



Leaf Disease Detection and Prevention Using Deep Learning

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Leaf disease detection and prevention using deep learning

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Abstract— Since time unknown, agriculture is the backbone of Indian economy. Many plants are eaten alive by plant diseases. These plant diseases should be detected in early stages itself which helps in preventing crop damage and stops advancement of disease. Generally, plant diseases can be easily found by their visible appearance on leaves. Most Plants like groundnut, sugarcane, potato, orange exhibit these disease patterns on their leaves. Farmers observe these patterns and conclude to the disease caused, which is a traditional method of identifying. The patterns that appear on leaves are taken as base to predict the related disease using some Deep Learning algorithms. In this work, Convolutional Neural Network (CNN) model is used to predict plant diseases which is highly suitable for image-based classification. This CNN model gives quicker and more proper predictions when compared to manual observation. In this work, pre trained models like Support Vector Machine, Artificial Neural Network and ResNet50 and CNN model are disciplined using the dataset. CNN model achieves more accuracy when compared to other algorithms.

Keywords— *Convolutional Neural Networks, Support Vector Machine, Artificial Neural Network, ResNet50.*

I. INTRODUCTION

In agriculture sector, detecting plant disease is a challenging task. This detection of plant diseases can be possible by observing detectable symptoms on leaves and instant action can be taken to prevent it. Detection of these plant diseases manually is not possible most of the times and even veteran farmers cannot predict these diseases accurately. Farmers use their wholesome knowledge and experience in detecting these plant diseases. Later much research were conducted by farmers, pathologists, botanists and agriculturists and started gathering knowledge over plant diseases. Then this knowledge is applied as datasets in Machine Learning and Deep Learning to predict the plant diseases accurately. Many

Machine Learning models and Deep Learning models are applied to analyze and predict plant diseases. Artificial Neural Networks from Deep Learning model is highly compatible for image-based classification and analyzation when compared to other Machine Learning models in image-based classification.

To classify various plant diseases, this model uses Transfer Learning, SVM, ANN and CNN. In Deep Learning, Convolutional Neural Networks algorithm shows higher success rate related to image classification. This suggested system works faster and gives authentic results when compared to manual analysis. By introducing this model to agriculture sector, farmers can analyze this plant disease preemptively and measures can be taken to control it. In this work, potato, corn, tomato plant diseases are taken to study these plant diseases to train plant diseases dataset. In this work, CNN model, SVM model, ANN model and ResNet50 models are trained under dataset. Out of all the models, CNN model is achieved the best accuracy with 98.27%.

II. RELATED WORK

During this phase, general solutions and Blockchain architectures were found, and other proposals focused on technologies like Cloud and Encryption. The solutions focus mainly on the problem of integrity, confidentiality, and privacy of health records while adding a different feature, component, or functionality.

Access control to health records is taken as a measure to prevent unauthorized access and enable the patient to be in control of his data. In this regard, Fan et al. [14] proposed an information management system using Blockchain that allows easier access and retrieval of patient data while keeping a high level of information security with access control protocols and symmetric cryptography. Roehrs et al. [15] proposed a distributed model for health records that interconnect the data across multiple devices and health organizations. Zhang et al. [8] proposed FHIRChain, an architecture based on Blockchain for sharing clinical data between distributed providers. It also demonstrated the practical capability with a decentralized application that shares specific structured information to improve readability. Christo et al. [16] proposed a disbursed

Blockchain to grant security in accessing the medical report of a patient through authentication, encryption, and data retrieval. Hyla & Pejaś [13] presented a Blockchain-based eHealth Integrity Model (BEIM) that allows transactional transparency across large healthcare systems using a Byzantine Fault Tolerant consensus. In contrast to the other solutions, our proposed architecture has a private Blockchain where each node will have its own set of permissions and roles according to the requirements for access.

Smart Contracts are used for completing transactions efficiently without the need of an intermediary, eliminating time delays caused by manual involvement. For example, Dagher et al. [17] proposed Ancile, a privacy-preserving framework based on Ethereum using six different smart contracts for access control and interoperability. A Blockchain based on the Ethereum protocol using Smart Contracts was proposed by Griggs et al. [18], where the remote IoT devices call smart contracts and write records of events on the Blockchain. Correspondingly, the proposed architecture will use smart contracts to facilitate agreements between nodes to share medical records in the Blockchain network.

II. RELATED WORKS

Plant diseases are detected by using imaging processing algorithms that focus on diseased regions. Image pattern categorization was utilized by A. Camargo and J.S. Smith to identify disease-causing pathogens in plants. Sanjay and Shrikant used smooth thresholding techniques to leaf part. Based on the bruise area on the Leaf, diseases are analyzed This model had an accuracy of 98.06%.

Jiang suggested an enhanced CNN-based deep learning approach for detecting apple leaf diseases and insect pests. An apple leaf disease dataset (ALDD) comprising of laboratory photographs and complicated images under real-world settings is created using data expansion and image annotation technologies. On this premise, a novel approach based on Google Net inception structure and rainbow concatenation is presented. To detect the five usual leaf diseases and to inspect pests, a INAR-SSD (SSD with perception module and rainbow condition) is proposed. According to the testing findings, the model obtained 78.80% map and a detection speed of up to 23.13 FPS.

P. Deepan and M. Akhila used Faster Region-based CNN (Faster R-CNN), and Single Shot Multibox Detector (SSD) and Region-based Fully Convolutional Network (R-FCN). This dataset consists of sugarcane, chilly, wheat, cotton, banana, potato and

brinjal. Image enhancements such as image intensity, rotations, transformations were used to maximize the dataset and to avoid the model from overfitting.

Particle Swarm Optimization is used by Revathi and Hemalatha for feature extraction to classify various cotton leaf diseases with approximate accuracy of 95%. Particle swarm optimization is used to extract shape, color, and texture information in order to identify various illnesses. The feature extraction strategy aids in the identification of disease leaf spots and improves the model's overall accuracy.

S. S. Sannakki and V. S. Rajpurohit, S. S. Sannakki introduced a "Classification of Pomegranate Diseases Based on Back Propagation Neural Network" which mainly concentrates on bruised area. In this work, texture and color are used as the features. They used Neural Network Classifier for classification of diseases. This model has an accuracy of 97.30% in detecting plant diseases by extracting chromaticity.

Kumar and Patil designed a model for plant disease detection using quality features like inertia, analogy, and correlation which are collected by measuring the gray level cooccurrence matrix. They experimented on finding diseases on maize leaves mixed with color extraction. These extracted features could classify the healthy and diseased patterns and these features were used to train the ANN model. This model obtained 91% of accuracy.

III. METHODOLOGY OF THE CLASSIFICATION MODEL

CNN:

In this work Convolutional Neural Network model is applied to analyze various plant diseases. The main goal of CNN model is to obtain features like color, edges, gradient etc. from the input images and this process take place at convolutional layer of CNN. With intermediate layers, it is accustomed to understanding the images in the dataset. And the Pooling layer can minimize the spatial size of convolved feature. This results in decrement of computational ability to process the data. Combining both Convolutional layer and Pooling layer, the i -th layer in CNN. Then the model understands the features of the dataset and the input images are converted into suitable form of Multi Level Perceptron and the image is flattened into column vector and is passed to fully connected layer. In this work ReLu activation function is applied for convolutional layer and for output layer, Softmax function is used. If the input value is greater than zero, rectified linear activation function gives output

value and if the input value is zero or less it returns zero.

$$f(x) = \max [0, x]$$

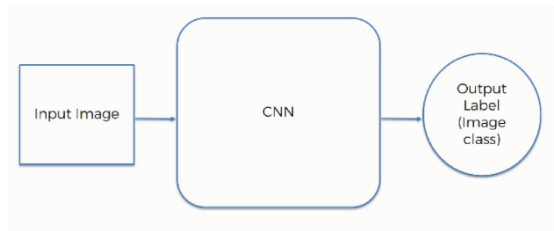


Figure 1: CNN model

ResNet50:

Residual Network was a new architecture proposed in 2015. ResNet50 overcomes vanishing gradients issues. In ResNet50, skip connections are introduced. The skip connection bypasses a few stages of training and links straight to the output. In ResNet50, network is allowed to fit the residual mapping instead of layers learning the underlying mapping. Adding skip connections enables if any layer is impaired then it will be bypassed by adjustments. This helps in training many deep neural networks without causing exploding gradient. ResNet50 uses 34 layered plain network architecture with connections being added. With five convolutional blocks and 13 identity blocks, ResNet50 is set for various parameters for fitting the architecture. Here the dataset is preprocessed and prepared for training. Then learning rate is adjusted based on number of epochs. Here learning rate is reduced if the number of epochs is increased.

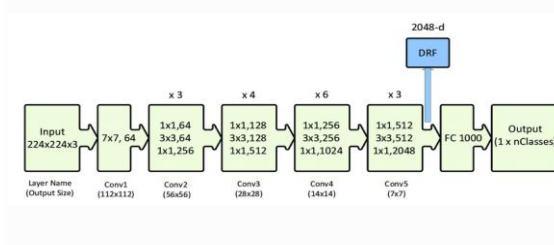


Figure 2: ResNet50 model

ANN:

The structure and function of a biological neural network serve as the foundation for ANN architecture. ANN consists of neurons classified in different layers just like neurons in a brain. A prominent neural network is the feed of forward neural network, which comprises of an input layer that receives external data to conduct pattern recognition, an output layer that provide solution to problems and a hidden layer which is also known as intermediate layer which divides other layers. Acyclic arcs are linked nearby neurons from the input layer to the output layer. To learn the datasets,

the ANN employs a training method that updates the neuron weights based on the error rate between the goal and actual output. To learn the datasets, ANN employs the back propagation algorithm as a training technique.

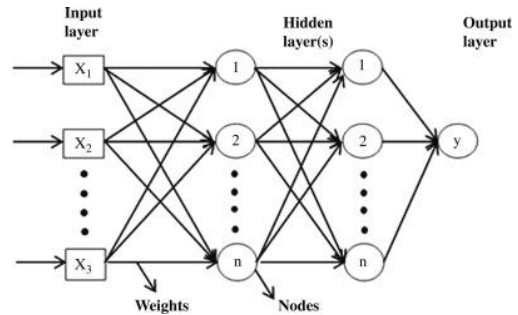


Figure 3:ANN model

SVM:

Although Support Vector Machine is considered as a classification technique, it can be used in both classification and regression situations. SVM can easily manage a large number of continuous and categorical variables. To differentiate various classes, SVM creates a Hyperplane in multidimensional space. SVM iteratively develops optimum Hyperplanes, which are utilized to minimize the errors. The basic principle behind SVM is to determine the optimum maximal marginal Hyperplane (MMH) for dividing a dataset into classes. Here the data points closest to the Hyperplane are the support vectors. By computing margins, these points will better define the separation line. These points are more significant to the classifier's creation. SVM method is implemented with the help of a kernel. A kernel converts an input data space into the desired format. Here the kernel turns a low-dimensional input space into a higher-dimensional one.

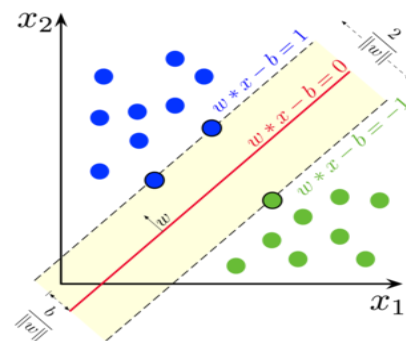


Figure 4: SVM model

ARCHITECTURE:

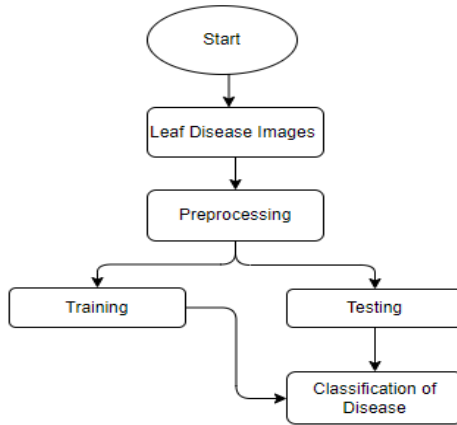


Figure 5: Architecture of classification system

IV. IMPLEMENTATION DETAILS

A. Dataset

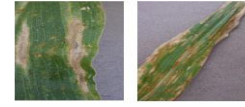
The leaves dataset was used to collect the data for this work. The leaves collection contains over 5,030 photos divided into 30 classes representing 18 distinct plant species. There are 19 healthy leaf classes and 28 unhealthy leaf classes among the 35 leaf classes.

In this study, the corn, potato, tomato leaf images are taken, consists of 4,392 images with different diseases. The diseases for corn leaves are Common rust, Northern leaf blight. The diseases for potato leaves are Early blight, Late blight and diseases for tomato leaves are Bacterial spot, Late blight. This dataset contains 332 healthy leaves, 1,230 Common rust affected corn leaves, 1,492 Northern leaf blight affected corn leaves, 1,339 Early blight affected potato leaves, 283 Late blight affected potato leaves, 112 Bacterial spot affected tomato leaves and 834 late blight affected tomato leaves. To get good performance, deep learning

models require a huge dataset. The photographs were downsized to 215x215 pixels using Keras' Image data generator, then augmentations such as rotation, zoom, and shift were added. The main goal of the augmentation procedure is to increase the dataset size and avoid overfitting during the training stage. To conduct the experiments, the dataset is divided into 70:30 training and validation sets. There are 5,030 photos in the training set and 812 images in the validation set. SVM, CNN, ResNet50, and ANN were used to compare popular pre-trained models. 224x224 is the default image size for CNN, SVM, ANN, and ResNet50.

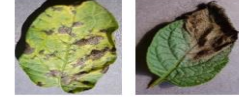


Figure 1: Healthy leaves of Corn, Potato, Tomato



Common rust Northern leaf blight

Figure 2: Corn leaf diseases



Early blight Late blight

Figure 3: Potato leaf diseases



Early blight Late blight

Figure 4: Tomato leaf diseases

$$\text{Accuracy} = (TN + TP) / (TN + TP + FN + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{F1 score} = 2 * [(precision * recall) / (precision + recall)]$$

TABLE I: SVM, ANN, CNN, RESNET MODELS CLASSIFICATION PERFORMANCE

A. Training Neural Network

Pre-trained models such as SVM, ResNet50, and ANN popular are trained using the plant dataset

Name of the Model	Precision	Recall	F1 score	Overall accuracy
SVM Model	96.50	96.32	96.21	96.59
ANN Model	91.25	91.12	91.43	91.92
CNN Model	89.33	89.30	89.52	89.92
RESNET Model	92.14	92.35	92.23	92.23

along with Convolutional Neural Network, then the results are contrasted. CNN model consists of convolution and pooling layers in which convolution layers operate filters on the input image for extraction of features and pooling layers

minimize the size of the input image which also minimize the computation done in the network.

The CNN model is trained for 20 epochs using the training set. Adam is the optimizer used here, and the loss function used is categorical cross-entropy. Adam is a stochastic gradient optimization approach that performs well with sparse data. The CNN model performed well by achieving 94.58% of overall accuracy.

According to this work, pre-trained models utilizing transfer learning are an effective technique for plant disease categorization. The experimental results are

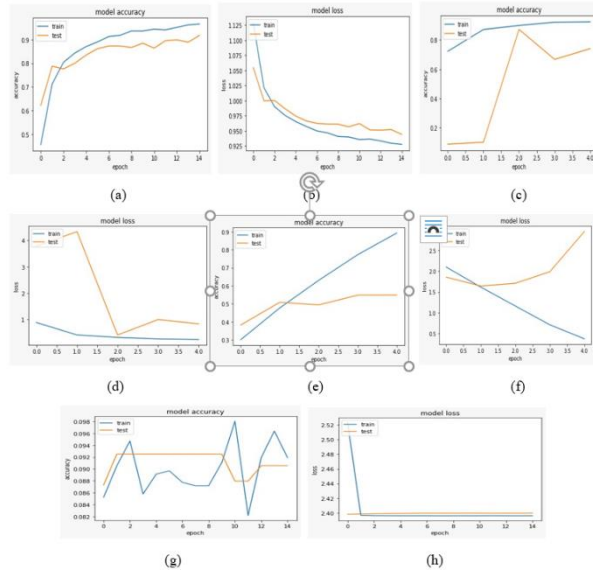


Figure 7 a-b) Accuracy and Loss curves of the SVM model. c-d) Accuracy and Loss curves of the ANN model e-f) Accuracy and Loss curves of the CNN model g-h) Accuracy and Loss curves of the ResNet model.

V. CONCLUSION

This work helps in diagnosing plant diseases in early stages and suggests the methods to prevent these plant diseases. By following these methods crop loss and disease spread can be prevented at early stages. Here the CNN model is implemented to detect and to predict different plant diseases accurately. This model also implements pre trained models like SVM, ANN, ResNet50 for detecting plant diseases. The CNN model gives more accuracy of 98%. The accuracy, precision, recall, and F1 score are used to evaluate the performance of this model. The vanishing gradient problem is one of the most common challenges encountered in a bigger neural network and this problem is overcome by ResNet50 model which deals with intermediate layers efficiently. SVM cannot perform efficiently when more noise is added and is not suited for larger datasets. It becomes difficult to ANN model to convert two

dimensional images to one dimensional image. All these issues are overcome by CNN which performs well on larger datasets and on images efficiently when compared to ANN, SVM, ResNet50. This work is more helpful to farmers, pathologists, agriculturists, and botanists in understanding the plant diseases. Thus, farmers can use this application/website to predict diseases and can be instructed to prevent diseases further. This work is helpful in maintaining crops which results in generating good income.

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