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POTATO PLANT'S DISEASE CLASSIFICATION USING CNN AND TRANSFER LEARNING

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ABSTRACT

Potato is one of the extensively consumed staple foods and the fourth most common staple food consumed worldwide. The main reason for the fall in the harvest's quality and quantity is the diseases of potato plants. The plant conditions will significantly deteriorate if the disease is improperly classified and discovered too late. Fortunately, several potato plant diseases can be recognized by looking at the state of the leaves. However, the performance of such systems is still constrained for practical uses. Therefore, an optimized CNN design was suggested for the classification of Potato Plant Disease. Comprehensive tests on various CNN architectures are carried out in order to justify the depth and structure of the proposed CNN-based framework. Using various cutting-edge feature extraction and data augmentation methods.

I. INTRODUCTION

Agriculture is a key industry in a country's economy and is essential to feeding the world's population. Scientists and farmers are working hard to provide the highest output while minimizing environmental harm. Using information technology, smart agricultural methods such as automation, precision farming, and eco-friendly farming are urgently needed. Crop disease management is a crucial component of smart agriculture. Multiple diseases that are brought on by insect infestations and pathogens including bacteria, viruses, and fungus affect crops. Early disease detection aids in damage control and reduces the possibility of crop loss. Additionally, crops can be treated with a small number of insecticides and fungicides when diseases are identified early on. One of the most important food crops is the potato. The pathogens Phytophthora infestans (late blight) and Alternaria solani are responsible for a significant yield loss in potatoes (early blight). The ability to prevent chronic diseases and reduce financial and production losses depends on their early detection. Expert observation with the naked eye has become the method of choice during the past few decades for the detection and identification of plant diseases. However, this method frequently proves impractical because farmers in remote locations cannot afford to hire professionals, and processing times are too long. Thus, the introduction of image analysis technologies proves to be a successful strategy for ongoing plant health monitoring and early disease diagnosis. Disease identification can be made easier since some illnesses leave visible symptoms on plants, particularly on leaves. Images of the observable patterns on leaves can be analyzed to find diseases. Consequently, combining image technology with machine learning provides a solution to the problem of agricultural productivity and secures food security. Consequently, this work's goal is to develop Effective and faultless imaging and machine learning plant disease detecting system. Agriculture provides a significant portion of a country's economic output and is essential for feeding the world's population. Farmers and scientists are working hard to produce the greatest results. Without causing environmental harm, produce. The situation calls for aims to use intelligent agricultural methods, such as automation and precision employing knowledge, eco-friendly farming methods technology. One crucial component of intelligent agriculture is agricultural disease management. Various pests harm crops. Diseases brought on by infections and pest infestations, such as viruses, fungus, and bacteria. Early disease identification aids in damage control and yield loss can be prevented. Moreover, when diseases crops can be treated if they are identified at an early stage. Low use of fungicides and insecticides one of the most important food crops is the potato.

II. LITERATURE SURVEY

Ungsumalee Suttapakti, Aekapop Bunpeng, et al. [1] in "Potato Leaf Disease Classification Based on Distinct Color and Texture Feature Extraction" proposed that the RGB image of the leaf is first converted to L*a*b* color space. Then the background and green are separated using the k-means clustering algorithm out of a region of interest (healthy leaf). The second step is to extract the suggested different color properties using utilizing the

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lowest color difference possible. The attributes of color are to classify potato leaf diseases in conjunction with statistical textural features. Euclidean distance is used here.

III. ALGORITHM

Step 1: Use k-means to divide a color image into three group images where K=3
Step 2: From the regions of interest extract the color and texture features.
Step 3: Use Euclidian distance to categorize the illnesses of potato leaves.
Three groups of RGB leaf images: early blight, late blight, and healthy leaf blight are converted into L*a*b color space for separation. The gray-level co-occurrence matrix (GLCM) approach is used to extract texture information. The texture is characterized via the GLCM approach, by figuring out the spatial relationships inside an image. CNN was used as the classification algorithm.
Sandika Biswas, Bir Pal Singh, Mehi Lalz, et al. [2]. in "Severity Identification of Potato Late Blight Disease from Crop Images Captured under Uncontrolled Environment", Proposed that to lower the algorithm's time complexity, the photos are first down-sampled to an eighth of their original size. To maintain image quality, images are resized using the bi-cubic interpolation approach. Then, device-independent color space transformation was applied, which converted the RGB color values in the enhanced image to CIELAB color values. The L*a*b - color space is a device-independent color space, which makes it easier to quantify the visual differences in colors present in a color image. Following that, clustering is used to group various regions or objects in an image based on similarities in certain attributes, ensuring that objects or regions inside a cluster or group share the same characteristics. FCM is used to distinguish the damaged area from the healthy leaf area. The suggested method computes the illness-affected area with very high accuracy of 97 percent.
Priyadarshini Patil, Nagaratna Yaligar, Meena S M Paper et al. [3] in "Comparison of Performance of Classifiers - SVM, RF and ANN in Potato Blight Disease Detection using Leaf Images" proposed that in preprocessing all images are resized to 512 * 512 pixels. This speeds up computation and the complexity of processing. The images are converted into HSV images. HSV is used to extract features. The well-known and precise fuzzy c-mean clustering algorithm and FCM is used for background removal. Then extracted texture features using GLCM. It was determined that ANN is the best classifier for the system with the greatest accuracy of 92 percent.

IV. PROPOSED SYSTEM

A machine learning model will be trained using pictures of potato leaves in order to recognise potato disease. The block diagram for the approach of forecasting potato disease is shown in Figure 4.1. This process is broken down into five main parts. We first gathered our data from the freely accessible image resource Plant Village (www.plantvillage.psu.edu). Pre-processing is the alteration of raw data before it is supplied to a deep learning or machine learning algorithm. In contrast to pre-processing, training a convolution neural network on raw pictures will likely result in poor classification performances. Pre-processing is essential to accelerating training methods. utilised the subsequent pre-processing. Divide the data into training and testing data after pre-processing. used 80% for training purposes and 20% for testing. Both the training data set and the testing data set were utilised to develop the model and evaluate its performance. A machine learning model will be trained using training data to recognise potato disease. Following that, a training model was created, starting with a sequential CNN model with seven layers. Performance was tuned using the Adam optimizer, and error was measured using cross entropy. Use the test data to test the model after the training phase is complete. When comparing the models, consider overall accuracy. Additionally, display loss over several epochs. For all analytical and evaluation purposes, Python 3.X is used. It uses Keras (with a tensor flow backend).

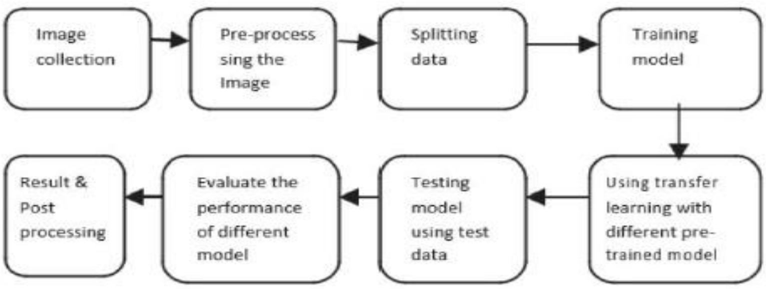

Fig: 4.1 – Proposed System

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V. SYSTEM IMPLEMENTATION

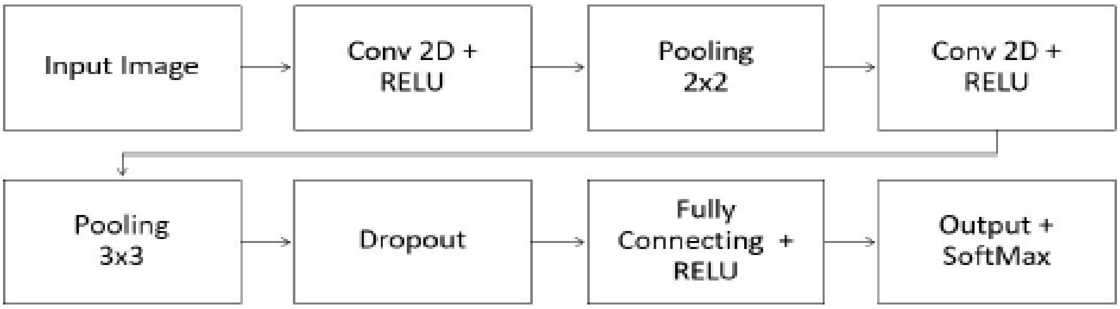

Fig: 5.1- CNN Overview

CNNs are a class of Deep Neural Networks that can recognize and classify particular features from images and are widely used for analyzing visual images. Their applications range from image and video recognition, image classification, medical image analysis, computer vision and natural language processing. The term 'Convolution" in CNN denotes the mathematical function of convolution which is a special kind of linear operation wherein two functions are multiplied to produce a third function which expresses how the shape of one function is modified by the other. In simple terms, two images which can be represented as matrices are multiplied to give an output that is used to extract features from the image. There are two main parts to a CNN architecture. First is a convolution tool that separates and identifies the various features of the image for analysis in a process called as Feature Extraction and second is a fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages. There are three types of layers that make up the CNN which are the convolutional layers, pooling layers, and fully-connected (FC) layers. When these layers are stacked, a CNN architecture will be formed. In addition to these three layers, there are two more important parameters which are the dropout layer and the activation function which are defined below.

1. Convolutional Layer: This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM). The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

2. Pooling Layer: In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.

3. Fully Connected Layer: The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture. In this, the input image from the previous layers are flattened and fed to the FC layer. The flattened vector then undergoes few more FC layers where the mathematical functions operations usually take place. In this stage, the classification process begins to take place.

4. Dropout: Usually, when all the features are connected to the FC layer, it can cause overfitting in the training dataset. Overfitting occurs when a particular model works so well on the training data causing a negative impact in the model's performance when used on a new data. To overcome this problem, a dropout layer is utilised wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model. On passing a dropout of 0.3, 30% of the nodes are dropped out randomly from the neural network.

5. Activation Functions: In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network. It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, Softmax, tanH and the Sigmoid functions. Each of these functions have a specific usage. For a binary classification CNN model, sigmoid and softmax functions are preferred an for a multi-class classification, generally softmax is used.

The Model used CNN for training prediction model. It is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data. Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are CNN layer, pooling l ayer, and fully-connected (FC) layer. The convolutional layer is the first layer of a convolutional network. While convolutional layers can be followed by additional convolutional layers or pooling layers, the fully-connected layer is the final layer. With each layer, the CNN increases in its complexity, identifying greater portions of the image. Earlier layers focus on simple features, such as colors and edges. As the image data progresses through the layers of the CNN, it starts to recognize larger elements or shapes of the object until it finally identifies the intended object. The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map. Let's assume that the input will be a color image, which is made up of a matrix of pixels in 3D. This means that the input will have three dimensions—a height, width, and depth—which correspond to RGB in an image. It also have a feature detector, also known as a kernel or a filter, which will move across the receptive fields of the image, checking if the feature is present. This process is known as a convolution.

VI. RESULTS AND DISCUSSION

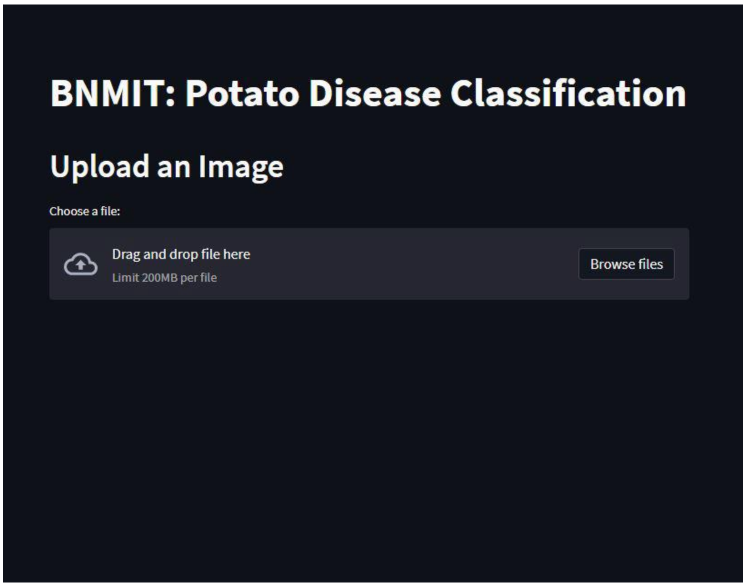

Fig: 6.1- Start Page

Above figure no.6.1, shows the start page user interface of the web application. Title of this web-page is potato disease classification. Here user can see the browse file button. It can be used for uploading image of image format jpg or png. Image can be of any dimension but size should be less than 256Mb. Uploaded file will be sent for prediction to the backend.

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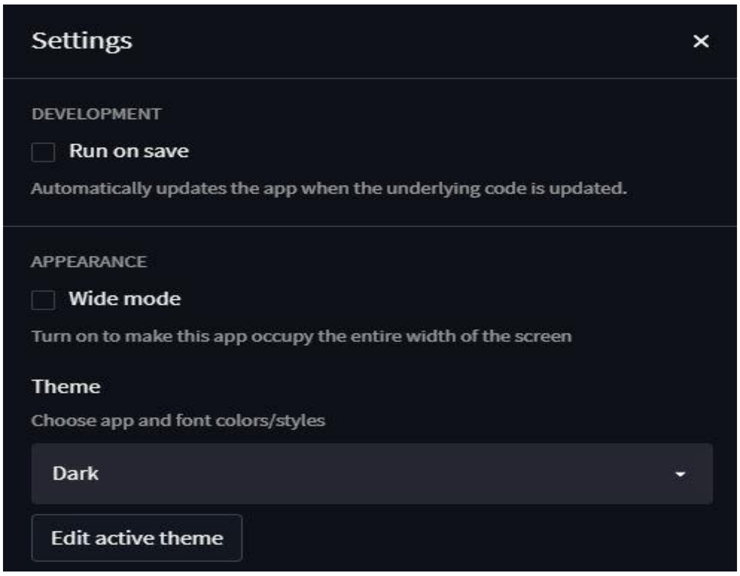

Fig: 6.2- Setting Page

Above figure no. 6.2, is the setting page of our web application. Here user can modify various settings for enhanced user experience. Run on save option updates the front-end user interface when code in the backed is updated and saved. Wide mode option is for changing screen layout from portrait to landscape. User can also change the theme of the web-page from dark mode to light mode and vice-versa using drop down option under theme. And can also change the font style and font color using edit active theme button.

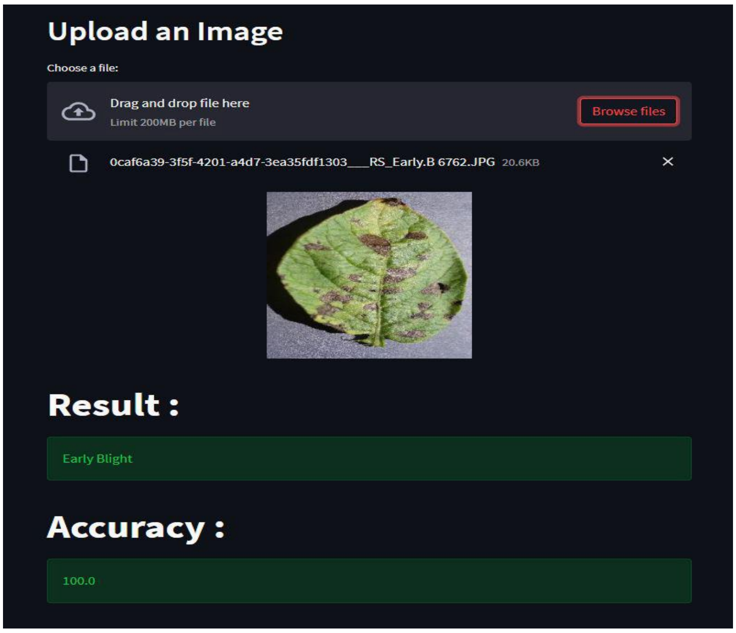

Fig: 6.3- Result Page - Early Blight

Above fig no 6.3 shows the result page of our web application it appears after uploading image. It shows that potato plant is having early blight disease. Below that in result section it shows the output whether image is health or not. In Accuracy section it shows what is the accuracy of above prediction. From numbers of experiments its be observed that our prediction model accuracy is 99% and loss of the model is 1% on average.

VII. CONCLUSION

Convolutional neural networks offer great accuracy while building models. Convolutional neural networks are far more accurate than artificial neural networks. Any image classification model's accuracy is mostly dependent on the size and calibre of the dataset. Transfer Learning models are simple to use and have a high degree of accuracy. Transfer Learning Model fails if a new type of potato plant disease is discovered since it was not trained on it. Since CNN is still one of the top classification algorithms, adopting it in these situations is the best choice. Pre-processing and feature extraction procedures can greatly improve the accuracy of the results. Some of the datasets need to be improved in the future, while the new datasets are quite small and out-of-date. Combining all of the available datasets is one method that may be done to provide the model access to a large number of recent photos in a single dataset. After merging, images must be adjusted to prevent mistakes during training. By doing this, a variety of skin tumours can be accurately detected.

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VIII. REFERENCES

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