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Prediction of Disease in Apple Leaf Using Convolution Neural Networks

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Abstract: ***Apple tree diseases can significantly impact fruit quality and yield, making early detection and intervention crucial for orchard management. To avoid the impact on apple production a novel approach is required for the early and accurate prediction of apple leaf diseases through Convolutional Neural Networks (CNNs). Our proposed system contains a comprehensive dataset of high-resolution pictures of apple leaves exhibiting various disease symptoms, including common issues like apple scab, apple rust, and powdery mildew. The dataset was carefully annotated to train and validate the CNN model effectively. The proposed CNN model makes use of its ability to automatically learn applicable features from images, making it highly suitable for the task of disease prediction in apple leaves. This model contributes to the field of precision agriculture by offering a cost-effective and efficient tool for apple disease detection.***

Keywords: Apple diseases, convolutional neural network, classification, deep learning, disease identification, image processing.

I. INTRODUCTION

In the last few years, the agricultural sector has witnessed a surge in the utilization of advanced technologies, particularly in disease identification and management. Among various crops, apple cultivation holds significant economic importance worldwide. However, one of the most difficult tasks for apple growers is the early detection and control of diseases that can have a noteworthy effect on yield and quality. Apple is among the globally consumed fruits among the four after bananas, grapes, and oranges. Globally, using pests and fertilizers can affect the apple plant and also the standard of fruit which should show an influence on the overall production of the apple crop In India, fungal diseases are the major ones that affect the apple fruit quality in particular apple producer state i.e. Himachal Pradesh, which is the second-biggest apple producer in India.

Infections in plants include diseases such as biotic and abiotic. Biotic diseases like scab, cedar rust, leafy blotch, powdery mildew, blight, mosaic, black rot, etc are very dangerous compared to abiotic diseases. It is crucial to increase apple production and early identification of disease. There are some serological method-based techniques for disease identification such as Fluorescence in-situ hybridization (FISH), polymer chain reaction (PCR), immunofluorescence (IF), and flow cytometry used by experts and can only be performed in a laboratory.

Machine learning-based approaches such as K-nearest Neighbor (KNN), Artificial Neural Networks (ANN), and Support Vector Machine (SVM) are mostly employed for disease identification. Convolution Neural Networks (CNN), one type of deep learning technique, have efficiency and it has also proved their suitability for plant disease identification. A deep CNN model consisting of three convolution layers is developed for disease detection based on apple leaf images. This model can self-learn hierarchical features, making it ideal for tasks such as image categorization and object detection. The objective is to create a robust and accurate a model capable of identifying common diseases affecting apple trees such as scab, rust (or) black rot.

II. LITERARATURE REVIEW

A. Transfer Learning Approach

[1] In this research study, a transfer learning strategy was employed to identify apple leaf disease using the CNN model. Transfer learning is a method of using a pre-trained model as a starting point for a new task. This study shows that a transfer learning strategy can accomplish high detection of apple leaf disease using a relatively small dataset (consisting of 2897 images) of training data.

First, you need to choose a pre-trained CNN model trained on a large dataset such as image-Net. At the top of the trained network, remove the fully linked layer. Freeze the convolutional layer weights if necessary. This prevents updates during training and preserves previously learned features. Add a new fully connected layer above the convolutional base. Train the model using the collected dataset. Experimentation results on a gathered dataset of 2897 images with data augmentation demonstrated that AppleNet can be effectively used to detect apple diseases on apple leaves with a classification accuracy of 96.00%.

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B. Mobilenet CNN Model

[2] The study proposed a MobileNet CNN model for identifying disease in apple leaves.MobileNet is a lightweight CNN architecture that is designed for mobile devices. This study found that MobileNet can achieve high accuracy in apple leaf disease identification using a small model size and low computational cost.

MobileNet has several variants, such as MobilenetV1, and MobileNetV3. Each has improved performance, efficiency, and capabilities. We practiced and examined the MobileNet model using a dataset containing 334 images. Finally, the highest accuracy achieved by this model is 74.

C. Lightweight and Efficient CNN Model

[3] In this study, we suggested a lightweight and efficient CNN model for the identification of apple leaf disease. The model was trained using a collected dataset of apple leaf pictures labeled with different disease types. This study found that the model succeeded in achieving 95.5% accuracy in identifying the apple leaf disease while maintaining a small model size and low computational requirements. It provides a more systematic and practical solution for identifying illnesses of the apple leaf on mobile devices.

To make a lightweight and efficient CNN model, Use fewer layers and fewer filters in each layer. This reduces the complexity of the model. Instead of big filters, use smaller ones. Instead of always reducing the size of the image, find ways to do it only when necessary. This saves computing power. And pick a model that's designed to be efficient, like MobileNet or SqueezeNet. They are built to be fast and use less memory.

D. Comparison of Plant Leaf Classification Using Modified AlexNet and Support Vector Machine

[4 Farmers find it challenging to detect leaf diseases early. As technology advances, many models for detecting diseases have been introduced that are superior to older methods such as apple leaf collection and laboratory process validation. This article uses a pre-trained Model Alexnet using Transfer Learning to classify leaves. A dataset is collected which consists of 3200 images with the measurements of 226 x 226 x 3. Pre-process the collected data and perform the training and evaluation with different variations. Then, modify and apply deep learning techniques like Alexnet which can classify 1000 classes and calculate the performance parameters. The classification can be done based on accuracy and confusion matrix. For this model, the obtained accuracy is 91.15%.

III. MATERIALS AND METHOD

A. Dataset and Pre-processing

The proposed deep Convolution Neural Network model is to predict diseases based on apple leaves, such as apple scab, black rot, cedar rust, and unaffected leaves. A total of 3171 images are collected including healthy and unhealthy leaves of black rot, rust, and powdery apple diseases. A total of 4 labels are created.

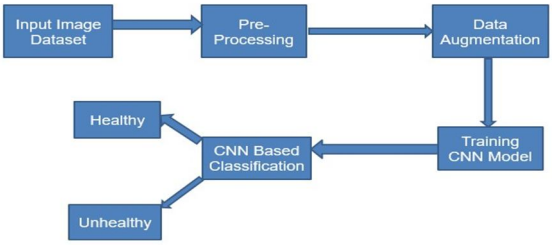


Fig 1: Block Diagram

The apple leaf images dataset is taken from the Kaggle website which dataset is composed of 3171 images of apple plant leaves. This model contains four classes of which the three classes correlate with 3 apple diseases namely black rot, scab, and apple cedar rust while the other class contains healthy apple leaf images. The apple leaf images of size 256 × 256 of all four categories were captured with a simple background at various plant development stages.

It is crucially important to have a wide variety of leaf photos within the collection. Hence, the model can learn important variations throughout the instruction phase. It helpfully assists in enhancing the generalizability of the CNN model. Augmentation presents itself as an approach to artificially create various variations of the image. In this work, amazing transformations like panning, shearing, scaling, zooming, and flipping are used to transform images. These transformations add minor variations in images, which inherently help in introducing variety in the training set. It turns out to assist in reducing overfitting and helps the model achieve better tolerance and an enhanced ability to generalize.

B. Convolution Neural Network

CNN is a feed-forward ANN-based deep learning methodology and is an attractive method. CNN is employed to display more layers within the CNN. Here, we construct a deep CNN by stacking several constructing elements such as convolutional layers, pooling layers, and fully connected levels with typical nonlinear activation units. It has exhibited certain advantages over state-of-the-art ML-based methods like magic! It doesn't require any additional effort for feature engineering. It is successfully used in several applications including image/text classification, NLP, precision agriculture, etc.

1) Convolution Layer

Convolutional layers are in charge of performing the convolution of a filter (kernel) on an input image. Feature maps are produced via convolutional layers by finding local connections that appeared in previous layers. Fundamentally, the first layer (convolutional layer) comprises two components: a linear convolution operation and a nonlinear activation unit. Convolution operations are performed on image volumes that have multiple channels, such as RGB images. Convolutional layers are a crucial component of the picture-processing process and play a key role in identifying patterns and features in visual data. By applying filters to input images, the layer can extract key information and generate feature maps that aid in subsequent analysis tasks. The process of convolution is expressed as in (1):

$$Conv(I,K)_{x,y} = \sum_{i=1}^{nH}\sum_{j=1}^{nW}\sum_{k=1}^{nC} Ki,j,kI_{x+i-1,y+j-1,k} \quad (1)$$

Where the kernel K (f□, f_w, n_C) convolves with the picture I (n_H, n_W, n_C) of different sizes but of similar no. of channels n_C and generate a feature map O (o_H, o_W, z). The f□ represents the height and breadth (width) of the kernel. And, n_H, n_W denote the height and breadth(width) of the specified image. Conventionally, the kernel is considered as an odd-dimensional square window, i.e., $f_H = f_W = f$. The generated feature map dimension is defined as in (2):

$$Feature_map\ (O_H, O_W, z) = (\lfloor\frac{n_H+2p-f}{s}\rfloor + 1, \lfloor\frac{n_W+2p-f}{s}\rfloor + 1, z) \quad (2)$$

where symbol p indicates the padding value, s indicates the stride, and z is the no. of kernels convolved with the input image.

Rectified linear unit (ReLU) is the most widely used activation function. Rectified linear unit do not activate all neurons simultaneously. When the yield or other direct change of the convolution unit rises to or is more prominent than zero, the neurons are essentially activated. It is expressed as in (3):

$$f(z) = \max(0, z) \quad (3)$$

2) Pooling layer

A pooling layer is accustomed to downsampling the feature map produced by convolution. It can lower the dimensions of activation maps that contain a larger number of parameters. Hence, it helps in lowering the computational burden, controls the process-related overfitting, and ultimately reduces the time required for training. The major pooling operations include max, min, and average. However, the most popular method of pooling resources is max-pooling, which selects the highest value from each input patch. The max pooling procedure is given in (4):

$$Max_{Pooling}: y_j = \max_{i \in R_j}(P_i) \quad (4)$$

where R indicates a receptive field containing P pixels. The dimension of the feature map that was produced is defined as in (5):

$$Feature_map\ (O_H, O_W, n_C) = (\lfloor\frac{n_H+2p-f}{s}\rfloor + 1, \lfloor\frac{n_W+2p-f}{s}\rfloor + 1, n_C) \quad (5)$$

The pooling operation only modifies the dimensions nH and nW whereas nC remains unchanged.

3) Fully Connected Layer

The fully connected (FC) or dense layers of a CNN are almost identical to the layers of a traditional neural network. They are typically connected at the final stage of CNN to form an output layer with the desired number of outputs. The FC layers operate on 1-D data. The flattened layer arranges the 2-D output of the preceding layers in a 1-D representation. The FC layers conduct two types of functioning: linear and, nonlinear transformations. These transformations can be expressed as in (6):

$$Z = W^T.X + b$$
$$O = f(z) \quad (6)$$

where X represents the input feature map, W denotes weight, b denotes bias terms, and O represents the output of the fully connected layer. For better prediction, optimal weights are eventually needed to lower the loss function. The Gradient descent is the most frequently utilized technique for determining optimization weights. Adam algorithm is another technique to get a less noisy and smoother path while optimizing the gradients. It performs learning rate annealing based on finding the adaptive estimates of the lower-order moments.

C. Proposed Method

The proposed deep CNN (Conv-3 DCNN) model consists of three collaborative layers and 2 fully connected layers after the three max-pooling units. ReLU is explored as a nonlinear activation function at each convolution zone and the first dense layer. The function of Softmax is employed at the layer of output to classify apple plant diseases. The softmax function is responsibly responsible for multiclass classification and assumes that each sample belongs to exactly one class.

The developed deep CNN model uses different layers along with activation functions. A dropout layer is as additionally employed as well at the third max pool layer to cause overfitting. The dropout unit eliminates some randomly selected neurons. The network could not rely on any one feature. Therefore, some neurons are ignored to spread out the weights for better generalization.

Initially, at the first convolution level, 32 filters (3 × 3) with valid padding and stride (1, 1) are selected to convolute over RGB images of size 256 × 256. It produces 32 feature maps of size 254 × 254. In the resulting feature map, the no. of channels corresponds to the no. of filters applied. At the first pooling level, the foregoing produced feature maps are downsampled by a kernel of size 2 × 2, and 32 feature maps of size 127 × 127 are generated. The same kernels are used at respective higher layers. The proposed deep CNN model will show promising results in the classification of apple plant diseases.

IV. RESULTS AND DISCUSSION



Fig 2: Home Page

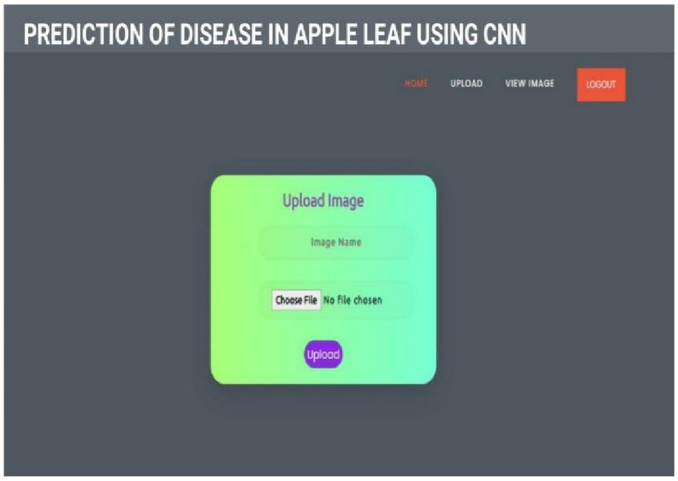


Fig 3: Select the input picture

Fig 2 shows the Home page which is the main web page of a website. It may also refer to the start page which will shown in a web browser when the application first opens.

Fig 3 selects the Input picture from the dataset. Drag and drop to upload the dataset we click the button named Upload. The dataset is uploaded successfully.

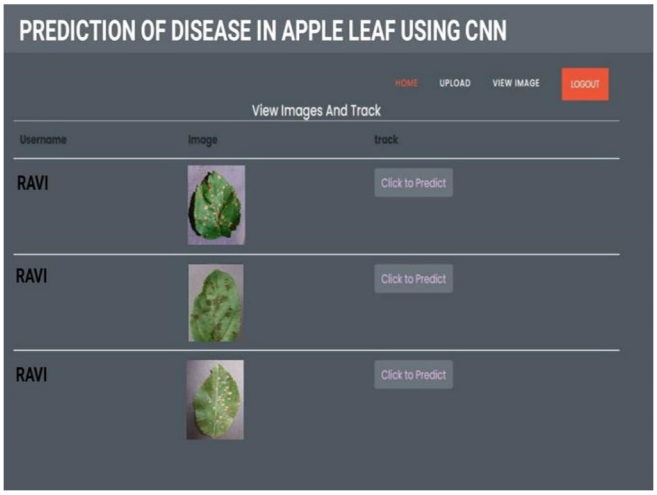


Fig 4: Predict Disease



Fig 5: Predicted Result

In Fig 4 dataset is uploaded successfully, we view images and track then click to predict. It verifies the image and predicts the diseases.

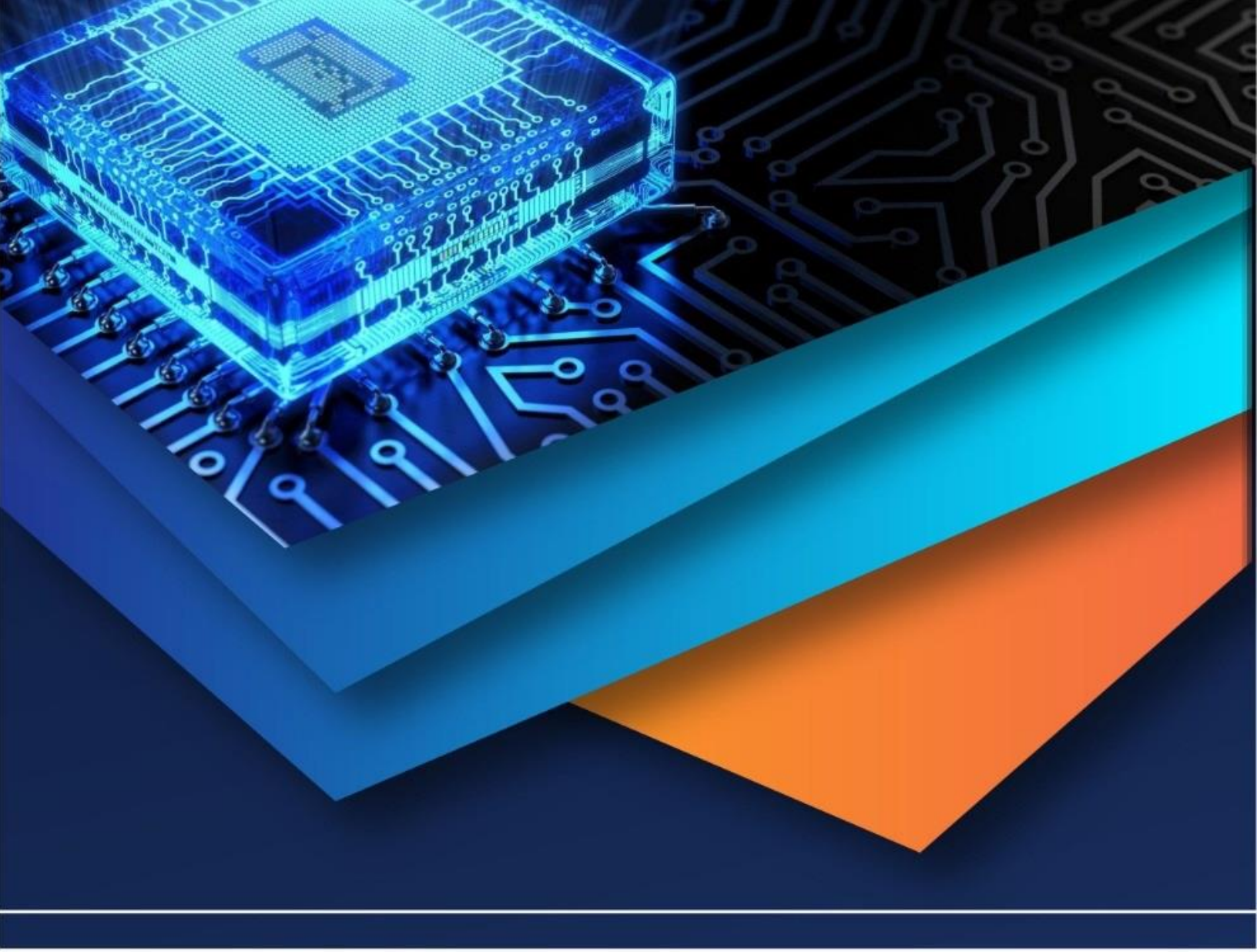
Fig 5 shows the predicted disease. It will display the result of which disease is predicted.

V. CONCLUSION

In this work, a CNN model was developed to recognize diseases in apple crops based on apple leaf images. It can assist non-expert farmers in apple orchards and lower the pressure on plant pathologists. Over 1000 epochs were used to train the model on 3171 apple leaves. On the PlantVillage dataset, the model's accuracy is evaluated to 98%. The rigorous investigation manifests the proposed model as much better than various pre-trained CNN models. The method was also found superior to other existing models based on various parameters including accuracy and memory requirements. For several diseases, this model achieves good accuracy, ranging from 97% to 99%. The model will successfully balance the accuracy and precision. The AUC-ROC curve shows that the proposed approach is reliable and consistent.

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