FOLIAR DISEASE DETECTION USING ML AND DEEP LEARNING

Progress report of Major Project

BACHELOR OF TECHNOLOGY in INFORMATION TECHNOLOGY

Submitted by

Roll Number	Name	Year	Branch	Section	Outcome (Patent/Research Paper/ Application Project deployable)
2100290130023	AMAN SINGH	3	IT	A	Research Paper
21002901300062	DEV PRATAP SINGH	3	IT	A	
2100290130038	ARPIT PAL	3	IT	A	
2100290130177	SUMIT CHAUDHARY	3	IT	C	

DEPARTMENT OF INFORMATION TECHNOLOGY

KIET GROUP OF INSTITUTIONS, GHAZIABAD, UTTAR PARDESH

(Affiliated to Dr. A.P.J. Abdul Kalam Technical University, Lucknow, UP, India)
Odd Semester, Session 2023-24

PROPOSED METHODOLOGY

In this section, we discuss pertinent initiatives in categorization problems utilizing deep learning architectures. Deep learning techniques have generally been the subject of much research for applications such as object recognition and image categorization. When used to solve recognition and classification issues, convolutional neural networks (CNNs), a deep learning technology, achieve state-of-the-art performance in picture classification.The first CNN architecture known as MobileNet for object recognition was evaluated using the dataset for tomato disease. To determine the degree of tomato leaf disease from photos of tomato leaves, pre-trained CNN architectures VGG16, MobileNet, and ResNet50 were implemented. Performance was improved by adding ResNet50 features to the traditional CNN model.

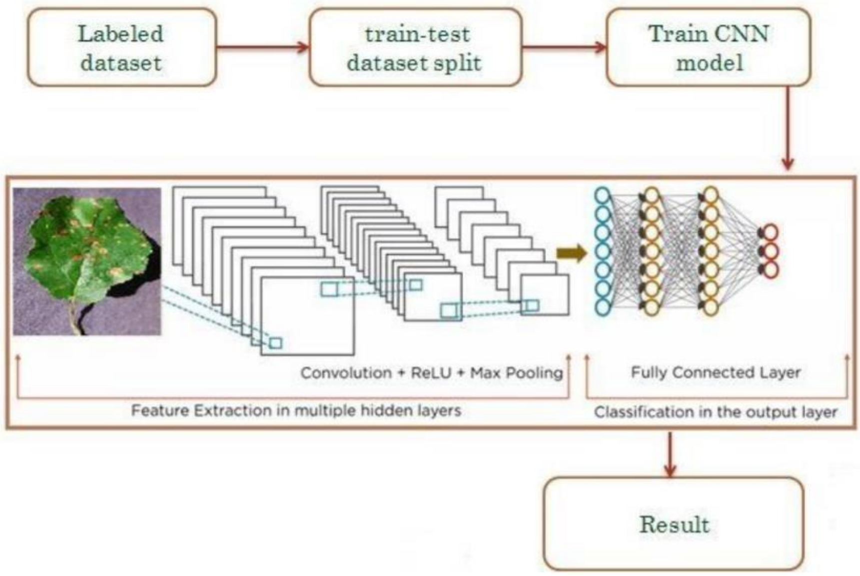


Fig 1: Proposed Workflow

The spatial links between the image's constituent parts are not taken into consideration by CNN architectures, making them ineffective for geometric transformations. By routing features from one layer to another in CNN, the max-pooling layer has a tendency to lose data. They are unable to model the rotational invariance of an item.The section presents a Capsule Network with Dynamic Routing algorithm to alleviate the shortcomings of CNN design. Capsule networks were used in the experiments to classify illnesses based on medical imaging, and they performed better than regular CNN in doing so.

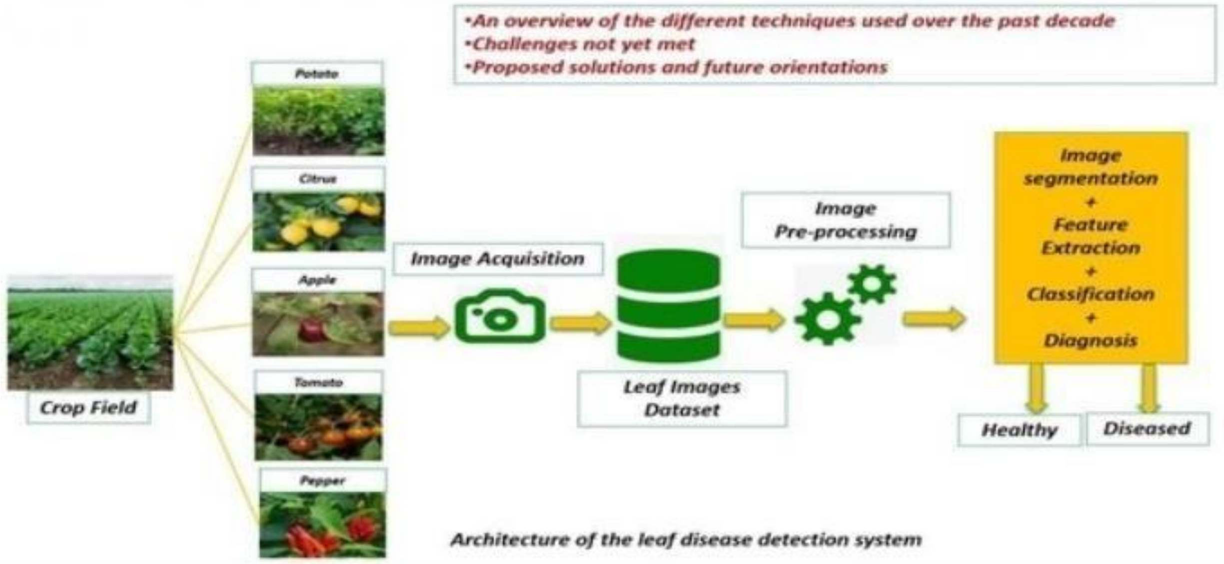


Fig 2: Architecture of the leaf disease detection system

- **Dataset Classification**
- **Building the CNN using transfer learning**
- **Factorizing Convolutions**
- **Testing**

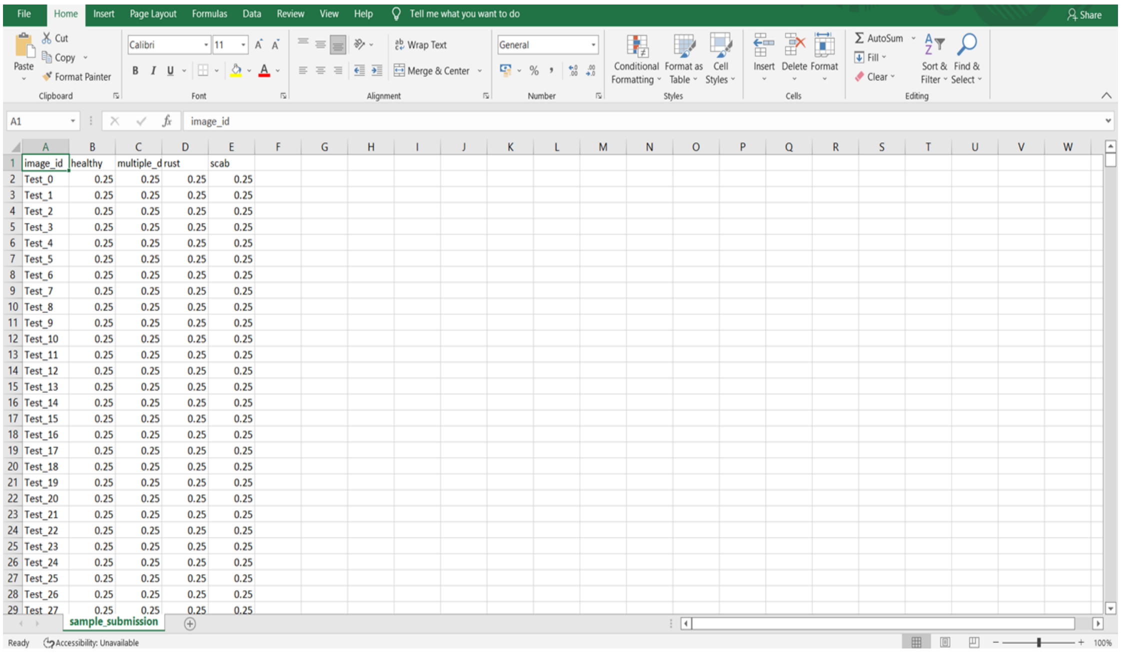
3.1 DATASET CLASSIFICATION
3.2

Selection of proper set of images for training of model is a significant task.Centroid of each imageis calculated to retrieve select images.Centroid can be calculated by use of contours. Contour is a curve that joins all the points along the periphery of a shape. Contour scan much be detected much precisely on binary images. Hence, every image has to be converted to gray scale with a threshold applie do it.

Having found the contours, the image moments are calculated. Image moments are used to calculatethe centre of mass or the centroid of an object.The function cv2.Moments return a dictionary of all moment values. From this moments one can extract data such as centroid , area, etc.As we only need centroid of the image, it is given by the relations,

Cx=(M[—m10‖]/M[—m00‖]) and Cy=(M["m01"] /M["m00"])

here,M is the dictionary of moments.



image_id	healthy	multiple_d	rust	scab
Test_0	0.25	0.25	0.25	0.25
Test_1	0.25	0.25	0.25	0.25
Test_2	0.25	0.25	0.25	0.25
Test_3	0.25	0.25	0.25	0.25
Test_4	0.25	0.25	0.25	0.25
Test_5	0.25	0.25	0.25	0.25
Test_6	0.25	0.25	0.25	0.25
Test_7	0.25	0.25	0.25	0.25
Test_8	0.25	0.25	0.25	0.25
Test_9	0.25	0.25	0.25	0.25
Test_10	0.25	0.25	0.25	0.25
Test_11	0.25	0.25	0.25	0.25
Test_12	0.25	0.25	0.25	0.25
Test_13	0.25	0.25	0.25	0.25
Test_14	0.25	0.25	0.25	0.25
Test_15	0.25	0.25	0.25	0.25
Test_16	0.25	0.25	0.25	0.25
Test_17	0.25	0.25	0.25	0.25
Test_18	0.25	0.25	0.25	0.25
Test_19	0.25	0.25	0.25	0.25
Test_20	0.25	0.25	0.25	0.25
Test_21	0.25	0.25	0.25	0.25
Test_22	0.25	0.25	0.25	0.25
Test_23	0.25	0.25	0.25	0.25
Test_24	0.25	0.25	0.25	0.25
Test_25	0.25	0.25	0.25	0.25
Test_26	0.25	0.25	0.25	0.25
Test_27	0.25	0.25	0.25	0.25

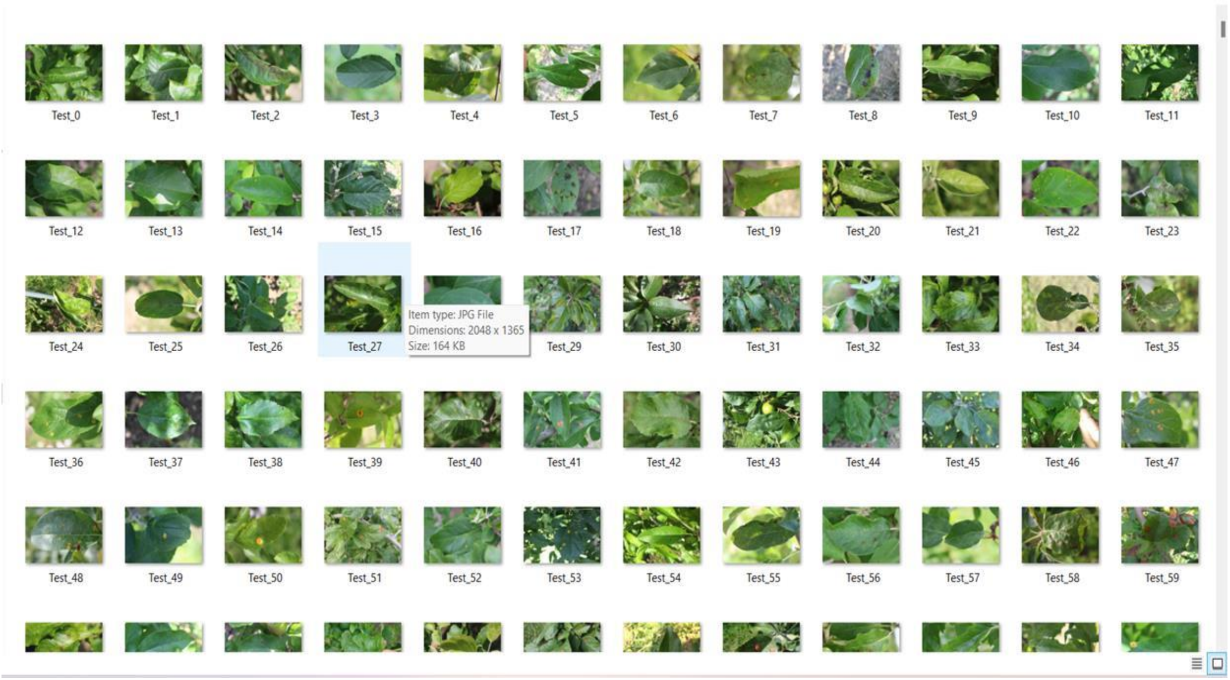


Fig 3: DataSet Examples

3.3 BUILDING THE CNN USING TRANSFER LEARNING

Image identification has become feasible with the advent of Convolutional Neural Networks.Butdesigning a CNN that identifies objects and classifies them into distinct classes is a complextask.By making use of transfer learning it can be simplified. In transfer learning we have trained our model that has been trained on Plant Pathalogy dataset .Also Transfer learning significantly reduces training time and gives much better performance for relatively small dataset.

3.4 FACTORIZING CONVOLUTIONS

By means of factorizing convolutions the no. of connections and parameters are reduced to aconsiderable degree without adversly affecting the efficiency of the system. Factorization can be into smaller convolutions such as,two 3 by 3 convolutions replace one 5 by 5 convolution; or as symetric convolutions such as 3 by 1 convolution followed by 1 by 3 replaces 3 by 3 convolution.

3.4.1 AUXILARY CLASSIFIER

InInception-v3,auxiliary classifier isused as regularizer. Batch normalization,introduced in Inceptionv2,is also used in the auxiliary classifier.

3.4.2 EFFICIENT GRID SIZE REDUCTION

Usually feature map downsizing is done by maxpooling.But the approach either tends to be too greedy or too expensive. In inception v3 320 feature maps are obatined by max pooling and these are concatenated to obatin 640 feature maps. Efficient grid size reduction inInception v3 produces inexpensive yet effective network. 3) Training the network The deep convolutional model can be used to classify labels specific to the task at hand. For this theInception v3 model is loaded. New classes to be recognised are specified and Inception v3 model is trained over different batches for certain number of epoches, thus harnessing the image classifying abilities of Inception v3 to classify diseased plants.

3.5 TESTING

The trained model is tested on a set of images. Random images are introduced to thenetwork and output label is compared to the original known label of the image. Parameters used for evaluation are F1 score,precision and recall.Precision is the proportion of predicted positives that are truly positives. Recall gives the proportion of actual positives correctively classified.F1 score helps in maintaining a balance between precision and recall.

3.6 REQUIREMENT ANALYSIS

3.6.1 NON-FUNCTIONAL REQUIREMENTS

Non-functional requirements illustrate how a system must behave and create constraints of its functionality.This type of constraints is also known as the system's quality features. Attributes such as performance, security, usability, compatibility are notthe feature of the system, they are a required characteristic. They are "developing" properties that emerge from the whole arrangement and hence wecan't compose a particular line of code to execute them. Any attributes required by the user are described by the specification.We must contain only those needs that are appropriate for our design.

Some Non-Functional Requirements areas follows:Availability, Maintainability, Performance, Portability

Scalability, Flexibility.

3.5.3 AVAILABILITY

Availability is a general term used to depict how much an item, gadget, administration, or condition is open by however many individuals as would be prudent. In our venture individuals who have enrolled with the cloud can get to the cloud to store and recover their information with the assistance of a mystery key sent to their emai lids. UI is straight forward and productive and simple to utilize.

3.5.4 MAINTAINABILITY

In programming designing, viability is the simplicity with which a product item can be altered as:Correct absconds Meet new necessities New functionalities can be included in the task based the client necessities just by adding the proper documents to existing venture utilizing ASP. Net and C# programming dialects.

3.5.5 SCALABILITY

Framework is fit for taking care of increment all out throughput under an expanded burden when assets(commonly equipment)are included.Framework can work ordinarily under circumstances, for example, low data transfer capacity and substantial number of clients.

3.5.6 PORTABILITY

Portability is one of the key ideas of abnormal state programming. Convenient is the product code base component to have the capacity to reuse the current code as opposed to making new code while moving programming from a domain to another. Venture can be executed under various activity conditions gave it meet its base setups.Just frame work records congregations would need to be designed in such case.

3.5.7 HARDWARE REQUIREMENTS

Processor	Any Processor Above 500 MHz
RAM	4GB
HardDisk	500 GB
System	Intel i3 6Gen 2.4 GHz

Table 1:Hardware Requirements

3.5.8 SOFTWARE REQUIREMENTS

Operating System	Windows
7/8/10/11 Programming language	Python,Machine Learning,CNN
IDE	Jupyter Notebook/Google CollabNoteBook
Tools	Anaconda,Pycharm

Table 2:Software Requirements

3.7 IMPLEMENTATION

- The categorised leaves of tomato, potato, grape, and apple plants have 24 distinct types of labels. Information on Apple labels includes the following: healthy rust, scabs, and black rot. specifically:Cercospora of Corn Grey spot, healthy corn, corn blight, and corn rust. The individual grape labelsare Leaf blight, Black rot, Esca, and healthy. The dataset consists of 31,119 images of various produce, including tomatoes, apples, maize, grapes, and potatoes. The images were downsized to 256 x 256 and divided into training and testing datasets with an 80-20 split. Out of the total dataset, 24,000 images were utilized for developing the CNN model.

- The dataset includes images of plants affected by different pests and illnesses such as bacterial spot, early blight, healthy, late blight, leaf mould, septoria leaf spot, spider mite, target spot, mosaic virus, and yellow leaf curl virus. The objective of the model is to classify potato images into three categories: early blight, healthy, and late blight, which can help identify and manage diseases effectively. The convolution layer uses a convolution method to extract information. As the depth increases, the complexity of the recovered characteristics increases. The number of filters steadily rises as we move from one block to the next, but their size is constant at 5*5. There are 20 filters in the starting convolution block, 50 in the 2nd, and 80 in the 3rd.

- The size of the feature maps was lowered as a result of the pooling layers being used in each of theblocks, which required more filters. After the convolution procedure is used, feature maps are null-padded to retain the dimesnions of the image. To shorten the length, utilise the max pooling layer.Transfer learning is a technique for sharing knowledge that employs 224*224 fixed-size pictures and requires the least amount of training data possible. Transfer learning is useful for transferring knowledge from one model to another. Sentiment analysis, activity recognition, software defect prediction, and plant categorization are just a few of the activities that have utilised transfer learning. In this study, the performance of the suggested Deep CNN model is compared to that of the well-liked VGG16 transfer learning technique. Three layers come after a stack of convolutional layers. The third device employs a 1000-way ILSVRC classification and has 1000 channels, compared to the preceding two devices' 4096 channels apiece. The last layer is the soft- max layer. The entirely connected layer design makes it easier to identify the leaf disease