
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

Deep Learning-Based Web Application for Real-Time Apple Leaf Disease Detection and Classification

[1]Mr. P. S. S. K. Sarma, [2] Kadali Krupa Mani,

[1]Associate Professor, Dept.of CSE, Rajamahendri Institute of Engineering & Technology, Bhoopalapatnam, Near Pidimgoyyi,Rajahmundry,E.G.Dist.A.P. 533107.

[2]Students, Dept.of CSE, Rajamahendri Institute of Engineering & Technology, Bhoopalapatnam, Near Pidimgoyyi,Rajahmundry,E.G.Dist.A.P. 533107.

Abstract:When it comes to India's economy, agriculture is king. There are a number of plant diseases that impact agricultural yields by attacking plant leaves. Problems with disease prevention and increasing crop output are ongoing issues for apple growers. 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). To fix this, we suggest a DL-model-based web tool that can detect and forecast diseases such as Healthy and Alternaria, Leaf Spot, Marssonina Blotch, and Powdery mildew on the afflicted leaf.

Keywords:Leafdiseaseprediction,ConvolutionalNeuralNetwork(CNN),DL,ALD-4C.

I. Introduction

A large portion of India's GDP is generated by the agricultural sector. It grows a wide variety of crops, and almost 70% of the population works in agriculture in some way, according to a poll. 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. Therefore, it is really critical to resolve this matter. Due to a dearth of technological understanding, the majority of Indian farmers are turning to manual farming methods. The role of leaves in stimulating quick plant development and increasing harvest yields is critical. A challenge that researchers and farmers face is the detection of plant leaf diseases [2]. In order to simplify farming and forecast three different ALD classes, a "web App" is created. simply find out whether a leaf is sick or not, farmers need simply take a picture of it and send it to the app. This breakthrough gives farmers the ability to better predict and deal with illnesses, which in turn increases their profitability and decreases their losses. Technology in agriculture streamlines agricultural processes and gives farmers access to information that helps them make better decisions. 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 immediately and accurately. Therefore, this leads to increased harvest yields. Additionally, this online tool promotes preventative disease measures, which reduces the use of dangerous pesticides and guarantees farmers and customers better harvests.

II. BackgroundStudy

In the field of agriculture, automating the process of disease detection is of utmost worldwide significance. Methods for detecting diseases have been the focus of a great deal of research. The following are a number of studies that looked at plant diseases and the methods that were used to get at this goal. To find lesion locations and segments, L. Li et al. [3] employed three models of semantic segmentation networks: PSPNet, DeepLabV3+, and GCNet. Apple leaves in good health and those with two different diseases were both included in the picture collection. The parameters of the model were fine-tuned using Transfer Learning (TL) since the dataset was restricted. With an MPA of 97.26 percent and a MIoU of 83.5 percent, the segmentation model was successful. Y. Gao et al. in [4]et al. developed BAM-Net, a network that can identify ALD in difficult environments. In order to verify that BAM-Net works with the complicated backdrop, BAM-Networks use a five-fold cross-validation strategy. When tested on six distinct apple leaf types, our model performed well, 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]. It improved feature extraction with the help of Res2Net and a feature pyramid network architecture. Object localization candidate areas were accurately generated using RoIAlign instead of RoIPool. To further enhance the accuracy of ALD detection, it made use of gentle non-maximum suppression during inference. With an average precise accuracy of 63.1%, the suggested model was successful. The MGA-YOLO lightweight model for real-time ALD detection was suggested by Y. Wang et al. 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. Because it used the Ghost module, CBAM, and other effective tactics, MGA-YOLO fared better 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. The 94.0% mean average accuracy (mAP) achieved by this approach represents an improvement. A DL-based detector for ALD identification was suggested by S. Liu et al. 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. Both the convergence rate and the overall performance are enhanced when BSConv and CIoU loss are used. On the MSALDD dataset, it achieves a mAP of 91.08%, but on the public dataset, it reaches 58.85% mAP. For the purpose of ALD detection, Q. Yang et al. presented the EfficientNet- MG model 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. The outcome was an accuracy rate of 99.11% for EfficientNet-MG. An improved Faster R-CNN model using the Inception v2 architecture was suggested by M. Sardogan et al. in [9]. Orchards of apples in Yalova, Turkey, were the sites of disease detection field trials. The accuracy attained by this model was 84.5%, and it was trained using leaf photos gathered over two years from varied apple orchards. An improved CNN model based on the VGG16 architecture was suggested by Q. Yan et al. in [10]. Model 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. These additions were made in response to challenges to decrease the number of training parameters and speed up convergence. The 2,141 apple leaves that made up the training set were used to train the proposed algorithm to detect ALD. A remarkable 99.01% test accuracy was attained by the model. A client-server mobile system using Gabor was proposed by S. Prasad et al. in [11]. illness detection in leaves using wavelet transformation (GWT). The procedure begins with device-dependent color conversion to a color space model. The next step is mobile pre-processing, which follows leaf capture and color space conversion. By adjusting the a and b component output curves, an a*b color space was developed to mimic human vision and enhance the perceived brightness. Data from leaf images was analyzed using the K-means unsupervised approach, with features extracted using Gabor wavelet conversion. In order to conduct their studies, the researchers consulted a proprietary dataset. S. Zhang et al. provided a hybrid clustering method that is crucial for leaf segmentation in [12]. Using a superpixel clustering method, the author created cohesive patches out of neighboring pixels that shared certain brightness, texture, and color attributes. By using fewer pixels, this method successfully simplified the picture. Also, the author suggested the Expectation Maximization (EM) technique, which she said may be a good way to segment color images. The DL technique was suggested by M. Brahimi et al. as a classifier for illness identification in [13]. It helped comprehend the illness by localizing affected areas using the occlusion concept. The datasets used in this study were made public by our esteemed colleague Bengio. An automated method for detecting and classifying plant diseases was suggested by H. Al-Hiary et al. in [14]. This technique uses the feature sets of pixels to divide them into k classes. When a leaf shows signs of more than one illness, the model creates new clusters to reflect those diseases. 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]. Using the Otsu approach, we were able to complete 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. By using a genetic algorithm, training durations were significantly reduced and recognition accuracy was significantly improved. 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. Using the K-means clustering technique, they began the process of region segmentation in the photographs of the affected areas. Image extraction from the dataset and subsequent RGB-to-Luminance ab* color space conversion constitute the system's first phase. After that, k-means clustering is used to classify colors. A number of preparation procedures are performed on each picture, such as enhancement, smoothing, denoising, alignment, and segmentation using k-means clustering algorithms. A. K. Dey suggested a method for detecting betel vine leaf rot disease using image processing in [17]. A vision-based technique was the core of their strategy for detecting and analyzing peripheral illness features. Color characteristics inside the afflicted portions of the leaves were used for disease identification. For their investigation, the authors chose to focus on Bangla desi kinds of betel vine. Specifically, they used a Canon scanner that has a 300 PPI resolution to look for diseases. Level of illness the total area of the leaves and the percentage of diseased area were used to quantify it. For the purpose of illness segmentation, the author used the Otsu thresholding approach. S. Sladojevic et al. suggested a classification algorithm for identifying leaf diseases using a deep convolutional network in their research article [18]. Climate change, according to the research, might alter the phases of development and the rates of pathogen proliferation. The training of a DN network allowed for the separation of leaf environments. In addition, squares around the leaves were manually cropped from all of the photos in order to highlight the areas of interest [19-21]. In order to increase the size of the dataset, the author used an augmentation procedure that included affine transformations, rotations, and transformations. Caffeine was presented in this study as the basis for the deep convolutional neural network (CNN).

III. WebApplicationWorkflow

Down below, you can see Figure 1 that shows how the web application works. Users must first log onto the site in order to verify their identity. Users are automatically sent to the homepage after logging in successfully. For those who haven't already done so, the homepage is accessible when they've finished signing up. Users are given with many options after they successfully log in and get access to the site. A user may choose a picture, upload one from their phone's gallery, or take a photograph in real time. Users may begin the procedure further after making their pick. After making these choices, users may start 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. As a result of the model's analysis of the picture, the user may see its illness prognosis shown on the screen.

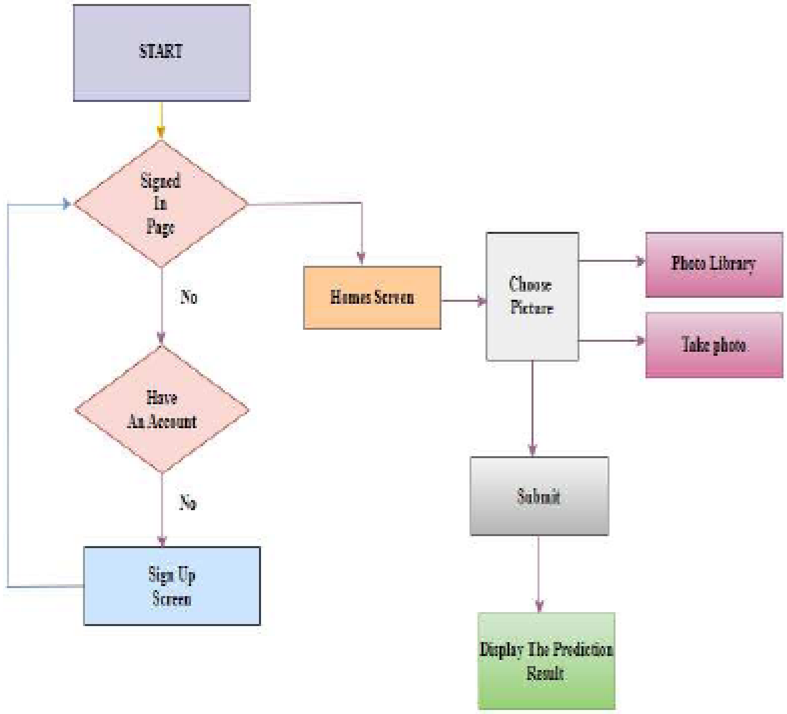
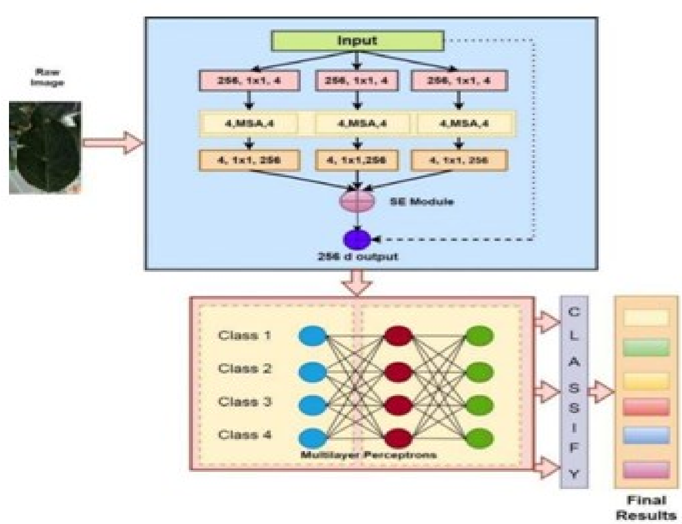


Figure 1. Webapp workflow diagram

The web application development process leverages varioustechnologies.Inthefrontend,weemploya combination of HTML, CSS, JavaScript, and Bootstrap to enhancetheuserinterfaceandinteractivity.Inthebackend,the system is built using Python, Python Django, and the Jinja2 Template Engine to handle server-side logic and template rendering. The database is powered by MySQL, while Nginx serves as the web server, handling HTTP requests and responses.FortrainingandtestingDLmodels,weutilizeColab Pro+, a cloud-based platform that offers high computational capabilities and convenient access to GPU resources, facilitating efficient model development and evaluation.

IV. PROPOSEDSYSTEM

For ALD-4C Detection and Classification, the Proposed Model adjusted SE-ResNeXt-50. The three bottle-neck transformer blocks illustrated in Figure 2 above make up the modified SE-ResNeXt-50 model. Each of these three-layer blocks receives the input picture separately. 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. The activation function used by each of these blocks is SiLU. After that, SE (Squeeze-and-Excitation) is used to combine the results from each block into a single output, which is then transmitted via an MLP (Multi-Layer Perceptron Layer). Following the MLP's input, a SoftMax layer is used for classification.



ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

Figure2. ProposedDLmodel

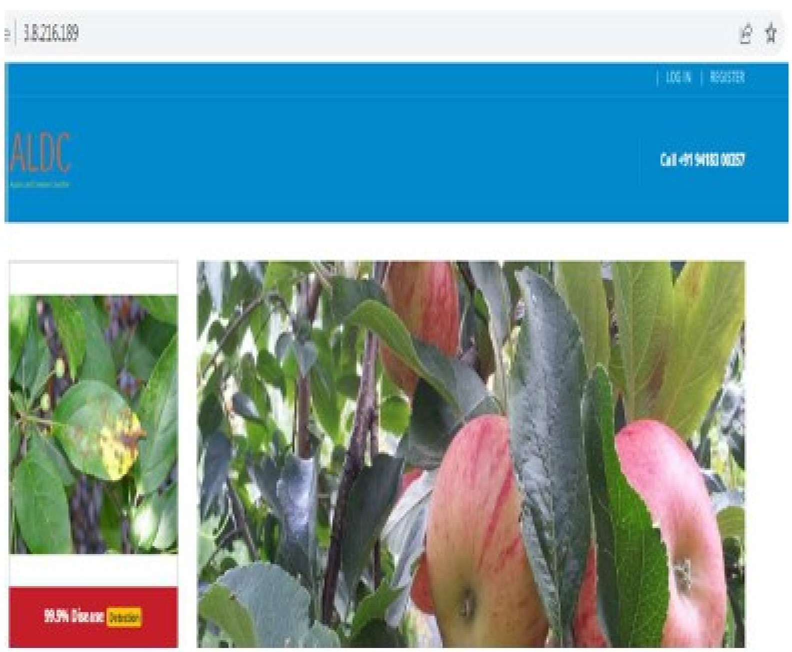
V. ResultFormation

The initial step in the proposed system involves the farmer or user uploading a leaf image within the application. After the image upload, users can activate the prediction process by clicking the designated button and waiting for the results. The primary dataset used for this purpose is the ALD4C apple leaf dataset, enabling both model training and validation. Upon imageupload,thesystemassessestwopotentialoutcomes:a

plantleafinfectionorahealthyleafcondition.Ifaninfectionis detected,thesystemdisplaystheimageoftheleafandthename of the disease on the screen. Otherwise, it will show a healthy leaf.TheALDdetectionsystem'sFlowchartisshownbelowin 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. Figure 4 shows the ALD detection web app's homepage, which provides a summary of the app's first landing page. Figure 5 displays the ALD detection web application's login and sign-up interface, which sheds light on the authentication procedure for users. Figure 6 displays the condition of the web application's UI after user authentication has been successful. Predicted illness outcomes are shown in the article, which further digs into the application's capabilities. To illustrate the system's illness categorization capacity, Figure 7 depicts the expected results for the Alternaria ALD. Figure 8 shows the web app's visualization of the anticipated healthy apple leaf, which shows that the algorithm can discern between healthy and unhealthy leaves. The online application's capacity to reliably detect particular illnesses is seen in Figure 9, which shows the anticipated findings for Powdery Mildew in ALD. 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. When it comes to assessing the efficacy of the web tool for disease detection in apple leaves, these screenshots are vital visual aids.



ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

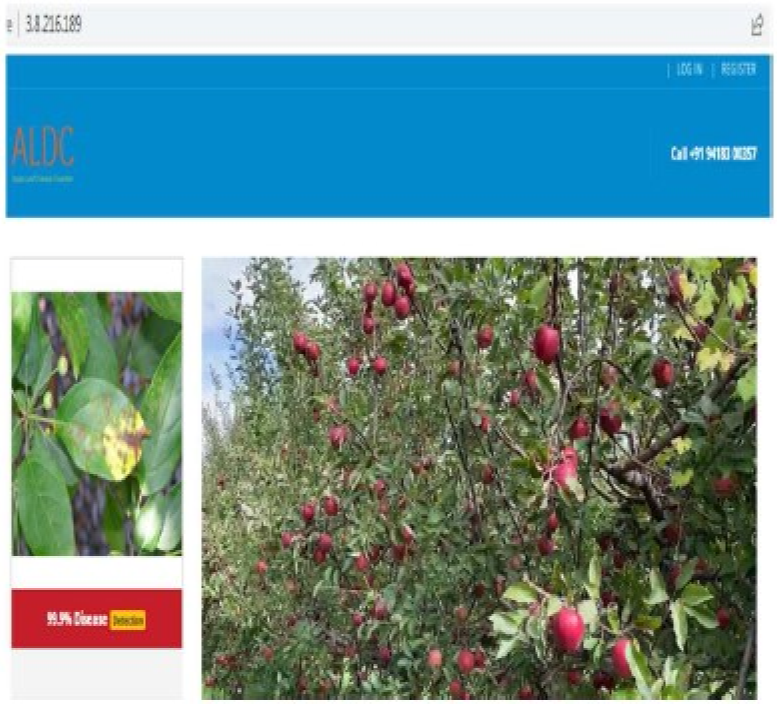


Figure 4. Homepage of ALD detection Web App

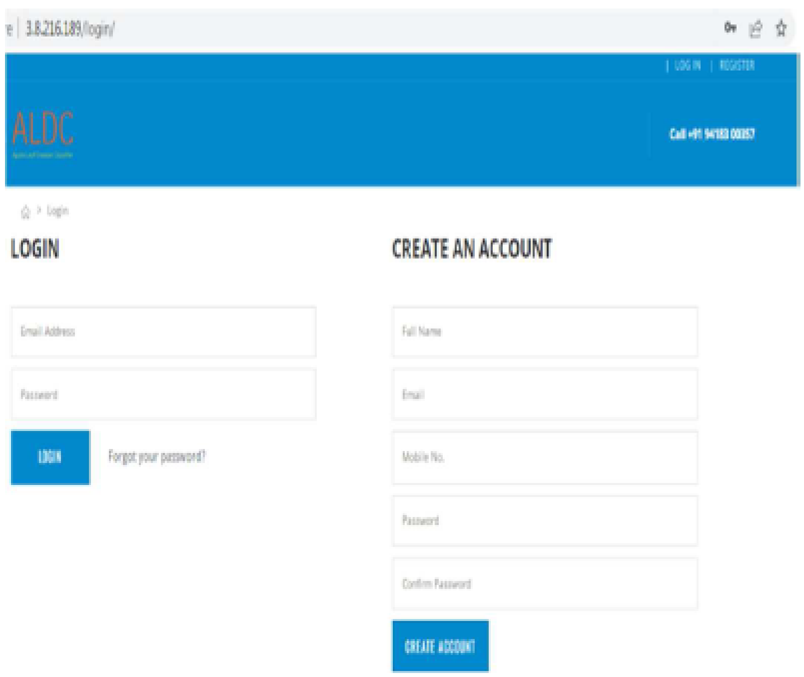


Figure 5. The Login / Sign Up Screen for ALD Detection Web App

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

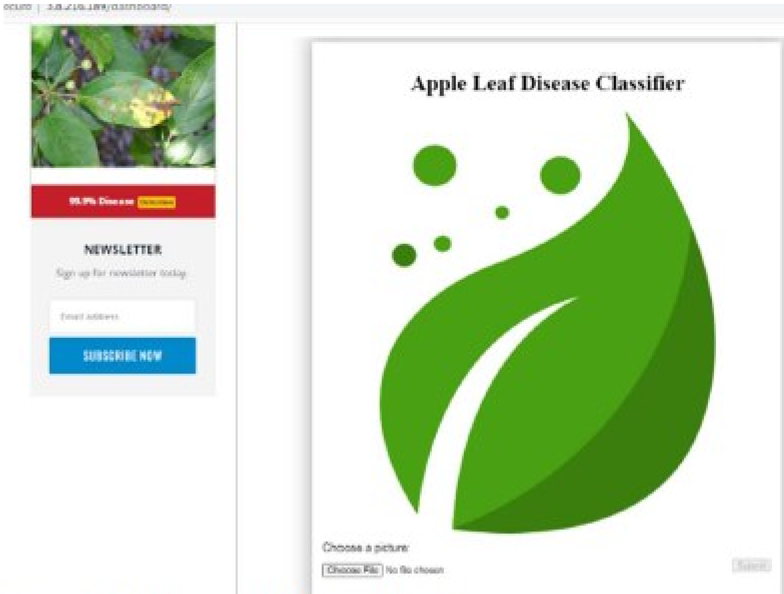


Figure 6. ALD detection Web App After the login

Alternaria - 99.8257219791%

Figure 7. Predicted Alternaria ALD

Figure 8. Predicted Healthy Apple Leaf

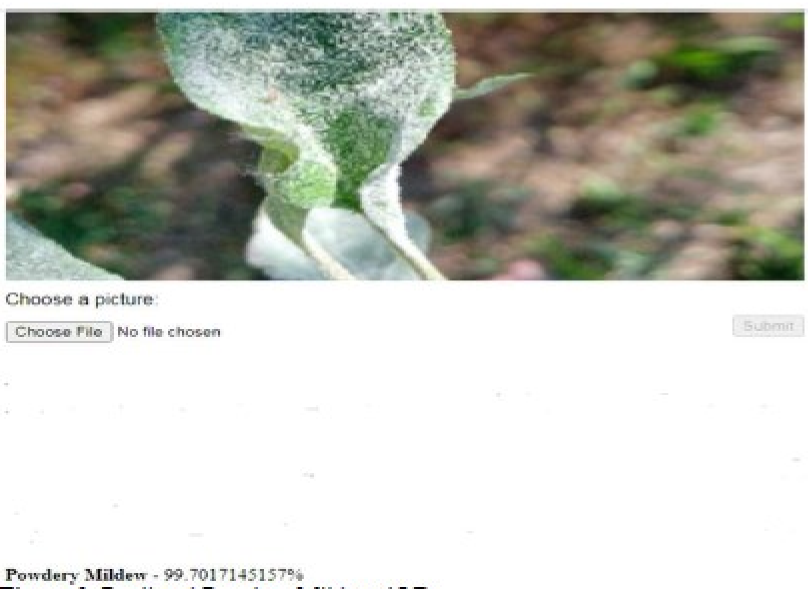


Figure 9. Predicted Powdery Mildew ALD

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

Figure10. PredictedMarssoninaLeafBlotchALD

VI. Conclusion and FutureScope

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. Better crop yields with less pesticide use are possible with the help of a web-based tool that helps orchard owners and farmers spot diseases early. To improve accuracy and enable the identification of more illnesses and changes in the future, it is vital to constantly enhance and increase the dataset used to train the DL model.

VII. References

[1]. S. S. Kumar and B. K. Raghavendra, “Diseases detection of various plant leaf using image processing techniques: A review,” In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 313-316)., (2019, March). IEEE.
[2]. Jain, S., Tripathy, H. K., Mallik, S., Qin, H., Shaalan, Y., & Shaalan, K. (2023). Autism Detection of MRI Brain Images Using Hybrid Deep CNN With DM-Resnet Classifier. IEEE Access.
[3]. L. Li, B. Wang, Y. Li, and H. Yang, “Diagnosis and mobile application of apple leaf disease degree based on a small-sample dataset,” *Plants*, vol. *12, no.* 4, pp. 786, 2023.
[4]. Y. Gao, Z. Cao, W. Cai, G. Gong, G. Zhou, and L. Li, “Apple Leaf Disease Identification in Complex Background Based on BAM-Net,” *Agronomy*, vol. *13, no.* 5, pp. 1240, 2023.
[5]. X. Gong, S. Zhang, “A high-precision detection method of apple leaf diseases using improved faster R-CNN,” *Agriculture*, vol. *13, no.* 2, pp. 240, 2023.
[6]. Y. Wang, Y. Wang, J. Zhao, “MGA-YOLO: A lightweight one-stage network for apple leaf disease detection,” *Frontiers in Plant Science*, vol. *13*, no. 927424, 2022.
[7]. S. Liu, Y. Qiao, J. Li, H. Zhang, M. Zhang, and M. Wang, “An Improved Lightweight Network for Real-Time Detection of Apple Leaf Diseases in Natural Scenes. *Agronomy*,” vol. *12, no.* 10, pp. 2363, 2022.
[8]. Q. Yang, S. Duan, and L. Wang, “Efficient identification of apple leaf diseases in the wild using convolutional neural networks,” *Agronomy*, vol. *12,no.* 11, pp. 2784, 2022.
[9]. M. SARDOĞAN, Ö. Z. E. N. Yunus, and A. Tuncer, “Detection of apple leaf diseases using faster R-CNN,” *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, vol. *8, no.* 1, pp. 1110-1117, 2020.
[10]. Q. Yan, B. Yang, W. Wang, B. Wang, P. Chen, and J. Zhang, “Apple leaf diseases recognition based on an improved convolutional neural network,” *Sensors*, vol. *20, no.* 12, 3535, 2020.
[11]. S. Prasad, S. K. Peddoju, and D. Ghosh, “Multi-resolution mobile vision system for plant leaf disease diagnosis,” *Signal, image and video processing*, vol. *10, no.* 2, pp. 379-388, 2016.
[12]. S. Zhang, Z. You, and X. Wu, “Plant disease leaf image segmentation based on superpixel clustering and EM algorithm,” *Neural Computing and Applications*, no. *31*, vol. 1225-1232, 2019.
[13]. M. Brahimi, K. Boukhalfa, and A. Moussaoui, “Deep learning for tomato diseases: classification and symptoms visualization,” *Applied Artificial Intelligence*, vol. *31, no.* 4, pp. 299-315, 2017.
[14]. H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik, and Z. Alrahamneh, “Fast and accurate detection and classification of plant diseases,” *International Journal of Computer Applications*, vol. *17, no.* 1, pp. 31-38, 2011.
[15]. Y. Shao, G. Xuan, Y. Zhu, Y. Zhang, H. Peng, Z. Liu, and J. Hou, “Research on automatic identification system of tobacco diseases,” *The Imaging Science Journal*, vol. *65, no.* 4, pp. 252-259, 2017.
[16]. S. Zhang, X. Wu, Z. You, and L. Zhang, “Leaf image based cucumber disease recognition using sparse representation classification,” *Computers and electronics in agriculture*, vol. *134*, pp. 135-141, 2017.
[17]. A. K. Dey, M. Sharma, and M. R. Meshram, “Image processing based leaf rot disease, detection of betel vine (Piper BetleL.),” Procedia Computer Science, vol. 85, pp. 748-754, 2016.
[18]. S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep neural networks based recognition of plant diseases by leaf image classification,” Computational intelligence and neuroscience, 2016.

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

[19]. G. I. Sayed, M. A. Ali, T. Gaber, A. E. Hassanien and V. Snasel, "A hybrid segmentation approach based on Neutrosophic sets and modified watershed: A case of abdominal CT Liver parenchyma," 2015 11th International Computer Engineering Conference (ICENCO), Cairo, 2015, pp. 144-149, doi: 10.1109/ICENCO.2015.7416339.
[20]. Applebaum, S., Gaber, T., & Ahmed, A. (2021). Signature-based and Machine-Learning-based Web Application Firewalls: A Short Survey. International Conference on Arabic Computational Linguistics.
[21]. Tahoun, M., Almazroi, A.A., Alqarni, M.A., Gaber, T., Mahmoud, E.E., & Eltoukhy, M.M. (2020). A Grey Wolf-Based Method for Mammographic Mass Classification. Applied Sciences.