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An Online Tool for Identifying and Classifying Apple Leaf Diseases Using Deep Learning in Real Time

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Abstract:

The agricultural sector accounts for the lion's share of India's GDP. The yield of crops is affected by a variety of diseases that impact 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. The ability to anticipate leaf diseases is a skill that farmers could lack. To efficiently manage and reduce these problems in orchards, rapid and precise detection of apple leaf diseases (ALD) is essential. Novel approaches to computer vision based on Deep Learning (DL) have made it possible to detect and comprehend these illnesses in their earliest stages right on the leaves. To solve this problem, we suggest a DL-model-based web tool that can detect and forecast health issues such as Alternaria, Leaf Spot, Marssonina Blotch, and Powdery mildew on afflicted leaves. Information needed to make well-informed decisions. By using AI and picture recognition skills, the "web App" revolutionizes plant disease identification and prevention for farmers, leading to increased production and more sustainable 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. The farmer will provide the right therapy at the right time when the ailment has been identified. As a consequence, crop yields are increased. In addition, this online tool promotes preventative disease measures, which means fewer pesticides are needed and farmers and customers may enjoy better crops.

Keywords: Leaf disease prediction, Convolutional Neural Network (CNN), DL, ALD-4C.

Introduction

Agriculture is a major contributor to India's economy. Approximately 70% of the population is involved in agriculture, and the study indicates that it grows a variety of crops. Manual labor is becoming the primary method of production for many Indian farmers [1]. So, making sure you're using the right cultivation techniques is crucial. A major obstacle for farmers is plant diseases, which reduce harvest yields and cost them 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]. To facilitate the prediction of three ALD classes and to simplify farming, a "web App" is created. The program can tell farmers whether a leaf is harmed or not only by looking at a picture of it. Because to this breakthrough, farmers can now better foresee and deal with disease outbreaks, which in turn increases yields and decreases losses. Technological advancements in farming have the dual benefit of streamlining processes and providing farmers with new tools. The parts of this work are well defined. Section II delves into the previous studies conducted by different researchers on the identification and classification of ALD. In part III, we cover the process of web applications. Section IV focuses on our suggested model, including its formulation and discussion. Section V presents the discussion of the development of 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. Methods for detecting diseases have been the focus of a great deal of academic inquiry. What follows is a compilation of research on plant diseases and the methods used to study them. 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. 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]. In order to verify that BAM-Net works with the complicated backdrop, BAM-Networks use a five-fold cross-validation strategy. Classifying six distinct types of apple leaves, our model achieved an impressive 95.64% accuracy and an F1-score of 95.25%. An improved version of the Faster Region-Based CNN (Faster R-CNN) approach was suggested by X. Gong and S. Zhang in [5] to better object identification. To enhance feature extraction, it used the advanced Res2Net and feature pyramid network architecture. Object localization candidate areas were accurately generated using RoIAlign instead of RoIPool. For better ALD detection, it used soft non-maximum suppression inference as well. 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]. The ALDOD dataset was built from four public dataset categories, personally annotated, and augmented using several augmentation approaches to make it better at detecting ALDs. With the help of the Ghost module, CBAM, and other effective tactics, MGA YOLO surpassed other state-of-the-art (SOTA) methods on the ALDOD testing set. It achieved the best average accuracy, quickest detection time, and smallest model size. The mAP, or mean average precision, of this approach increased to 94.0 percent. 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. You can get even better results and faster convergence by using BSConv with CIoU loss. It achieves a mAP of 58.85% on the public dataset and 91.08% on the MSALDD dataset. An Efficient Net 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. This led to Efficient Net-MG achieving 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]. 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]. In order to address the challenges of reducing the number of training parameters and speeding up 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. A remarkable 99.01% test accuracy was attained by the model. S. Prasad et al. proposed a client-server mobile system for disease detection in leaves using Gabor wavelet transformation (GWT) in [11]. The first stage involves converting colors to a color space model depending on the device. Next, we go on to mobile pre-processing, which follows leaf collection and

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color space conversion. To make brightness seem better, the output curves of the and b components were adjusted to form 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].

By using a super pixel clustering method, the author was able to organize nearby pixels into cohesive areas based on their brightness, texture, and color. By using fewer pixels, this method successfully simplified the picture. 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 condition, it employed the occlusion idea to pinpoint its locations. The datasets used in this study were made public by our esteemed colleague Bengio. 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. Neural networks are used to identify and categorize diseases. 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. Tobacco illnesses may be identified in real-time using a mobile client, and users can submit their conditions 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. A new method for identifying cucumber leaf diseases was suggested by S. Zhang et al. in [16]. Problems with intricacy, uneven forms, and shadows make traditional classifiers useless for this job. The authors used a technique that took use of both the shape and color information included in leaf pictures. Using the K-means clustering technique, they began the process of region segmentation in the photographs of the affected areas. Images are retrieved from the dataset and converted from RGB to Luminance ab* color model as the first stage of the system. Afterwards, k-means clustering is used for color categorization. Smoothing, enhancing, denoising, aligning, and segmentation using k-means clustering algorithms are all part of the preparation procedures that each picture goes through. A. K. Dey suggested a method for detecting betel vine leaf rot disease using image processing in [17]. Their strategy revolved on a vision-based technique to identify and evaluate peripheral illness traits. 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. Leaf rot infections were segmented using the Otsu thresholding approach. For the purpose of disease detection in leaves, S. Sladojevic et al. [18] suggested a deep Convolutional network technique based on classification methodology. The results show that the phases of development and the rates of pathogen proliferation might be affected by climate change. We trained a DN network to help distinguish between various types 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]. Rotations, transformations, and affine transformations were all part of the author's dataset expansion augmentation procedure. Caffeine was first proposed in this research as a building block for deep Convolutional Neural Networks (CNNs).

Web Application Workflow

Below is Figure 1, which shows the web application's process. 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. 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. Users may then begin processing their selected picture by clicking the predict button after making these settings. For illness prediction, the user's chosen picture is thereafter sent to the CNN model, a DL model. After analyzing the picture, the

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model displays its illness prognosis on the screen so the user may see it.

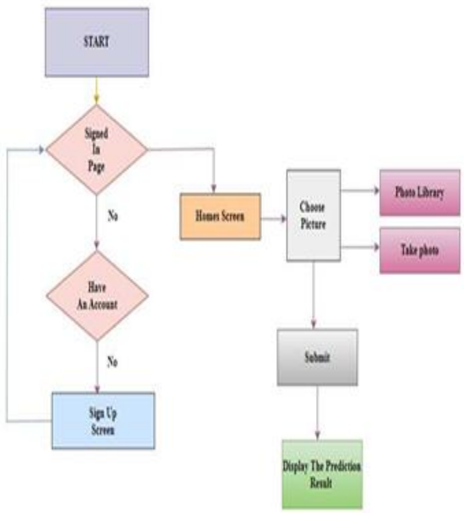

Figure 1. Webapp workflow diagram

The process of developing web applications makes use of a number of technologies. We utilize a mix of front-end technologies including HTML, CSS, JavaScript, and Bootstrap 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. We use Colab Pro+, a cloud-based platform with strong computational capabilities and easy access to GPU resources, for training and testing DL models. It helps us construct and evaluate models efficiently. Section IV: The Endeavor In order to classify and detect ALD-4C, the proposed model adjusted SE-ResNeXt-50. Three bottle-neck transformer blocks, as illustrated in Figure 2, 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 convolutions. This process is known as contraction, and it produces an output with dimensions 4 by 4. The last layer of the proposed block receives the contracted output, which is then passed on to the attention layer. 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. The results from each block are then combined into one output, which is then transmitted via SE (Squeeze and Excitation), and finally through an MLP. The output from the MLP is then classified using a SoftMax layer.

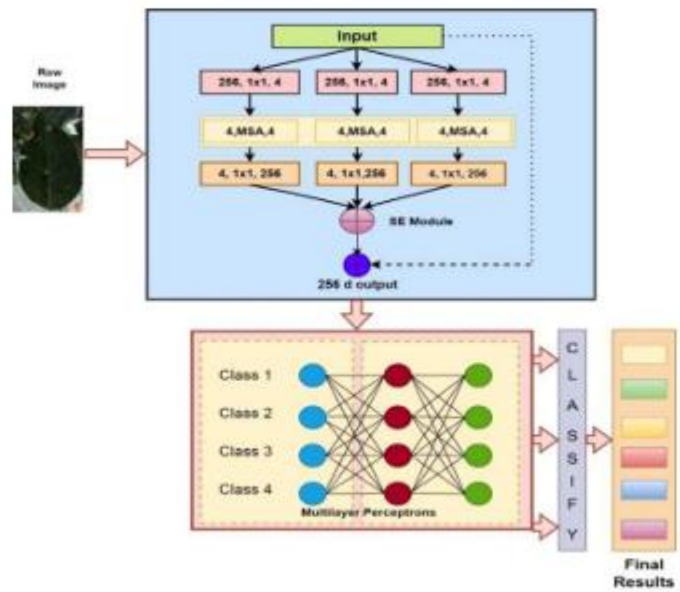

Figure 2. Proposed DL model

Result Formation

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. For this objective, the ALD4C apple leaf dataset is primarily used for training and validating models. The algorithm can tell whether a plant leaf is infected or in good condition based on the uploaded photograph. Upon detection of an illness, the system will show the leaf picture together with the disease's name on the screen. In any other case, a healthy leaf will be shown. Figure 3 below shows the flow diagram of the ALD detecting system.

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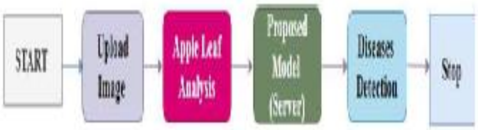

Figure 3. Flowchart of ALD detection system

You may see the web app in action in the study report via the screenshots that are cited in the figures that follow. This is the main landing page of the ALD detection web app, as shown in Figure 4, which provides an overview of the software. Figure 5 shows the ALD detection web app's login and sign-up interface, which sheds light on the authentication procedure. As shown in Figure 6, the web application's interface displays the status after user authentication when the login is successful. In the study, the capabilities of the program are further explored, with the expected illness consequences shown. Figure 7 shows the expected results for the Alternaria ALD, which shows that the algorithm can classify diseases. Figure 8 shows the web apps 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. Figure 10 shows the projected result for Marssonina Leaf Blotch in ALD, illustrating the system's ability to visually describe and classify diseases. When it comes to assessing the efficacy of the web tool for disease detection in apple leaves, these screenshots are vital visual aids.

Figure 4. Homepage of ALD detection Web App

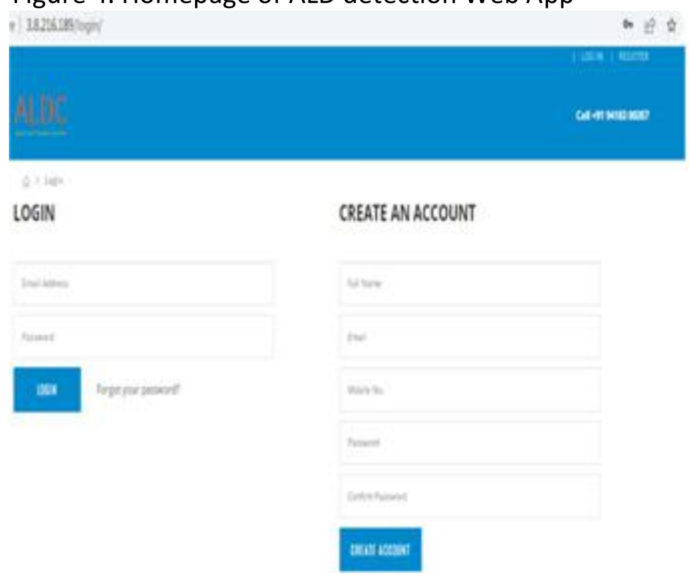

Figure 5. The Login / Sign up Screen for ALD Detection Web App

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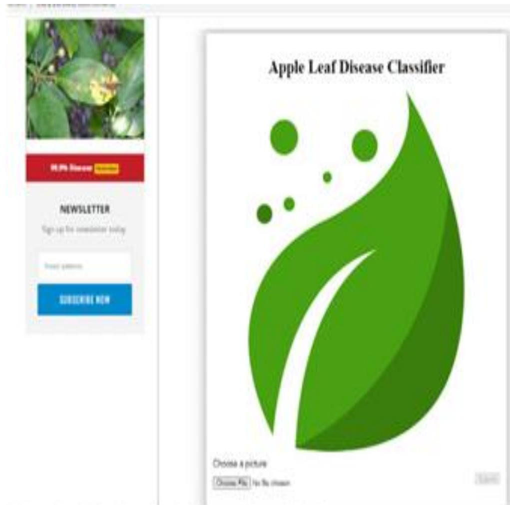

Figure 6. ALD detection Web App After the login

Figure 7. Predicted Alternaria ALD

Figure 8. Predicted Healthy Apple Leaf

Figure 9. Predicted Powdery Mildew ALD

Conclusion and Future Scope

The use of deep learning to create a web app that can identify ALDs (Alternaria, Leaf Spot, Marssonina Blotch, and Powdery mildew) is a huge step forward for agricultural and plant health management technologies. 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. 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.

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.

[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.