Deep Learning and IoT Enabled Model for Plant Disease Detection

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in
Computer Science & Technology

By

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Certificate

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Declaration

I hereby declare that the dissertation work entitled **"Deep Learning and IoT Enabled Model for Plant Disease Detection"** in partial fulfillment of the requirements for the award of degree of **"Master of Technology"** in **"Computer Science &Technology"** and submitted to the School of Computer & Systems Sciences, Jawaharlal Nehru University, New Delhi-110067, India is the authentic record of my own work carried out during the time of Master of Technology under the supervision of **Dr. Sushil Kumar.** This dissertation comprises only my own work. The matter personified in the dissertation has not been submitted for the award of any other degree or diploma.

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Abstract

Plant diseases are unfavourable elements that drastically reduce crops' quality and output. When examining plants for illness, seasoned scientists or farmers frequently use their naked eyes. However, this technique is often inaccurate and can take a long time.

The most recent convolutional neural networks (CNNs) in image categorisation have produced excellent results. A model for identifying plant diseases is built in this dissertation utilising a novel technique for classifying leaf pictures using deep neural networks. The approach and novel training methods are used to make quick and straightforward system implementation in practice. Out of 4188 total photos from the corn or maze datasets, the proposed model can distinguish between three different forms of plant illnesses and healthy leaves. This approach to identifying plant diseases has, as far as we know, never been put forth before. The entire process of putting this disease recognition model into practice, from obtaining photos to building a database that agricultural specialists have approved, is comprehensively documented throughout the publication. The experimental findings on the created model showed the accuracy of 96.47 per cent on training datasets and 97.82 per cent on test datasets, respectively.

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Chapter -1
INTRODUCTION

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Modern technologies have enabled society to create a crop that would feed 7 billion or more people. Plant diseases threaten provision of food and for smallholder farmers, can have disastrous effects whose income depends on producing strong harvests. Agriculture production is incredibly important to India's economy. As a result, disease detection in plants is highly crucial in agriculture. It's direct impacts are seen on food safety, agrarian yield, and long-term development. The early detection of plant disease is a critical task. Early detection reduces the severity of the damage and allows for less intensive countermeasures. IoT technologies help farmers close the supply-demand gap by ensuring excellent yields, profit, and environmental preservation. Data on agricultural areas can be provided through sensors connected to the internet of things. Farmers can use this technology to check their crops' current state without going out into the field.

The Cercospora zeae-maydis fungi cause the grey leaf spot on the leaf part of the plant. It's now well recognised as among the planet's most crucial maise (corn) yield-limiting diseases. In several parts of the eastern United States and Africa, it has grown to be a serious danger to the development of mazes. Typically, the lower leaves will exhibit its symptoms. [1]

The disease name common rust infected by the pathogen Puccinia sorghi, and the disease was favoured by low humidity and high temperature. The cause of illness affects the leaf part of the maze plant on both sides of a leaf. Another disease is 'Blight', caused by a fungus called Exserohilum turcicum. This disease more spread when certain environmental conditions are met, such as temperatures ranging from excellent to mild, with high humidity. The symptoms can be identified by the enormous grey cup lesions that might appear on leaves. [1]

Artificial intelligence's development and deep learning models are frequently used in precision agriculture. The central research area in agriculture is the irrigation system, pest monitoring and crop monitoring. Recognising crop diseases in particular has been a regular research topic. Diseases in fruits and vegetables crops are used to recognise crop disease. Various models of deep learning have shown precise and accurate results in classification and detection of diseases. The quality of the datasets, the colour spectrum, and vegetable characteristics, as well as the diverse stages of the disease have an active role in the effectiveness of these models. The limited availability of datasets also contributes to the same. A review of current methods for predicting crop disease have shown that convolution neural network (CNN) has particular limitations, whereas VGG and AlexNet have good recognition accuracies.

Convolution neural networks are part of deep learning, which gives noticeable results in image recognition tasks. CNN does not require as much pre-processing as other approaches. CNN's, in particular, are the most effective method for automatically discovering meaningful and distinct traits. . The CNN architecture has different learning layers that realise the most notable features from the data. For the plant disease recognition task, CNN produces a better result in less processing time. Many active researcher groups use CNN for image recognition tasks, and many variants of CNN are famous as a primary architecture.

1.1 Background

1.1.1 Progress and History of CNN:

CNN has played a significant role in the legacy and inception of artificial NN. CNN was introduced around 1980 and used to recognize handwritten numbers. Convolutional neural networks have received a lot of media attention over the past ten years (CNNs).

Artificial Neural Networks (ANN), also referred to as brain networks, are electronic models that are based on biological neural networks. The connection-ism of cognitive science is where its central idea came from: intelligent behavior is produced by connecting a great number of basic computational units. A similar idea can be used to the computational units in computational models as well as the neurons in a real neural network. As a result, research into the neural system is motivated by how creatures' brains can be used to create intelligent systems. This is followed by research into the intelligent behaviours of the species that make up these systems. Lee et al. (2018)

There are just two possible states for neuronal cells in the brain: fire and non-fire (restriction). Only the frequency changes; the strength of the signal transmission stays constant. When the total number of additional signals reaches a certain threshold, neural cells are stimulated and enter the state of fire. Neural cells use specific techniques to aggregate all added signals into neurons. If the total number is less than the threshold, the neural cells will remain confined and not give any electrical signals. Otherwise, electrical impulses will be transferred to other neural cells. A standard neuron model with two components is seen in Figure 1. The first section is the signal accumulation, in which the input signals (input data) are added together to produce a sum. [2]

The function's activation is the second phase, during which a non-linear compressed transformation is employed to extract a non-linear eigenvalue using the activation value that was acquired. ReLU, Sigmoid, and Tanh are some of the widely utilized activation functions. [2]

1.1.2 Deep Learning and Neural Networks:

ML includes "deep learning". We can also say that subset of ML. In the deep learning, the algorithm analyzing data similar as humans behaviors and deep learning using multi layered structured algorithm, which is called neural network.

In this multi layered structure, there are many nodes, which are connect each other and form a structure of neurons similar to available in brain. We can also called ANN.

Neurons or Perceptron:-

- *Neurons*: The constructing blocks of neural networks.

The very fundamental aspect of any artificial neural network is the artificial neuron. They're now not simplest named after their opposite biological numbers but also are modeled after the conduct of the neurons in our brain.

- *Biology v/s Technology:*

Artificial neurons that take input process them, and give output are motivated by the biological neural system concept. The main components of biological neurons are axons, dendrites, and the cell body. The function of the axon is to send the signal to other neurons, and the dendrite is connected to other neurons to receive the signal from the attached neurons.

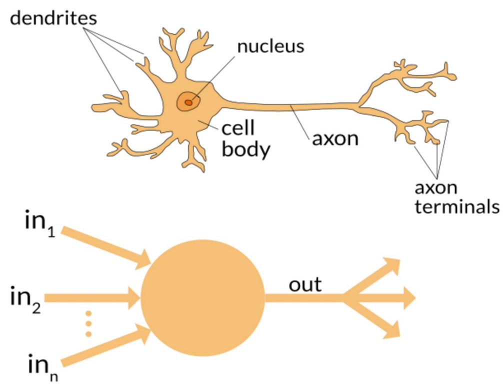


Figure 1. 6 Structure of Biological vs Artificial Neuron [30]

- *Inside an Artificial Neuron:*

Real data is sent into an artificial neural network, which then multiplies it while adding associated bias and weights.

$$f(y) = w_1x_1 + w_2x_2 + \cdots + w_ix_i + b \qquad (1.1)$$

Initially, weight is initialized randomly. After that model predicts the values, the loss is calculated using some loss function (RMSE or cross-entropy). After this, based on the error, weights get updated. This process continues until the optimal value of the loss and bias is captured by the model, which minimizes the loss. Learning algorithm:

Initialize w, b

Iterate over data:

Find predicted value ($\hat{y}$)

Find loss (L)

$w_{t+1} = w_t - \eta\, \Delta w_t$

$B_{t+1} = b_t - \eta\, \Delta b_t$

till satisfied.

- *Activation function in NN:*

Activation function in neural network is a function that decides when a neuron fires. That means based on some threshold value neurons gives the output.

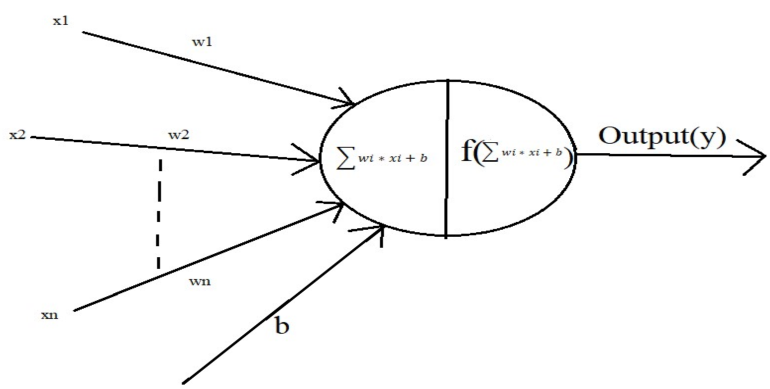


Figure 1. 7 Structure of Neurons with inside work

$$y = f(\sum wi * xi + b) \tag{1.2}$$

Here x_i are inputs and wi are weight corresponding to x_i's and b is bais. 'f' is activation function.

There are many activation function we use like linear, sigmoid, thah, Relu etc.

For a perceptron if activation function of neurons gives value 1 for positive and zero input and activation function gives value 0 for negative input.

Artificial Neural Network:

It is a complex structure of many neurons or perceptron's**.** Which contain three layers: input comes first, followed by a hidden layer, then an output layer.

A basic neural network structure is shown below.

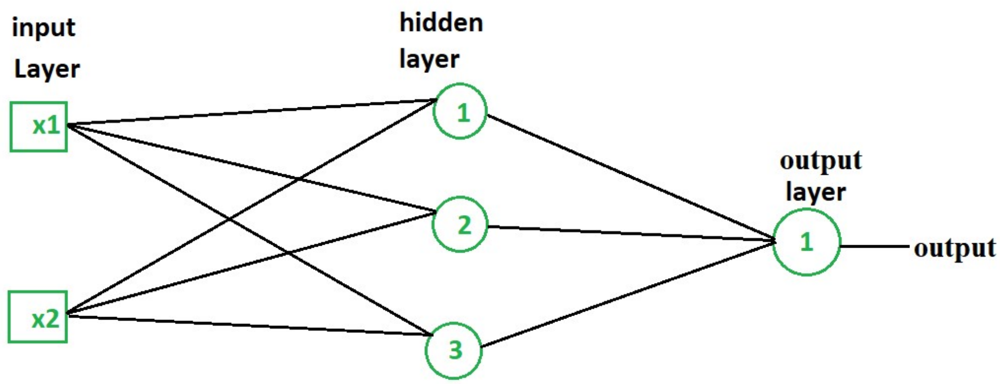


Figure 1. 8 A simple structure of ANN

The structure and functionality of the neural network are similar to the human brain. In this way, our brain identifies things or patterns and distributes different information in the same way NN works similar acts on data. Neural networks can do many actions or tasks like clustering, classification, regression, etc.

Feed forward NN:

In ANN, the neurons are arranged as a successive layer, and the output of the present layer of neurons is connected with the forthcoming layer as input. The NN is called feed-forward NN if the inter-community between layers and the hidden layer shifts its input into any applied impulse on information for the terminal predictions.

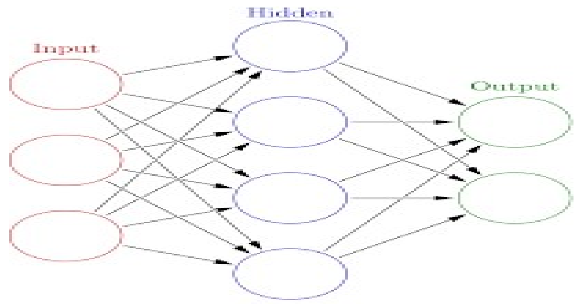


Figure 1. 9 Feed forward Neural Network

The above figure shows feed-forward NN, moving in one direction.

Convolutional Neural Network:

ConvNet, sometimes known as CNN, is a unique sort of ANN created primarily for image input without sacrificing the spatial structure of images. . Like ANN, CNN has multiple layers followed by output layers and has weights/parameters, activation, and loss functions. CNN has a sparse connection and weight sharing among hidden layers than ANN.

The basic building block of CNN are shown in fig -1.5.

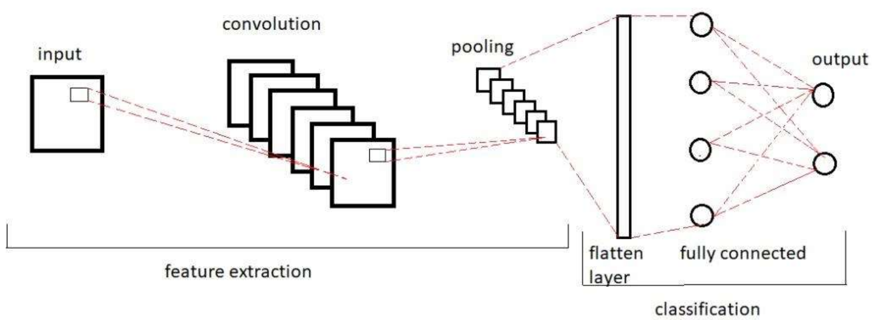


Figure 1. 10 Structure of CNN

Input, convolution, and pooling layers are present in the CNN and used to extract features. Flat, fully connected, and output layers are present and are used for classification.

1.2 Problem Statement and Objective

This dissertation's goal is to identify the infected leaves from the healthy leaves in maze or corn datasets. By feeding the input image to deep convolution neural network to determine the class of disease.

The procedure given in this study is a novel approach for diagnosing crop illnesses, which employs a deep convolutional neural network that has been built and calibrated to match precisely to a database of photos of a plant's leaves that was produced individually for corn plant or maze illness.

The remaining sections of the thesis are arranged as follows: The relevant work is presented in Section 2, the technique is discussed in Section 3, the results are discussed in Section 4, and our conclusions and suggestions are presented in Section 5.

Chapter -2

LITERATURE REVIEW

****

A web-based method was suggested by the author in (Bhange & Hingoliwala, 2015) that assisted farmers in the diagnosis of fruit illnesses by submitting fruit photographs to the system. The system made use of pomegranate fruit datasets that have already been trained. The user provided the photographs to be analysed, which underwent a number of processing stages in order to determine the severity of the diseases by contrasting them with the images from the trained dataset. The proposed method's experimental results showed that it can identify the pomegranate disease with an accuracy of 82 percent.

According to the author of (Sladojevic et al., 2016), machine learning algorithms are widely used to detect plant leaf disease. It was discovered that the accuracy of the machine learning models used to predict these plant leaf diseases varied. Currently, a variety of methods are being applied to computer vision to identify plant leaf diseases. Disease detection using image-extracted colour features is one of them. By using a colour feature extraction, CNNs have been known to outsmart categorisation and identification of images. Due to these factors, Sladojevic et al. trained deep CNN for the identification and categorisation of plant diseases. The generated model's test results showed correctness.

In (Waghmare et al., 2016), the author suggested that the 120 photos be obtained by mobile camera directly from farms. SVM is employed after comparing the accuracy of several techniques such as BPN, fuzzy, and SVM. The image is scaled down to 226 × 226 during image preparation. HSV colour space is converted from RGB pictures. To focus on the leaf area and eliminate distracting background elements from the image, background removal is used. The obtained accuracy is 89.3 percent on average.

In (Khirade & Patil, 2015), the authors used back propagation neural network (BPNN) technology and digital image processing approaches to address the issue of plant disease identification. Authors have developed many methods for spotting plant diseases using photographs of the leaves. Otsu's thresholding along with spot detection algorithms and border detection have been used to segment the contaminated portion of the leaf. For the purpose of classifying plant diseases further, the properties such as texture, morphology, colour, edges, etc. are extracted. BPNN is employed for classification for the final identification of the plant disease.

In [3], . A technique that can accurately estimate the level of fruit infection has been created by the authors. Utilising characteristics including hue, homogeneity, SD, correlation, mean, entropy, variance, edges, etc., the Bacterial Blight Detection System is developed for the Pomegranate plant. For the purpose of segmenting the image's region of interest, authors used grab cut segmentation. Canny edge detector was employed for the extraction of photo edges.

Authors used a convolutional neural network to identify the plant disease in (Shrestha et al., 2020). Authors correctly classified 12 plant diseases with accuracy of 88.80 percent. The experimentation used a collection of 3000 high resolution RGB photos. Three blocks of convolutional and pooling layers make up the network. This increases the network's computing cost. Additionally, the model's F1 score is 0.12, which is extremely poor due to the huge amount of false negative predictions.

In work presented in (Madiwalar & Wyawahare, 2017) authors examined various image processing techniques for plant disease identification [2]. For the purpose of detecting plant illness, authors looked at colour and textural traits. On the dataset of 110 RGB photos, they tested their algorithms. The features retrieved for classification were the mean and standard deviation of the GLCM features, as well as the standard deviation and mean of the YCbCr and RGB channels and the mean and standard deviation of the picture convolved with the Gabor filter. The classification process used a support vector machine classifier. The authors came to the conclusion that GCLM traits are useful for spotting healthy leaves. While colour features and Gabor filter features are thought to be the best for spotting leaf spots and anthracnose-affected leaves, respectively. They have attained the greatest level of

Authers showed how hyperspectral imaging may be used to detect plant diseases in (Moghadam et al., 2017) [3]. The study employed near-infrared (VNIR), the visible, and short-wave infrared (SWIR) spectrum. For the segmentation of leaves, they used the spectral domain K-means clustering algorithm. To eliminate the grid from hyperspectral photos, they have suggested a brand-new algorithm. The study showed promising results with accuracy of 83 percent for the vegetation indices in the VNIR spectral band and 93 percent with the complete spectrum. The solution is too expensive since even if the proposed method produced improved accuracy, it calls for a hyperspectral camera with 324 spectral bands.

In [4], The author claimed that by combining all of these properties, a strong feature set for image enhancement and improved categorisation is produced. The authors have provided an overview of popular traditional feature extraction techniques. This paper's work is primarily focused on putting these techniques and tactics into practise as a result of the rapid growth of Artificial Intelligence (AI) technology.

In (Babu et al., n.d.,2007), The authors created a number of techniques that make employment of a back propagation learning technique with feed-forward neural networks with a single input, a single output, and a single hidden layer in order to identify the species of leaf, pest, or disease. To give remedial measures for managing pests and illnesses in agricultural crops, they developed a software model. .

In [6], the author proposed By using the appropriate management techniques, such as disease-specific chemical applications, fungal applications and vector control through pesticide applications, early information on crop health and disease detection can be gained. This might help with disease management and boost output. The need for creating a quick, affordable, and dependable health-monitoring sensor that supports agricultural innovations is presented, reviewed, and acknowledged . They examined the technologies now in use, such as spectroscopic and volatile profiling-based approaches of plant disease detection, with the aim of developing ground-based sensor systems to help in monitoring plant health and illnesses under field settings.

In [7], Author suggested that Support Vector Machine techniques might be used to distinguish between different plant illnesses and detect them. This method was used for sugar beet illnesses and published in , where the classification accuracy ranged from 65% to 90%, Depending on the disease's type and stage .

In [8], Another method based on leaf photos was proposed by the author, who developed an automated approach for classifying and identifying agricultural diseases that integrated the K-means and clustering tfor the automatic spotting and grading of crop diseases echnique with ANNs. There were 10 hidden layers in the ANN. The total number of outputs was 6, with each class representing one healthy leaf and five different illnesses. The accuracy of categorisation using this method was 94.67 percent on average.

In [9] The author suggested using conventional methods, in which farmers manually identify healthy and damaged plants . When it comes to tracking important factors like humidity, soil type, temperature, the quantity of macro- and micronutrients in the soil, and these methods fall short of meeting the crop plant's nutritional needs at various phases of development. . The conventional methods also take a long time and require a lot of labour. In addition, Farmers require expert support for the precise identification of diseases in agricultural plants.

[10] The writers classified the healthy and sick leaves using the IoT's potential. They anchored the sensors used to measure humidity, temperature, and soil quality. They took pictures of crop plants with the camera. With the Raspberry Pi, the authors created a sensor and camera interface. in order to save and analyse the recorded data for in-the-moment predictions. To determine whether a leaf is sick or healthy, they used the K-means algorithm to cluster photos and then pixel masking.

In [11], 124 photos that were downloaded from the Internet were used in the experiments by the writers. The dataset was expanded to 711 photos using data augmentation techniques like magnification, rotation, flipping, and rescaling. Additionally, they stated that the validation accuracy was 89 percent, and training accuracy was 95 percent. The research's main flaws are its ineffective implementation utilising ubiquitous memory devices, such as cellphones, and its poor validation accuracy . Furthermore, they did not consider elements like soil type, humidity, temperature, nutrient needs, etc. while diagnosing illnesses. The authors' attention solely on identifying the pathogen "downy mildew" in pearl millet. In order to combat the commonest illnesses , such as blast and rust, there is a lot of opportunity for improvement in terms of performance.

[12] According to the author, Rice is one of the most important food crops in the world. In addition to having a severe impact on rice output, illnesses pose a serious danger to global food security. Using CNN, Lu and his colleagues have discovered illnesses affecting rice. On the basis of 500 photos of sick rice and stems, the study has defined 10 kinds of rice diseases. Experience has demonstrated that utilising machine learning and pattern recognition to diagnose illnesses in rice, CNN provides a better outcome than more conventional methods.

In [13], In a different approach, the author assesses the usefulness of transfer learning for the datasets of cassava pictures from a deep networked convolutional neural system . The model has detected the following five pest damage types: cassava brown streak disease (CBSD), red mite damage (RMD), and brown leaf spot (BLS). BLS has a detection rate of 98%, CBSD a detection rate of 98%, and CMD a detection rate of 96%.

.

In [14], AlexNet and VGG16 are two already-trained deep learning models. were utilised by the author to categorise healthy class of tomato crops and six distinct diseases from the image dataset. VGG16 and AlexNet both had classification accuracy of 99.24 percent and 96.51 percent, respectively.

In [15], The pooling mechanism and the first convolutional layer are activated by the input of a network, the pest of a picture, allowing the pest to be isolated from the rest of the image. Pests come in ten different varieties. Grinblat et al. advise utilising CNN to locate the morphological vein in plants. CNN has trained a group of plant vein patterns to recognise others with similar traits.

In [16], A VGG convolutional neural network has been proposed by the author for the aim of classifying and recognising plant leaves. The suggested approach separates the images into groups of good and unhealthy conditions. The result, which was confirmed on a big dataset, shows how accurate the deep learning method is.

[17] For the categorisation of sickness from a picture, the author has employed four distinct convolutional deep network designs, having VGG 16, Inception V4, ResNet, and DenseNets. the plantVillage dataset, through which the images are taken , which includes 14 healthy classes and 38 classes with diseases. When compared to alternative topologies, the DenseNets network achieves greater classification accuracy while requiring less processing time.

In [18] For precise disease identification, the authors presented the MDFC-ResNet model, which stands for multidimensional feature compensation residual neural network. Species, fine-grained diseases and coarse-grained diseases, are three dimensions that make up multidimensional data. MDFC-ResNet builds a compensation layer using a compensation method to mix these three dimensions of data. The AI Challenger dataset used in experiment. Dataset divided into 2 parts as training sample and testing samples. Training set and validation set are further separated from the training sample in an 8:2 ratio. For data-preprocessing singular value decomposition (SVD) techniques has been used. In this experiment, MDFC-ResNet model also compared with commonly used techniques for plant disease classification like AlexNet , VGG and ResNet-50. Among all models MDFC-ResNet performs admirably in terms of validation accuracy, training accuracy, and test accuracy.

In [19], author combining IoT and advanced learning , the authors create the "Automatic and Intelligent Data Collector and Classifier" (AIDCC) system for automating disease detection in the understudied crop "pearl millet" for the classification of blast and rust illnesses. The IOT system installed in the pearl millet farmlands collects real-time datasets automatically. As part of this research, the 'Custom-Net' model was developed and implemented on a cloud server. Furthermore, In order to show how transfer learning affects performance, the suggested model pre-trained by author on the publicly available ImageNet dataset. Performance metrics are compared between the pre-trained and untrained "Custom-Net" models.

In [20], a lightweight artificial intelligent system-based solution for detecting rice leaf disease is demonstrated in this paper. Edge computing as a concept is being used here and Raspberry Pi is edge gadget. The' Rice Diseases Images Datasets' dataset used from kaggle in experiment. Leaf Blast, Hispa, and Brown Spot are three diseases that affect rice plants. The authors have compared the performance of Random Forest (RF) , Naïve Bayes(NB) ,Decision Tress(DT) , Logistic Regression(LR) , Support Vector Machine(SVM) and K Nearest Neighbours (KNN) between each of them , random forest classifiers model is outperforms. This model only classify the healthy leaves from infected leaves and does not predict the disease type.

In [21], Authors suggested utilising the CNN model to categorise various plant diseases. The village dataset of 4,062 photos of grapes plant leaves was used to train the CNN model, VGG, ResNet, and denseNet models. The dataset has augmented with rotation, zoom and shift operation for prevention from overfitting during training. Regarding the F1-score, recall, precision, accuracy, and , denseNet outperforms all other models. All models were trained on small datasets , the performance could get affected , if dataset becomes large. The author does no t proposed the any mobile/web application that could directly connect to mobile of end users.

In [22], Author suggests employing Single Shot Multibox Detector, Region-based Fully Convolutional Network (R-FCN), and Faster Region-based CNN to classify various plant leaf diseases (SSD). The dataset contains pictures of plant leaf disease on commercial crops as banana, sugarcane, potatoes, carrots , cotton, chillies, brinjal, rice, wheat, and guava. Both personally taken photographs and images from the internet were used. Images were enhanced using affine and perspective transformations, rotations, and picture intensity adjustments to expand the dataset and prevent the model from overfitting.

Furthermore, In [23] the authors in utilise the visual transformer models in computer vision for identification and classification of images.in this study, the augmented version of plant village dataset is consider .This dataset includes photos of healthy plant leaves along side their damaged counterparts. This dataset contains 38 types of plant-disease pairs, with 80% of the data used for training and 20% for validation. Custom c, inceptionV3, small transformer network(NST) and large transformer network(LST) trained with different epochs and compared the validation accuracy metrics among them and LST outperforms. Because this design is still in its early stages, more study into the optimal application of transformers in computer vision applications is required.

In [24], The LWD (leaf wetness duration), according to the author, is one of the crucial factors involved in the fungal development on the leaf canopy . In this work [6], The LWS was manufactured by the authors on flexible substrates, and on the medicinal herb Ocimum tenuiflorum (Tulsi), they established the system. in order to record sensor data for LWD (leaf wetness duration). In this work authors have collected data for limited time period instead for one crop cycle.

Chapter 3

Materials & Methods

****

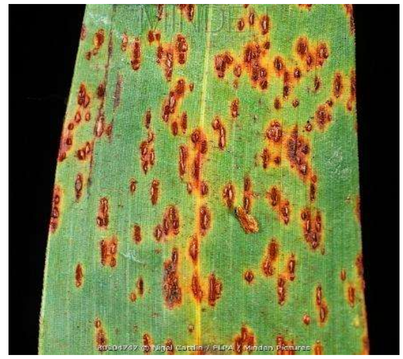
A more thorough explanation of the complete process of creating the deep CNN model for plant disease recognition is provided. The entire process is broken down into multiple necessary stages in the subsections below, beginning with acquiring photos for the deep neural network classification procedure.

3.1 Datasets:

These datasets were taken from the Kaggle, an online platform for uploading and finding datasets. The popular PlantVillage and PlantDoc databases were used to create this dataset. Sure, photos that were not deemed relevant were eliminated from the collection during its creation. This dataset contains 4188 leaf images belonging to four different classes. The classes are standard and rust contains 1306 images, grey leaf spot have 574 images, blight contains 1146 images, and healthy contain 1162 images.

The "image_dataset_from_directory" API was utilised to load all images in the TensorFlow dataset in this work. The size of each image is 260*260*3 and d Datasets were converted into batches of size 32. A total of 131 sets were created for 4188 images. To evaluate performance, Three subsets of the dataset to be separated out: training dataset to be used while training, testing against a validation dataset while training , and after the model has been trained, a test dataset will be used. The splitting was done in a ratio of 80-10-10. The entire batches and images for training are 131 and 3328, for validation are 13 and 416, and for the test are 14 and 448, respectively.

Corn Blight



Common Rust

Gray_leaf_spot

Healthy

Figure 3. 16 sample images from datasets

3.2 Data Pre-processing:

We should resize our photographs to the correct size before sending them over the network. Additionally, we should normalise the image pixel value to enhance model performance (keeping them in the range 0 and 1 by dividing by 256). Both inference and this should take place during training. So, we can layer that onto our Sequential Model.

3.3 Data Augmentation:

Augmentation is the process applied to the datasets to expand the collection of photographs in the datasets. This modifies the images somewhat, which helps to prevent overfitting during the training phase. Overfitting occurs when the models do not learn the underlying relationship in data and instead describe the noise and randomness. The transformation methods applied in image augmentation included affine transformation, perspective transformation, and fundamental image rotations. Simple picture rotations and rotations on other axes by varying degrees were used in the augmentation process. [25]

3.4 System Architecture:

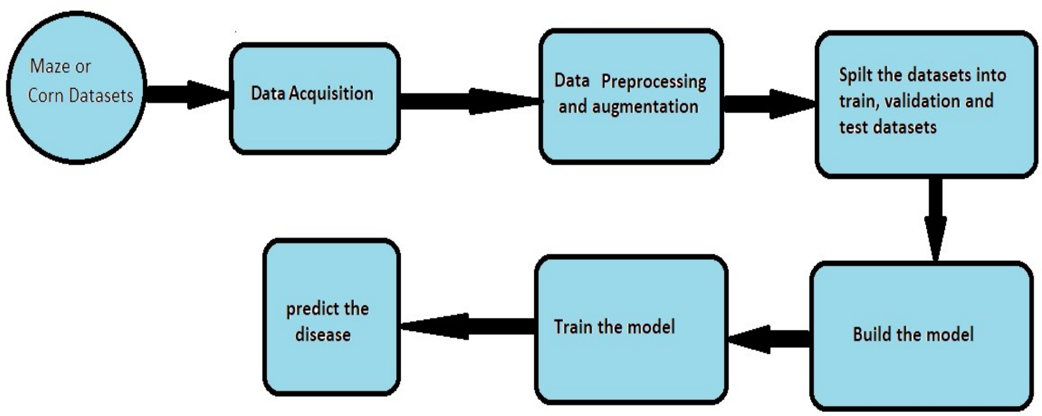


Figure 3. 17 Block schematic of the suggested system

Number of steps for spotting plant illnesses –

1. The datasets are collected from the Kaggle platform
2. The data-processing and augmentation process is performed using tensorflow and keras library in the Jupiter notebook.
3. The whole datasets are split into three subsets: training, validation and testing.
4. The model builds with different layers using several filters and relu activation functions.

5. Over the training datasets, the proposed model was trained.

   Test dataset used to gauge how well the model works with unseen data.

3.5 Convolution Neural Network:

A sort of deep learning network is convolutional neural networks (CNNs or ConvNets). that can learn from data without the aid of a person extracting the features. CNN uses a variety of regularisation methods in machine learning. It is less complicated than traditional regularisation models.

The layers are discussed in the following sections,

Input Layer –

The input layer represents the neural network's top layer. Exactly as many features are present in the entire image. There are precisely as many neurons. The total number of components in the image equals the units of pixels in the picture. The input is fed to this layer. [26]

Hidden layer –

The output of the input layer is transferred to this layer. The magnitude of the data and the model both play a role. Each hidden layer may contain a different number of neurons. [26]

Output Layer-

A softmax function receives data from the buried layer as input. The probability score for each class is calculated by using a softmax algorithm to translate the output of each type. It converts each class's production into a likelihood score for that same class. [26]

3.6 Convolutional Neural Networks for Features Extraction (CNN):

As the name suggests, CNNs are a particular class of neural networks that perform best when processing data in a network or grid architecture. In this network, the most prevalent types of data are images.

CNN has had a lot of success in a variety of applications. Human vision has recently been supplanted by picture utilising deep convolutional neural networks for identification . [27]

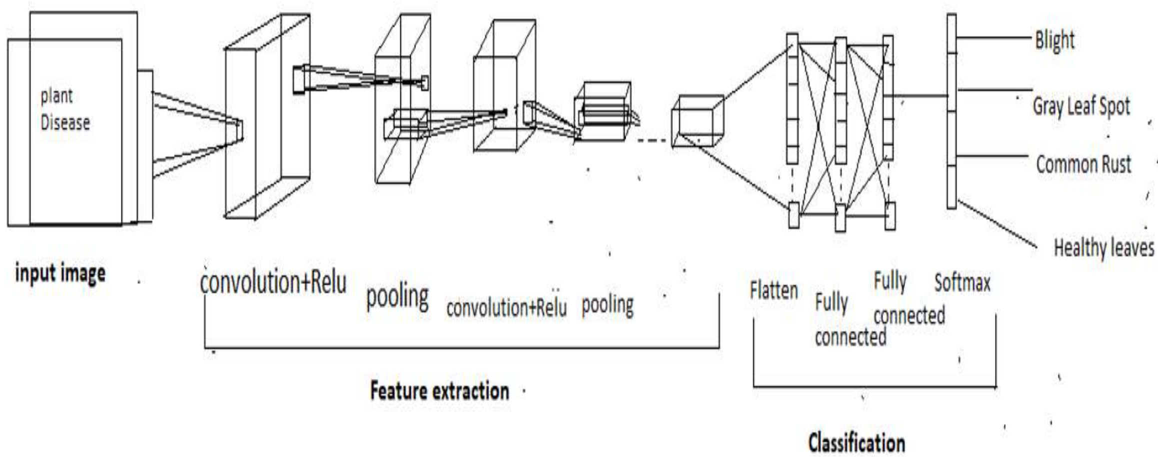


Figure 3. 18 Architecture of proposed Convolution neural network

Convolution operation-

Convolution is a mathematical operation performed on two functions using absolute numbers as arguments. The mathematical expression that defines the convolution operation is as follows:

$$h(t) = \int x(a)w(t-a)da$$

In most cases, the convolution operation is indicated by:

$$h(t) = (x * w)(t)$$

The first component (in this example (x)) is commonly referred to as the stable operation's input, while the second argument is referred to as the kernel. A feature map is the outcome of this procedure.

When dealing with a computer, discrete data might be utilised. The logical function in an integral part must be turned into a series of continuous "discrete" operates as follows:

$$H(t) = (x * w)(t) = \sum_{h=-\infty}^{\infty} x(h)w(t-h)$$

Applications of deep learning, The input could be defined as the kernel and multidimensional vector is a multidimensional parameter vector learned by the learning algorithm. With example, The image I as input and the 2-Dimensional kernel is used most often. [27]

$$S(i,j) = (I * K)(i,j) = \sum_{m}\sum_{n} I(i-m, j-n)K(m,n)$$

In reality, discrete convolutions can also be thought of as matrices multiplying.

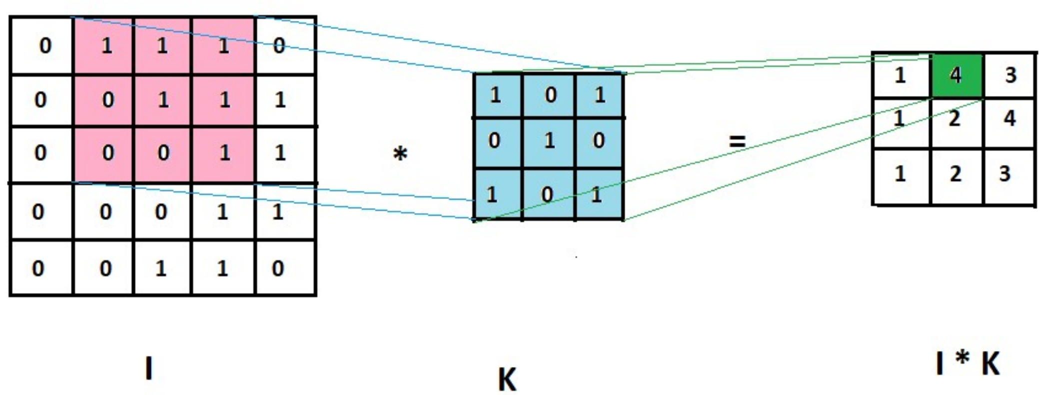


Figure 3. 19 Convolution operation where I represent images and K represent kernel

Relu Activation-

The Rectified Linear Unit, or ReLU, isn't a separate part of the convolutional neural network's process. It's a phrase that comes after the convolution procedure. To learn the non-linearity features in the image, the RELU activation function is used. It is simple to calculate, and its derivatives are either 0 or 1, depending on whether or not the input is negative.

It is defined as:

$$R(z) = \max(0, z)$$

where z is the activation function's input

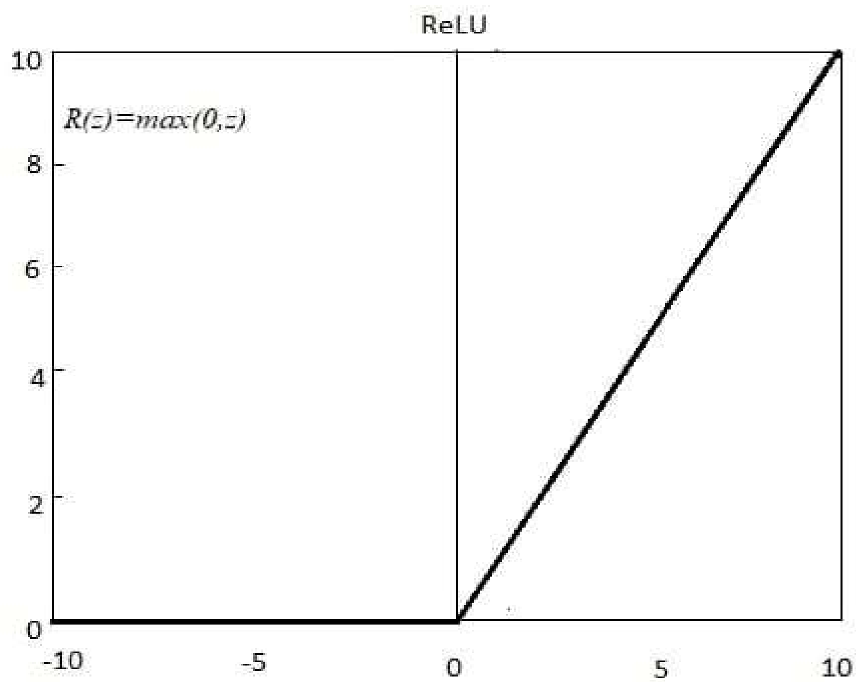


Figure 3. 20 Deep CNN with ReLUs accelerates training by multiple times.]

Pooling-

The type of translation invariance is determined by the pooling operation. It resizes the input spatially and functions independently on each depth slice.

The pooling layer conveys the features located within the area enclosed by the filter by sliding a 2D filter over each channel of the feature map. [26]

Max pooling layer-

Feature map area that the filter has concealed , selects the pixel value among all, which is maximum. As a result, the output of the max-pooling layer is a feature map that incorporates the most significant feature of the previous feature map. [26]

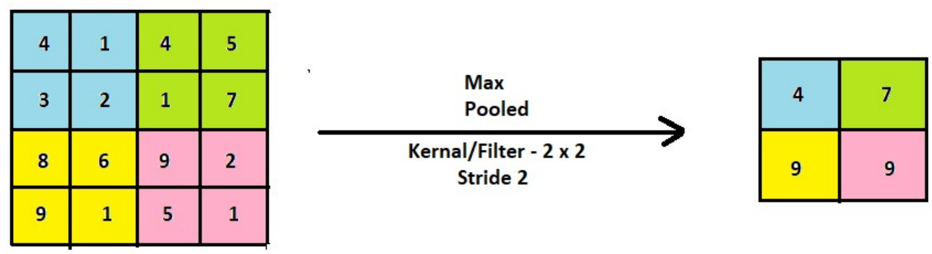


Figure 3. 21 Max-Pooling operation

Fully Connected layer-

In the architecture of ConvNet, multiple Fully Connected layers can be used and stacked on top of each other. The Fully Connected layer has neurons and is fully connected with the previous layer. Fully Connected, the final layer of CNN, may be employed for multiple-label regression and classification problems. Various activation functions, such as SOFTMAX, are used to categorise multi-class problems. [28]

This layer is also used as an encoded vector. In the training phase, this helps calculating the loss to train the neural network . The convolution layers hold several features, and each represents the local feature. The FC layer stores the most crucial composite and collects information from all the convolution layers. [26]

3.7 Fine Tuning:

Making adjustments through fine-tuning incremental changes to improve or maximise the output of a process or function to boost its effectiveness or efficiency. The fine-tuning procedure was repeated, with hidden layer and hyperparameter parameters being changed each time. The optimum model for detecting plant diseases was developed by an iterative process of adjusting the parameters. In the proposed model, adam optimizer was used with loss function SparseCategoricalCrossentropy with batch size 32. [25]

3.8 Equipment:

The plant disease detection algorithm described in this research was trained and tested entirely on a single PC. The CNN was prepared using the Graphics Processing Unit (GPU) mode in google colab. The total training time for training the model is 120 minutes.

3.9 Visualization of Filters:

Filters are the weights in CNN that learn from the deep neural network training. All the weights matrix is 3*3 shape. Here are some dark pixels, and some are lights. The dark colour pixels belong to lower weight, and light colour pixels belong to higher weight.

The affine transformation is performed in the input image with the filters. The model will pay greater attention to the parts of the image where the highest weight values.

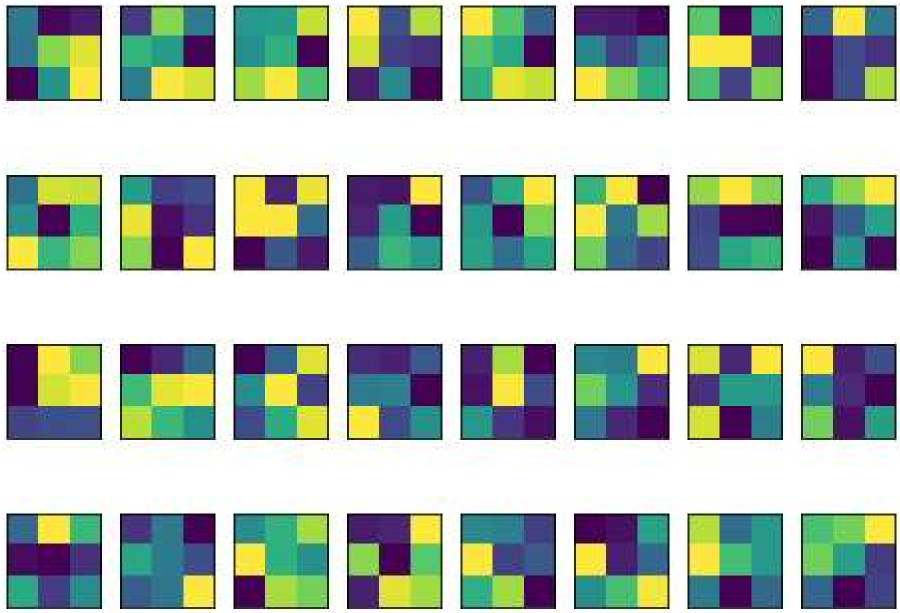


Figure 3. 22 samples from the filters of the first convolution layer

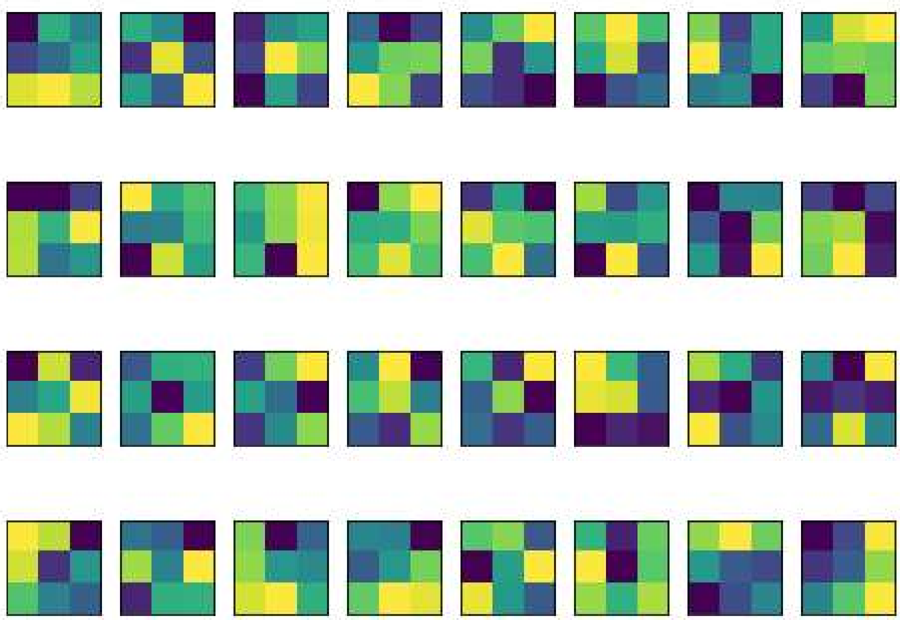


Figure 3. 23 samples from the filters of the last convolution layer

3.10 Visualization of feature maps:

Feature maps result from convolution operation between an input image and the filter. By visualizing the features map at every layer, gaining a deep understanding of what features are detected by the feature map.

Figure 3. 24 Input image for feature map visualisation

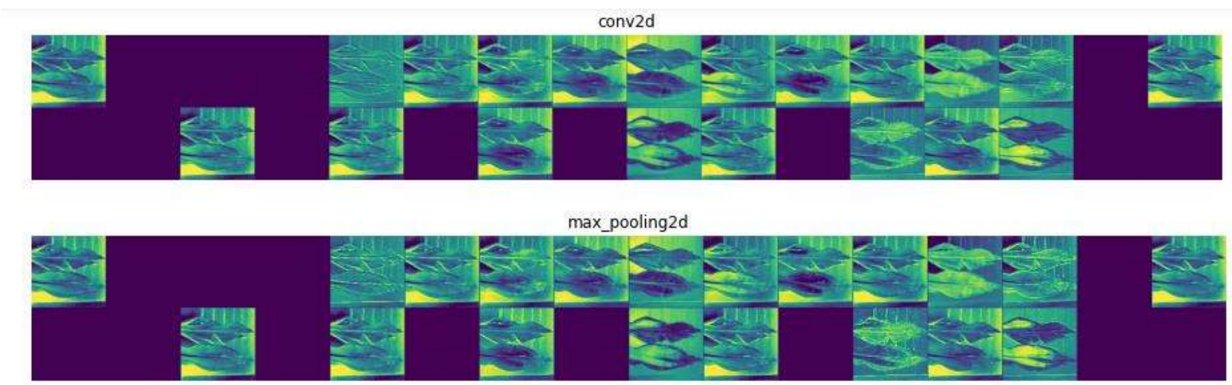
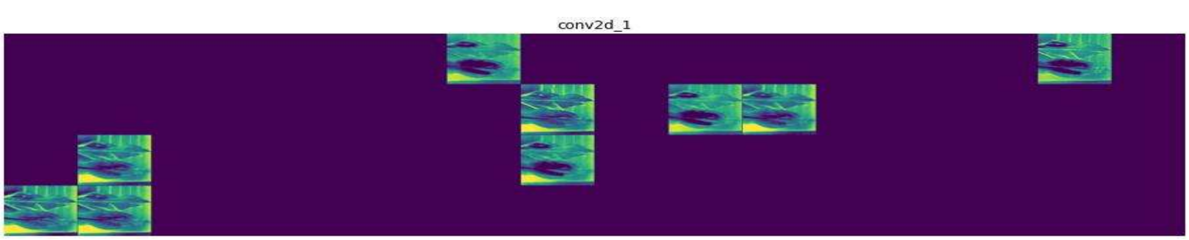


Figure 3. 25 Feature map after first convolution layer and max-pooling layer

following the initial convolution layer and the maximum-pooling layer, Several generic features of the image of a leaf were detected. Several Blocks are only in violet colour, meaning they do not learn anything from the input images.



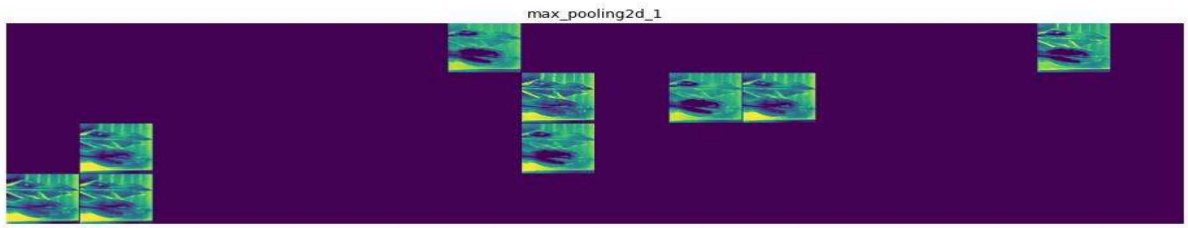


Figure 3. 26 Feature map after second convolution layer and max-pooling layer

The above image represents the feature map after the 2nd convolution and max-pooling layer. Some filter maps focus on the outline of the leaf image, some are on the background, and many are in violet colour, not learning anything.

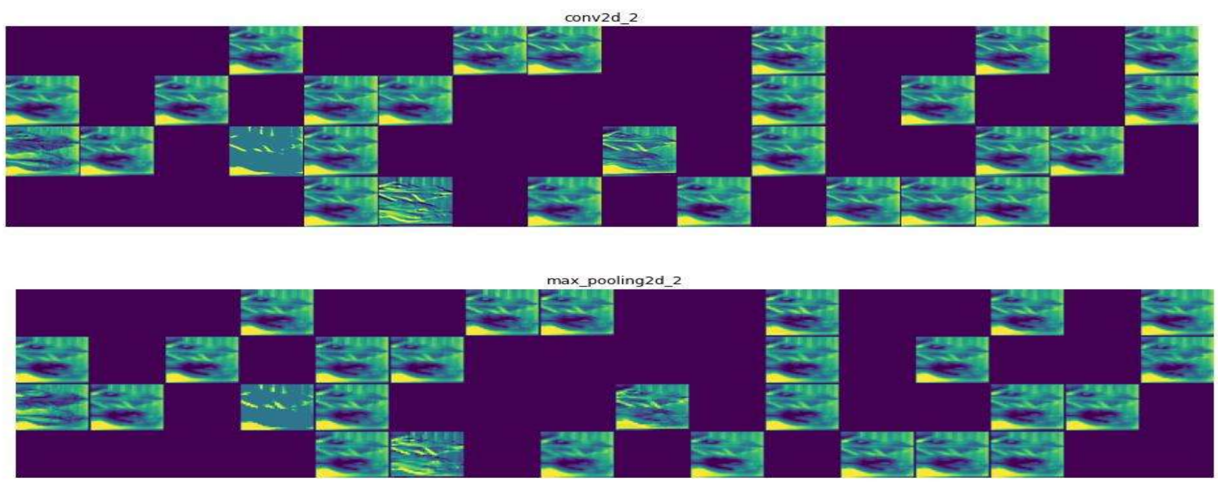
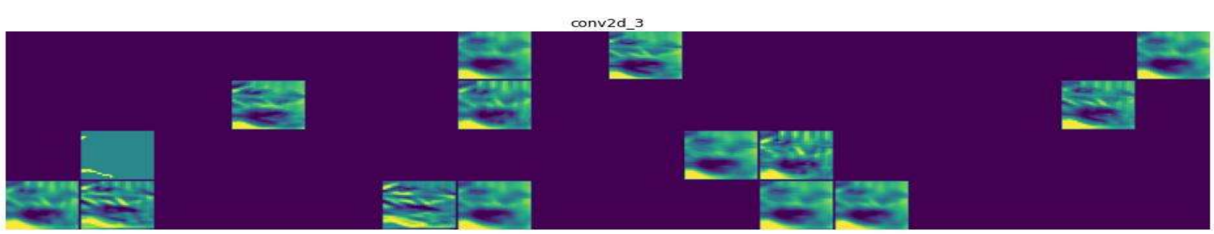


Figure 3. 27 Feature map after third convolution layer and max-pooling layer



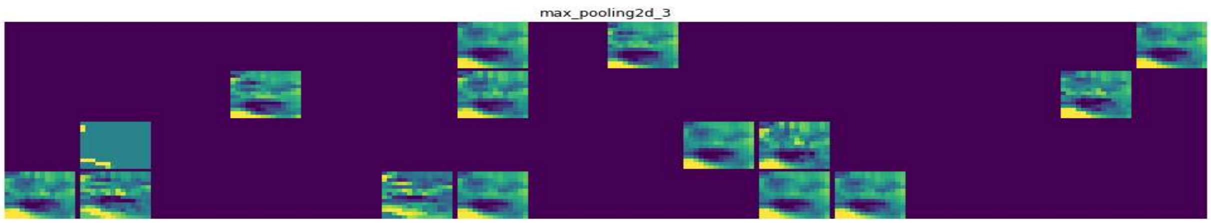


Figure 3. 28 Feature map after fourth convolution layer and max-pooling layer

As we go deeper and deeper into the deep neural network, layers learn more specific features from the input image.

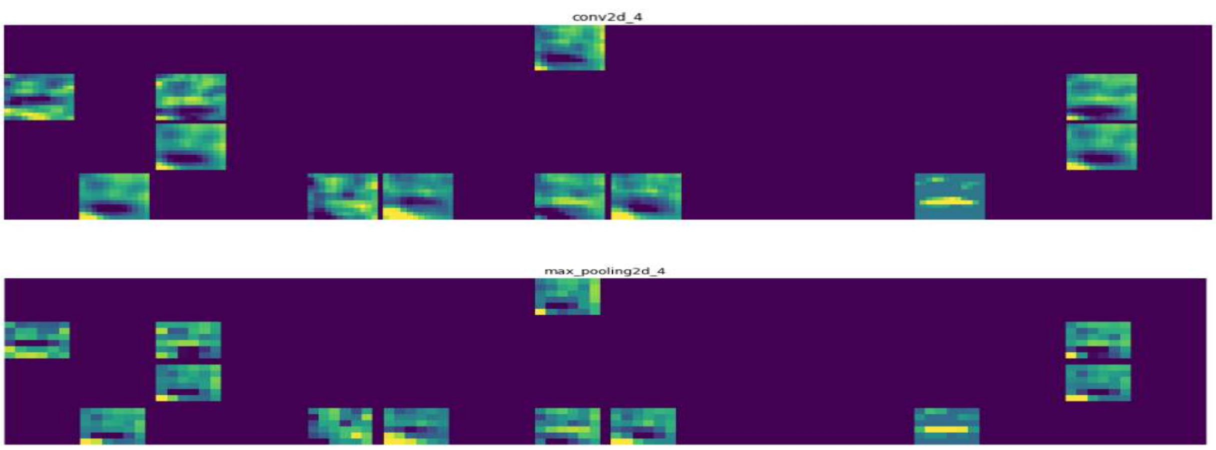


Figure 3. 29 Feature map after fifth convolution layer and max-pooling layer

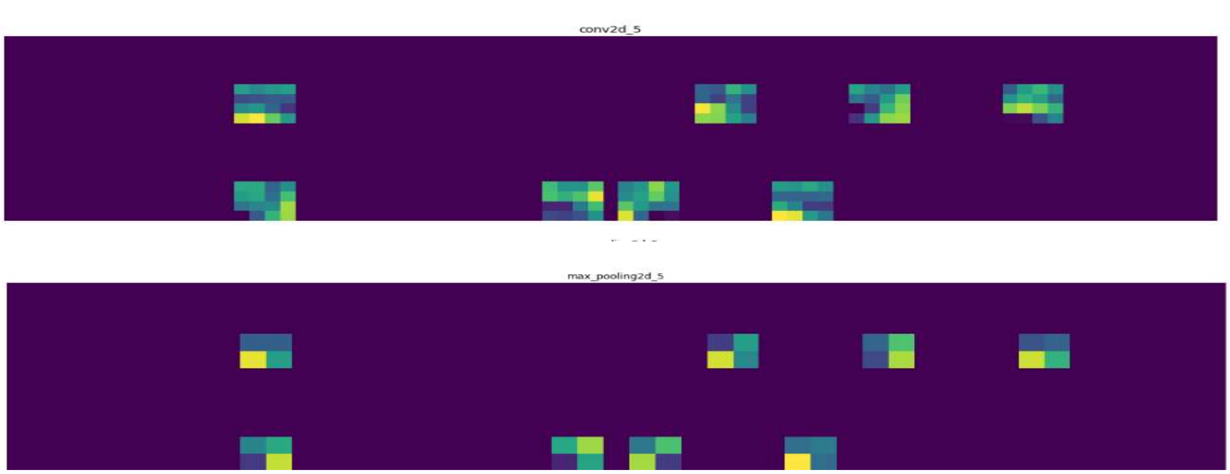


Figure 3. 30 Feature map after last convolution layer and max-pooling layer

As we reach the last layer of feature extraction of neural network, The feature maps learn more abstract features of input data which are useful for classification of plant disease.

3.11 Summary of the model:

In the convolution neural network, We rescale and resize images by presenting a first layer in the neural network. Further, we define the convolution and max-pooling layers in an alternate form in the neural network. The model consists a total of six convolution layer and six max-pooling layers. In the model, after the last convolution layer, the output becomes flattened by defining flatten layer and densely connecting the flattened layer with the fully connected layer. The model definition presents below in table1 and table 2.

Table 1. Model Summary 1

LAYER	OUTPUT SHAPE	PARAMETER
Sequential	(260,260,3)	0
Conv2d	(258,258,32)	896
Max_pooling2d	(129,129,32)	0
Conv2d_1	(127,127,64)	18496
Max_pooling2d_1	(63,63,64)	0
Conv2d_2	(61,61,64)	36928
Max_pooling2d_2	(30,30,64)	0
Conv2d_3	(28,28,64)	36928
Max_pooling2d_3	(14,14,64)	0
Conv2d_4	(12,12,64)	36928
Max_pooling2d_4	(6,6,64)	0
Conv2d_5	(4,4,64)	36928
Max_pooling2d_5	(2,2,64)	0

Flatten	(256)	0
Dense	(64)	16448
Dense_1	(4)	260

Table 2. Model Summary 2

Total Parameter	**183,812**
Trainable Parameter	183,812
Non – Trainable parameters	0

Chapter-4

Results

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4.1 Result and Analysis

The findings in this part come the whole database, which contains both the original and augmented photographs, throughout training. Because convolutional networks are known to be capable of learning features when trained on massive datasets, the outcomes obtained when introduced original photos with augmented photos will be investigated. A total accuracy of 96.43 percent was reached on test datasets after fine-tuning the network's parameters during the training.

Below are some images from each class. There shows the actual and predicted label of each class with confidence. The confidence is very high for the prediction of pictures in each category.

A few images were selected from the test datasets that were analysed and find the predicted class labels along with how much confidence the proposed CNN Model has.

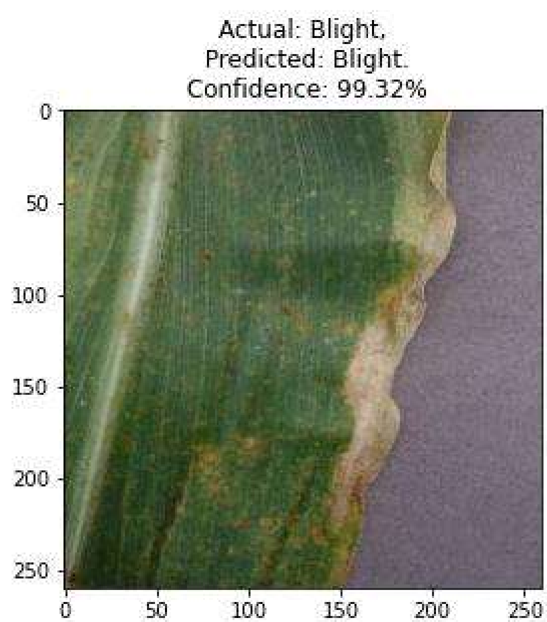

Figure 4. 7 Blight leaf predicted with confidence 99.32%

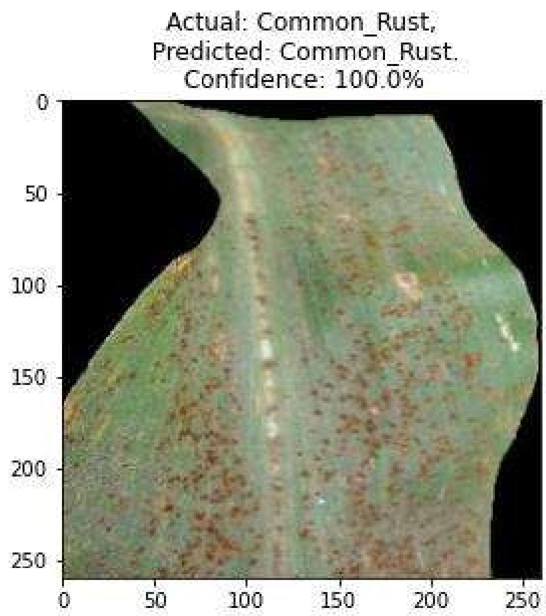

Figure 4. 8 Common_Rust predicted with confidence 100%

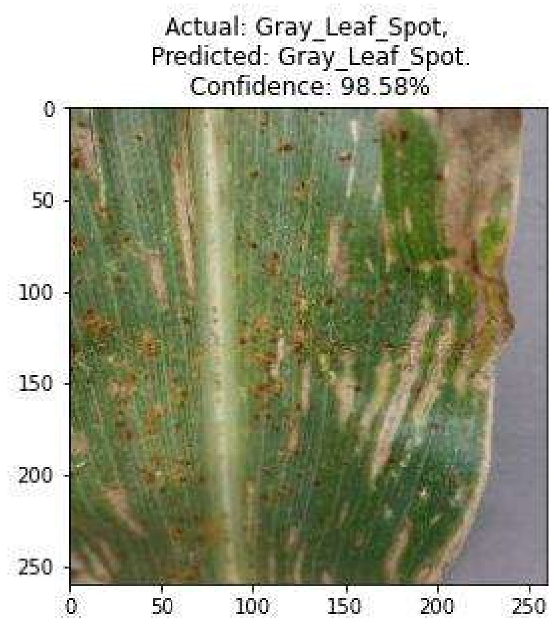

Figure 4. 9 Gray_Leaf_Spot Predicted with confidence 98.58%

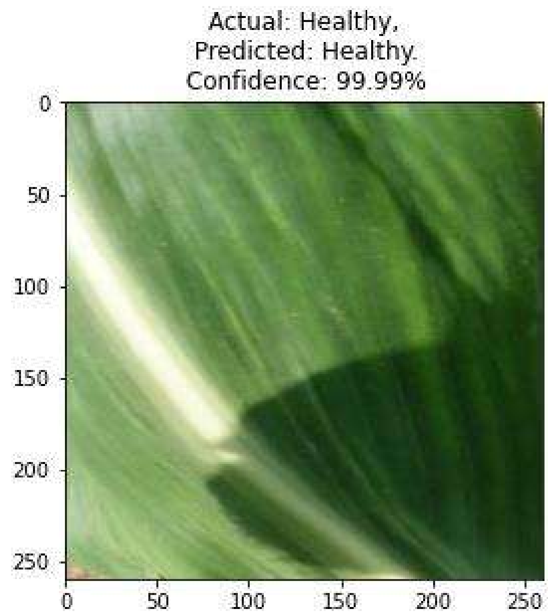

Figure 4. 10 Healthy leaf predicted with confidence 99.99%

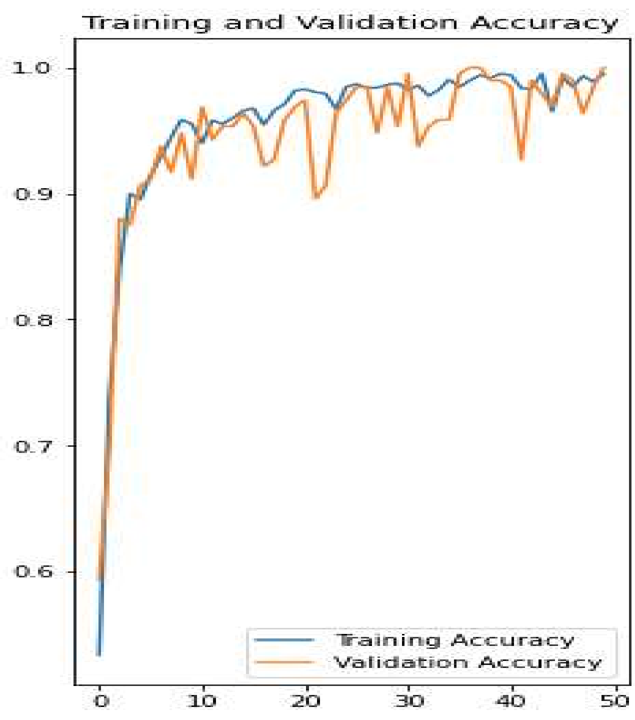

Figure 4. 11 Training and Validation Accuracy Graph

The validation accuracy and training accuracy starts with equal value. The accuracy of both training and validation sets is similar to 5 epochs. After the 5 epochs of training, validation accuracy and training accuracy fluctuate little. In the 10th training iteration, validation accuracy is 90.62%, and training accuracy is 89.65%. After the 30 epochs of training, the validation accuracy is 94%, and training accuracy reaches 92%. After the movement of the model, the training accuracy achieves its highest value of 96.47%. The performance of the network on the validation test set following training cycles. is depicted by the orange line in Figure 4.11's graph.

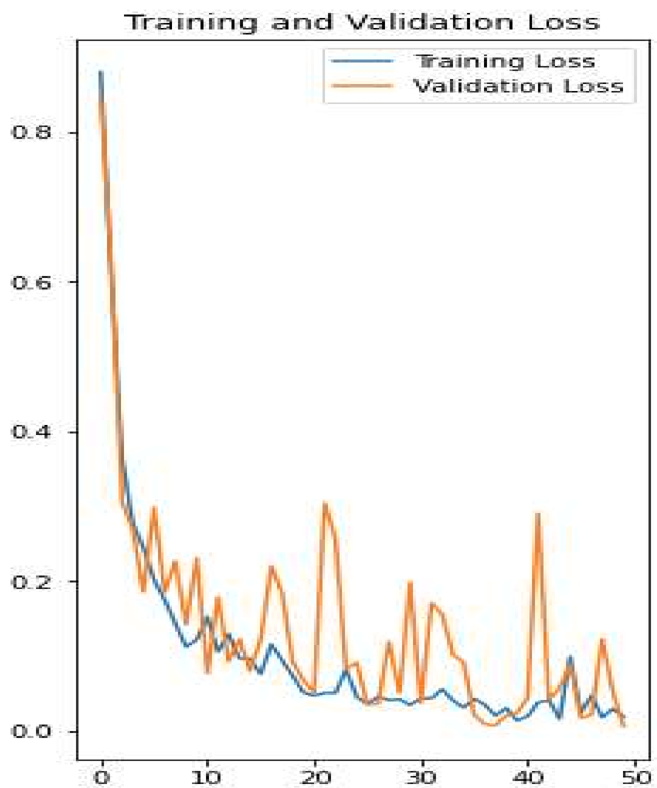

Figure 4. 12 Training and Validation Loss Graph

The above graph depicts the training and validation loss while training the model with 50 epochs of entire datasets. The validation curve with the orange line shows that the loss is reducing rapidly till 3rd iteration of training, and then it fluctuates and reaches its minimum value. The training loss curve represents the blue line, and both the training loss curve and validation loss curve are the same till 3^{rd} iteration of training after they start fluctuating and reach minimum values of 0.1406 and 0.1246, respectively.

Chapter 5

Conclusion and Future Work

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5.1 Conclusion

Although numerous approaches for detecting and classifying plant diseases using automated or computer vision exist, research in this area is still insufficient. Furthermore, there are currently no commercially available solutions, except for those that identify plant species using images of leaves. One kind of deep learning architecture is convolutional neural networks. that has gained a lot of traction when it comes to image recognition. The past few years , the convolution neural network has been one of the most effective machine learning models in deep learning. The convolution neural network has grown in size, available datasets have improved, and performance has improved.

This research investigated a novel strategy to automatically categorise and find plant ailments using deep learning methods from leaves photos. The proposed model could investigate the presence of leaves and differentiate between healthy and diseased leaves in 4 different conditions.

The entire procedure was discussed in detail. I was collecting data from the Kaggle and pre-processing and augmentation data for feeding into the convolution neural network. For training, validation, and testing purposes, the dataset was divided into an 8:1:1 ratio. After pre-processing of image datasets, various hyperparameters were tuned for training CNN and finding the performance of the selected model.

These datasets were taken from the Kaggle, an online platform for uploading and finding datasets. The popular PlantVillage and PlantDoc databases were used to create this dataset. This dataset contains 4188 leaf images belonging to four different classes. The classes are standard, rust contains 1306 images, grey leaf spot have 574 images, blight contains 1146 images, and healthy contain 1162 images. The size of each image is

260*260*3, and the dataset was converted into batches of size 32. A total of 131 sets were created for 4188 photos dataset should be divided into three subsets: a training dataset for model training, a validation dataset for model testing while training, and a test dataset for model testing following model training. The splitting was done in a ratio of 80-10-10. The entire batches and images for training are 131 and 3328, for validation are 13 and 416, and for the test are 14 and 448, respectively.

The training accuracy achieved after the 50^{th} iteration is 96.47%. The training of the proposed model is done with entire datasets with augmented datasets. The experimental results achieved the accuracy for the test datasets are 97.82%.

There was no comparison with similar outcomes obtained using the same technique. because the proposed technology has not been explored in the study of plant-identifying diseases as far as we know. Compared to the earlier methods described Similar or even better results were attained in Section 2, especially considering the more significant number of classes being studied. This research will be expanded to include image collection to enhance the database and improve the model's accuracy, to utilise fine-tuning and augmentation strategies.

Plant disease data sets have more stringent collecting and labelling standards than non-agricultural data sets. Not only does it necessitate professional expertise and technical staff, but it is also influenced by the crop growth cycle. The severity of diseases varies. Collecting data is crucial for identifying crop pests and illnesses using deep neural networks.

5.2 Future Work

The trained model is located on the system's server side. A software programme for smart mobile devices displays illnesses found in crops, Based on leaf photos taken by the smartphone camera, veggies and other plants are predicted. This request will help farmers. By enabling quick and precise identification of plant illnesses, they simplified the decision-making process for employing chemical pesticides.

The system can be enhanced in the future by adding new features, such as teaching it to identify diseases in other fruits and expanding the dataset size to boost the system's overall performance and detect diseases more precisely.

The effects of making treatment suggestions in accordance with best practices could be the subject of future research. These steps could increase penetration in training with the effective use of neural convolutional networks and IoT technology.

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