for ALD detection was suggested by Q. Yang et al. in [8].

For data preparation, they employed a variety of methods, one of which was Contrast Limited Adaptive Histogram Equalization (CLAHE). DMALR allows for more efficient training of CNN models. Due to this, EfficientNet-MG achieved an accuracy rating of 99.11%. An improved Faster R-CNN model using the Inception v2 architecture was suggested by M. Sardogan et al. in [9]. In Yalova, Turkey, apple orchards were used to test field apps for disease detection. Using data gathered from a variety of apple orchards over the course of two years, this model was able to reach an accuracy of 84.5%. An improved CNN model based on the VGG16 architecture was suggested by Q. Yan et al. in [10]. In order to decrease the amount of training parameters and accelerate convergence, the model's performance adjustments in the conventional VGG16 classifier were greatly improved with the addition of a batch normalization layer, a global average pooling layer, and a fully connected layer. The suggested algorithm was trained to detect ALD using a dataset that included 2,141 apple leaves. With a remarkable accuracy of 99.01%, the model passed all of the tests. An approach to disease detection in leaves using client-server mobile computing based on Gabor wavelet transformation (GWT) was proposed by S. Prasad et al. in [11].

The first stage involves converting colors to a color space model depending on the device. The mobile pre-processing phase follows the color space conversion and leaf capture phases. To make brightness seem better, the output curves of the a and b components were adjusted to form an a*b color space that mimics human vision. To analyze the leaf picture data, the K-means unsupervised approach was used, and features were extracted using Gabor wavelet conversion. The author of the study conducted their researches using a private dataset. An important hybrid clustering method for leaf segmentation was introduced by S. Zhang et al. in [12]. Using a superpixel clustering method, the author created cohesive patches out of neighboring pixels that shared certain brightness, texture, and color attributes. This method successfully simplified the picture by using fewer pixels. The Expectation Maximization (EM) technique was also suggested by the author as a potential approach to color picture segmentation. As a classifier for illness identification, M. Brahimi et al. suggested the DL approach in [13]. To better comprehend the illness and its localization, it made use of the occlusion concept. Good friend Bengio published the datasets used in this study. H. Al-Hiary et al. presented a method for the automatic identification and categorization of plant diseases in [14]. This technique uses the feature sets of pixels to divide them into k classes. The program creates new clusters to represent each illness when a leaf shows signs of more than one. Artificial Neural Networks (ANN) are used for disease detection and classification. A genetic algorithm-enhanced BP neural network and a multi-feature method were suggested by Y. Shao et al. in [15]. The Otsu technique was used to achieve the tasks of segmentation and extraction. A mobile client can do real-time tobacco illness detection in actual circumstances, and users may submit their ailments for server diagnosis. The Otsu approach was used for spot disease extraction in this scenario. The use of a genetic algorithm improved recognition accuracy and decreased training durations. S. Zhang et al. put up a fresh method for identifying cucumber leaf diseases in [16]. The uneven forms, intricacy, and shadows make this a job that traditional classifiers just can't handle. Authors used a mix of color and form characteristics taken from leaf pictures in this approach. They started by using the K-means clustering technique to the sick photos in order to separate the regions. Images are retrieved from the dataset and converted from RGB to Luminance ab* color model as the first stage of the system. We then use k-means clustering to classify the colors. Smoothing, enhancing, denoising, aligning, and segmentation using k-means clustering algorithms are all part of the preparation procedures that each picture goes through. To detect betel vine leaf rot disease, A. K. Dey suggested a technique for image processing in [17]. A vision-based technique was the core of their strategy for detecting and analyzing peripheral illness features. Characteristics of the diseased leaf regions' colors were used for diagnosis. For their investigation, the authors chose to focus on Bangla desi kinds of betel vine. In order to identify diseases, they used a Canon scanner that had a resolution of 300 PPI. Determined by dividing the total leaf area by the percentage of infected area, the severity of the illness was assessed. To separate illnesses caused by leaf rot, the author used the Otsu thresholding technique. In their study, S. Sladojevic et al. [18] suggested a technique for identifying leaf illnesses using a classification methodology and a deep convolutional network. Climate change, according to the research, might alter the phases of development and the rates of pathogen proliferation. In order to help with the distinction of leaf surrounds, a DN network was trained. In addition, squares around the leaves were manually cropped from all of the photos in order to highlight the areas of interest [19-21]. Rotations, transformations, and affine transformations were all part of the author's dataset expansion augmentation procedure. This research laid the groundwork for the deep Convolutional Neural Network (CNN) by introducing caffeine as its core framework.

I. Process for Web Applications The web application's process is shown in Figure 1 below. At the outset, users must verify their identity by signing in to the system. Users are automatically sent to the homepage after logging in successfully. Users who have not yet registered may visit the homepage when they have finished the sign-up procedure. After logging in and getting access to the site, users are given a few options to choose from. They have the option to take a picture at the moment, choose an existing one, or import one from their phone's gallery. Users may proceed to commence the procedure after making their option. Once the user has made these choices, they may begin processing their picture by clicking the "predict" button. The user's chosen picture is then fed into the CNN model, a DL model, in order to forecast the onset of sickness. For the user's convenience, the model analyses the picture and displays its illness prognosis on the screen. HTML, CSS, JavaScript, and Bootstrap are used together to improve the UI and make it more interactive. The system's backend is constructed using Python, namely Python Django. The server-side logic and template rendering are handled by the Jinja2 Template Engine. Database operations are performed by MySQL, while HTTP requests and replies are handled by Nginx, the web server. Our DL model training and testing is conducted using the cloud-based platform Colab Pro+, which provides easy access to GPU resources and powerful computing capabilities. This allows for quick model construction and assessment.

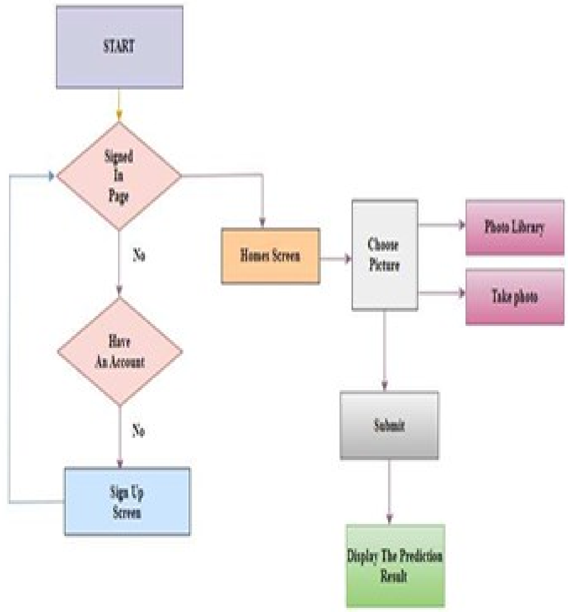

Figure 1. Webapp workflow diagram

PROPOSED SYSTEM

For ALD-4C Detection and Classification, the Proposed Model adjusted SE-ResNeXt-50. The three blocks shown in Figure 2 above are the components of the modified SE ResNeXt-50 model. These blocks, which consist of three layers each, receive the input picture one by one. The first layer uses 256x256 pixel pictures and is composed of 1x1 convolution. This process is known as contraction, and it produces an output with dimensions 4 by 4. Lastly, the output that has been contracted is sent to the attention layer of the proposed block, which is then passed on to the final layer of the block. The input to this layer is 4x4, while the extended output is 256x256, thanks to its 1x1 convolution. As an activation function, SiLU is used by each of these blocks. After that, a Multi-Layer Perceptron Layer (MLP) is applied to the combined output after SE (Squeeze and Excitation) processes all of the individual block outputs. The MLP's input is then classified using a SoftMax layer.

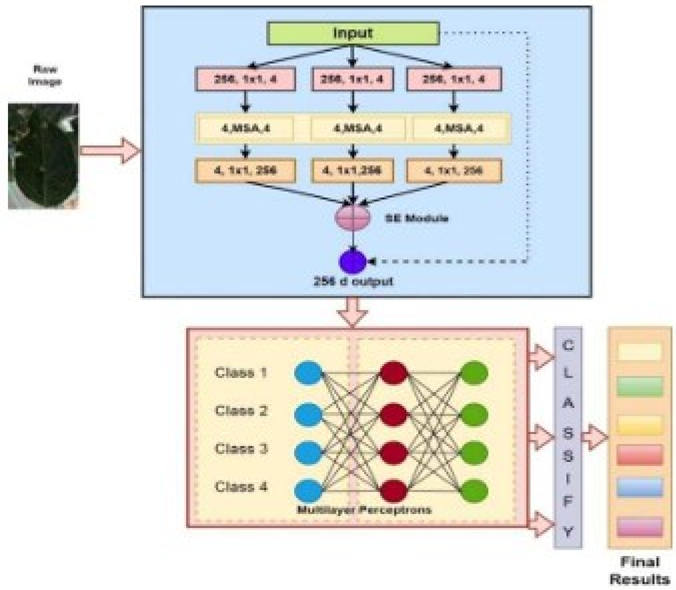

Figure 2. Proposed DL model

Result

The establishment Figure 1. Workflow flowchart for a web app The process of developing web applications makes use of a number of technologies. At the outset, we use a As a first stage in the suggested system, the user or farmer may utilize the app to submit a picture of a leaf. Clicking the appropriate button initiates the prediction process once users submit images. They may then wait for the results. The ALD4C apple leaf dataset is the main source for training and validating models for this purpose. The technology can tell whether a plant's leaves are infected or healthy once a photograph is uploaded. The system will show the leaf picture and illness name on the screen if an infection is found. Otherwise, a leaf that is healthy will be shown. Flowchart of the ALD detecting system may be shown in Figure 3.

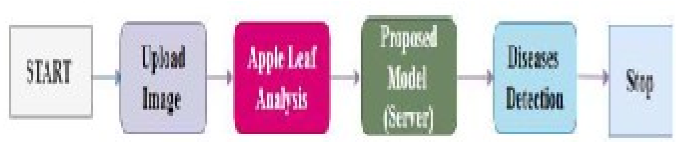

Figure 3. Flowchart of ALD detection system

You may see the web app in action in the study report via the screenshots that are cited in the figures that follow. The ALD detection web app's homepage is shown in Figure 4, which provides a glimpse of the app's first landing page. Figure 5 shows the ALD detection web app's login and sign-up interface, which sheds light on the authentication procedure. The situation following user authentication is shown in Figure 6, which exhibits the web application's UI upon successful login. In the study, the capabilities of the program are further explored, with the expected illness consequences shown. To illustrate the system's illness categorization capacity, Figure 7 depicts the expected results for the Alternaria ALD. Figure 8 shows how the web software depicts the expected healthy apple leaf, demonstrating the system's ability to differentiate between healthy and unhealthy leaves. Figure 9 shows the expected outcomes for Powdery Mildew in ALD, which demonstrates how well the online program can detect certain illnesses. Finally, the system's extensive disease categorization and visualization capabilities are shown in figure 10, which graphically depicts the expected prognosis for Marssonina Leaf Blotch in ALD. To better comprehend and assess the web app's functionality in the context of apple leaf disease detection, these images are vital visual assistance.

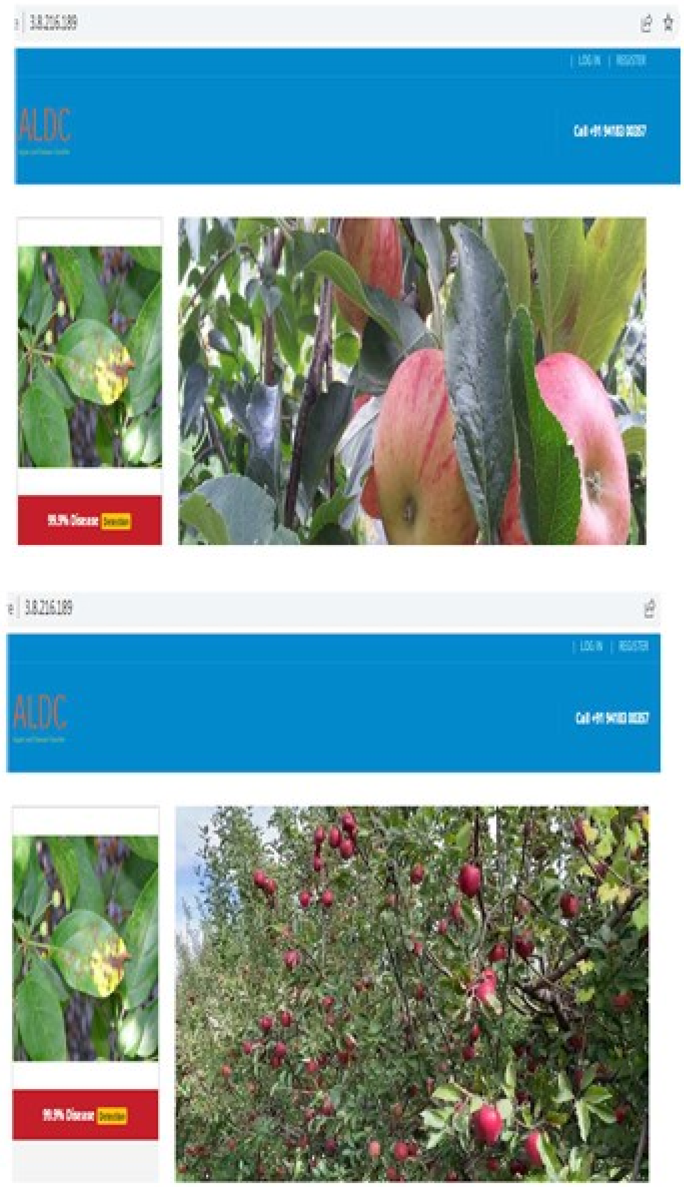

Figure 4. Homepage of ALD detection Web App

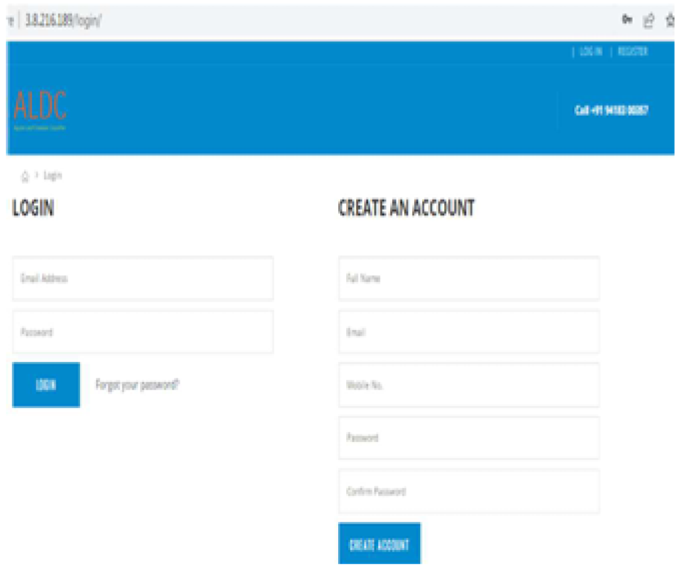

Figure 5. The Login / Sign Up Screen for ALD Detection Web App

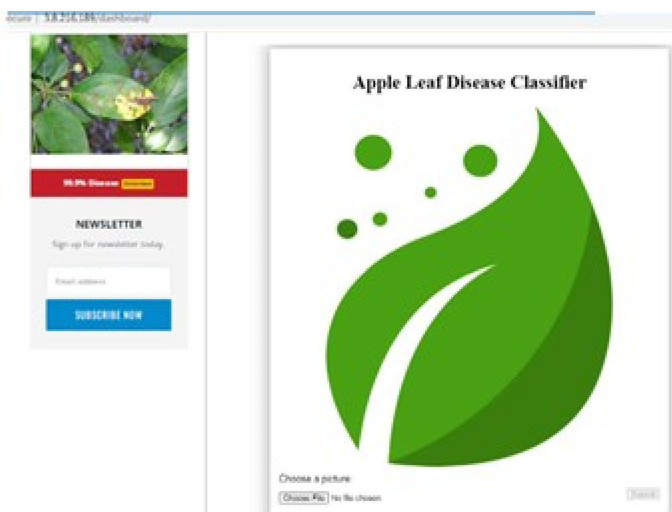

Figure 6. ALD detection Web App After the login

Figure 7. Predicted Alternaria ALD

Figure 8. Predicted Healthy Apple Leaf

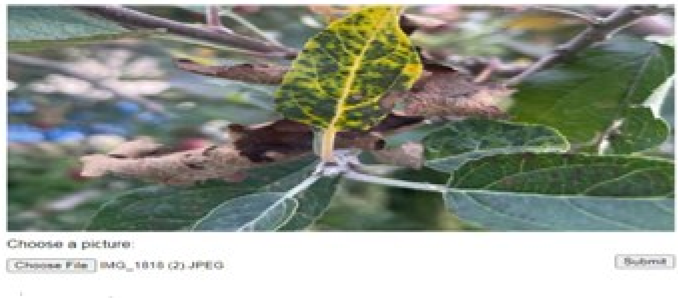

Figure 10. Predicted Marssonina Leaf Blotch ALD

Conclusion and Future Scope

Alternaria ALD Prediction (Figure 7) Figure 8 shows the expected apple leaf health. Figure 9: Powdery Mildew ALD Prediction Agriculture and plant health management are greatly enhanced by the development of a web-based program that detects ALDs such as Healthy and Alternaria, Leaf Spot, Marssonina Blotch, and Powdery mildew utilizing DL. Early disease diagnosis is a key component to improving crop yields while reducing pesticide consumption. This web-based program may help farmers and orchard owners do just that. If we want to make DL models more accurate and able to identify more illnesses and variants in the future, we need to make sure that the datasets used to train them are always growing and improving.

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