

MAKING A WEB APPLICATION WHICH DETECTS THE DISEASES OF THE PLANTS USING CNN ALGORITHM

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in
Information Technology

By

DURGA PRASAD KODE (Reg.No - 39120027)
BALAJI MANCHI (Reg.No – 39120015)



DEPARTMENT OF INFORMATION TECHNOLOGY
SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

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JEPPIAAR NAGAR, RAJIV GANDHI SALAI,
CHENNAI - 600119

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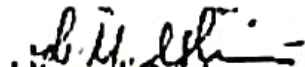


Accredited with —All grade by NAAC
Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai – 600 119
www.sathyabama.ac.in

DEPARTMENT OF INFORMATION TECHNOLOGY

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of Durga Prasad Kode(39120027) and Balaji Manchi(39120015) who carried out the Project Phase-1 entitled “MAKING A WEB APPLICATION WHICH DETECTS THE DISEASES OF THE PLANTS USING CNN ALGORITHM” under my supervision from January 2023 to May 2023.


Internal Guide

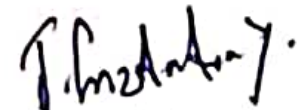
Dr. L. MARY GLADENCE, M.E., Ph.D.


Head of the Department

Dr. R.SUBHASHINI, M.E., Ph.D.

Submitted for Viva voce Examination held on 10-05-2023


Internal Examiner

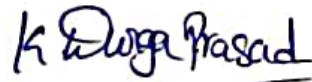

External Examiner

DECLARATION

I, Durga Prasad Kode(Reg.No- 39120027), hereby declare that the Project Phase-1 Report entitled "MAKING A WEB APPLICATION WHICH DETECTS THE DISEASES OF THE PLANTS USING CNN ALGORITHM" done by me under the guidance of Dr. L. Mary Gladence, M.E.,Ph.D is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Information Technology.

DATE: 10 - 5 - 23

PLACE:Chennai



SIGNATURE OF THECANDIDATE

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ABSTRACT

Economy contributes the most for the productivity of the agriculture. In agricultural field, the disease in plants is more common and the detection of disease in plants has become more feasible due to the above reason. These day's plant disease detection has acquired enlarging scrutiny in surveilling crops of large and various fields. Farmers undergo significant hassles in chop and changing from one disease administer principle to a different one. We can identify or spotting the tomato leaf diseases for detection for surveillance and monitoring experts is the standard approach for detection. The plants get seriously affected if the proper control hasn't been taken and this represents the quality of the pants the production of the plants will be affected. Detection of disease through some mechanized technique and methodology is efficient and constructive because it decreases an outsized toil of surveilling in the large cultivation. In the premature phase we can detect the symptoms of the plant diseases since their first appearance on their leaves of the plants. By using this paper we can identify the algorithm which is used for image segmentation and for automated classification used for the detection of diseases of leaves in the plants. It also covers distinct disease classification methods of working which is used for the detection of diseases in plants.

The application of deep learning in plant disease recognition can avoid the disadvantages caused by artificial selection of disease spot features, make plant disease feature extraction more objective, and improve the research efficiency and technology transformation speed. This review provides the research progress of deep learning technology in the field of crop leaf disease identification in recent years. In this paper, we present the current trends and challenges for the detection of plant leaf disease using deep learning and advanced imaging techniques. We hope that this work will be a valuable resource for researchers who study the detection of plant diseases and insect pests. At the same time, we also discussed some of the current challenges and problems that need to be resolved.

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CHAPTER 1

INTRODUCTION

Early plant disease detection is economically vital. State-of-the-art computer vision and machine learning can recognize and identify infections at a very early stage, thus reducing disease spread and increasing cure rates. Some disease symptoms appear too late for effective action to be taken, but in other this work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Rice, Tomato are the staple source of food in India as well as across the world. It is attacked by a variety of diseases in various stages of its cultivation. Therefore, early detection and remedy of such diseases are beneficial to ensure high quantity and best quality but this is very difficult due to the huge expanse of land under individual farmers and the huge variety of diseases as well as the occurrence of more than one disease in the same plant. Agricultural expert knowledge is not accessible in remote areas and it is a time taking process. Therefore, the Automated Systems are required. To aid the plight of the farmers and provide improved accuracy of plant disease detection, research work using various machine learning algorithms including Support Vector Machine(SVM), Artificial Neural Networks have been done.

The automated identification of plant diseases based on plant leaves is a major landmark in the field of agriculture. Moreover, the early and timely identification of plant diseases positively impacts crop yield and quality. Due to the cultivation of a large number of crop products, even an agriculturist and pathologist may often fail to identify the diseases in plants by visualizing disease-affected leaves. However, in the rural areas of developing countries, visual observation is still the primary approach of disease identification. It also requires continuous monitoring by experts. In remote areas, farmers may need to travel far to consult an expert, which is time-consuming and expensive. Automated computational systems for the detection and diagnosis of plant diseases assist farmers and agronomists with their high throughput and precision. In order to overcome the above problems, researchers have thought of several solutions. Various types of feature sets can be used in machine learning for the classification of plant diseases. Among these, the most popular feature sets are

traditional handcrafted and deep-learning (DL)-based features. Pre-processing, such as image enhancement, color transformation, and segmentation, is a prerequisite before efficiently extracting features. After feature extraction, different classifiers can be used.

The occurrence of plant diseases has a negative impact on agricultural production. If plant diseases are not discovered in time, food insecurity will increase. Early detection is the basis for effective prevention and control of plant diseases, and they play a vital role in the management and decision making of agricultural production. In recent years, plant disease identification has been a crucial issue. Disease-infected plants usually show obvious marks or lesions on leaves, stems, flowers, or fruits. Generally, each disease or pest condition presents a unique visible pattern that can be used to uniquely diagnose abnormalities. Usually, the leaves of plants are the primary source for identifying plant diseases, and most of the symptoms of diseases may begin to appear on the leaves. In most cases, agricultural and forestry experts are used to identify on-site or farmers identify fruit tree diseases and pests based on experience. This method is not only subjective, but also time-consuming, laborious, and inefficient. Farmers with less experience may miss judgement and use drugs blindly during the identification process. Quality and output will also bring environmental pollution, which will cause unnecessary economic losses. To counter these challenges, research into the use of image processing techniques for plant disease recognition has become a hot research topic.

The problem of efficient plant disease protection is closely related to the problems of sustainable agriculture and climate change. Research results indicate that climate change can alter stages and rates of pathogen development; it can also modify host resistance, which leads to physiological changes of host-pathogen interactions. The situation is further complicated by the fact that, today, diseases are transferred globally more easily than ever before. New diseases can occur in places where they were previously unidentified and, inherently, where there is no local expertise to combat them.

Inexperienced pesticide usage can cause the development of long-term resistance of the pathogens, severely reducing the ability to fight back. Timely and accurate diagnosis of plant diseases is one of the pillars of precision agriculture. It is crucial to prevent unnecessary waste of financial and other resources, thus achieving plant healthier production, by addressing the long-term pathogen resistance

development problem and mitigating the negative effects of climate change.

However, the accuracy of such systems is highly dependent on feature selection techniques. Recent researches on convolutional neural networks have provided great breakthrough in image based recognition by eliminating the need for image preprocessing as well as providing inbuilt feature selection. Another challenge is that it is very difficult to obtain large sized dataset for such problems. For cases where size of the dataset is relatively small, it is more preferable to use a model which is pretrained on a large dataset. This is called Transfer Learning and it can be utilized to create a model that can be used as a fixed feature extractor removing the last fully connected layer or by fine-tuning the last few layers that will work more specific to the concerned dataset.

Nowadays, mobile phones are accessible to everyone and so we have come up with the idea of an automated system where the farmers can upload the diseased leaf image and post it to our server where the neural network will be used to identify the disease and the disease classification along with the remedy can be sent back to the farmer. In this work we have proposed the architecture for the disease classification part of the automated system. Inspired by the work on convolutional neural networks, in this work, we have developed the deep learning approach on our rice disease dataset that we have collected over past several months. We have used the pre-trained MobileNet model (Trained on the huge ImageNet data) and using Transfer Learning we have finetuned the fully connected layers so that we can accommodate our own dataset and at the end we have done some error analysis and tried to explain the reasons for the error.

In this changing environment, appropriate and timely disease identification including early prevention has never been more important. There are several ways to detect plant pathologies. Some diseases do not have any visible symptoms, or the effect becomes noticeable too late to act, and in those situations, a sophisticated analysis is obligatory. However, most diseases generate some kind of manifestation in the visible spectrum, so the naked eye examination of a trained professional is the prime technique adopted in practice for plant disease detection. In order to achieve accurate plant disease diagnostics a plant pathologist should possess good observation skills so that one can identify characteristic symptoms. Variations in symptoms indicated by diseased plants may lead to an improper diagnosis since amateur gardeners and hobbyists could have more difficulties determining it than a

professional plant pathologist. An automated system designed to help identify plant diseases by the plant's appearance and visual symptoms could be of great help to amateurs in the gardening process and also trained professionals as a verification system in disease diagnostics.

Advances in computer vision present an opportunity to expand and enhance the practice of precise plant protection and extend the market of computer vision applications in the field of precision agriculture.

Exploiting common digital image processing techniques such as colour analysis and thresholding were used with the aim of detection and classification of plant diseases.

Various different approaches are currently used for detecting plant diseases and most common are artificial neural networks (ANNs) and Support Vector Machines (SVMs). They are combined with different methods of image pre-processing in favour of better feature extraction.

In machine learning and cognitive science, ANN is an information-processing paradigm that was inspired by the way biological nervous systems, such as the brain, process information. The brain is composed of a large number of highly interconnected neurons working together to solve specific problems.

An artificial neuron is a processing element with many inputs and one output. Although artificial neurons can have many outputs, only those with exactly one output will be considered. Their inputs can also take on any value between 0 and 1. Also, the neuron has weights for each input and an overall bias.

Detecting plant diseases using the deep convolutional neural network trained and fine-tuned to fit accurately to the database of a plant's leaves that was gathered independently for diverse plant diseases. The advance and novelty of the developed model lie in its simplicity; plant healthy leaves and background images are in line with other classes, enabling the model to distinguish between diseased leaves and plant healthy ones or from the environment by using deep CNN.

Implementing the appropriate management strategies like fungicide applications, disease-specific chemical applications, and vector control through pesticide applications could lead to early information on crop plant health and disease detection. This could facilitate the control of diseases and improve productivity.

Plant Disease Detection using CNN

CNN is trained using 87,848 images, with 25 plant varieties having 58 classes which includes plant healthy plants. Different types of models were trained, of which the best model provided 99.53% accuracy in correct identification. CNN was used to train 54306 images of 14 crop types, with 26 diseases and plant healthy leaves. The success rate of 99.35% reduced to 31.4% when tested on another dataset collected from real life scenario. In the problem of disease severity and the reason for it being more challenging than disease classification is discussed. The high intra-class similarity among the various images belonging to same class makes its identification even more difficult.

CHAPTER 2

LITERATURE SURVEY

[1] Maniyath, S. R., P V, V., M, N., R, P., N, P. B., N, S., & Hebbar, R: Crop diseases are a noteworthy risk to sustenance security, however their quick distinguishing proof stays troublesome in numerous parts of the world because of the non-attendance of the important foundation. Emergence of accurate techniques in the field of leaf-based image classification has shown impressive results. This paper makes use of Random Forest in identifying between plant healthy and diseased leaf from the data sets created. Our proposed paper includes various phases of implementation namely dataset creation, feature extraction, training the classifier and classification. The created datasets of diseased and plant healthy leaves are collectively trained under Random Forest to classify the diseased and plant healthy images. For extracting features of an image we use Histogram of an Oriented Gradient (HOG). Overall, using machine learning to train the large data sets available publicly gives us a clear way to detect the disease present in plants in a colossal scale. The agriculturist in provincial regions may think that it's hard to differentiate the malady which may be available in their harvests. It's not moderate for them to go to agribusiness office and discover what the infection may be. Our principle objective is to distinguish the illness introduce in a plant by watching its morphology by picture handling and machine learning. A modern approach such as machine learning and deep learning algorithm has been employed to increase the recognition rate and the accuracy of the results. Various researches have taken place under the field of machine learning for plant disease detection and diagnosis.

[2] Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E.: The timely identification and early prevention of crop diseases are essential for improving production. In this paper, deep convolutional-neural-network (CNN) models are implemented to identify and diagnose diseases in plants from their leaves, since CNNs have achieved impressive results in the field of machine vision. Standard CNN models require a large number of parameters and higher computation cost. In this paper, we replaced standard convolution with depth=separable convolution, which reduces the parameter number and computation cost. The implemented models were trained with an open dataset consisting of 14 different plant species, and 38 different categorical disease classes and plant healthy plant leaves. To evaluate the performance of the models, different parameters such as batch size, dropout, and

different numbers of epochs were incorporated. The implemented models achieved a disease-classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56% using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, respectively, which were greater than that of traditional handcrafted-feature-based approaches. In comparison with other deep-learning models, the implemented model achieved better performance in terms of accuracy and it required less training time. Moreover, the MobileNetV2 architecture is compatible with mobile devices using the optimized parameter. The accuracy results in the identification of diseases showed that the deep CNN model is promising and can greatly impact the efficient identification of the diseases, and may have potential in the detection of diseases in real-time agricultural systems.

[3] Muhammad E.H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Nabil Ibtehaz,: Plants are a major source of food for the world population. Plant diseases contribute to production loss, which can be tackled with continuous monitoring. Manual plant disease monitoring is both laborious and error-prone. Early detection of plant diseases using computer vision and artificial intelligence (AI) can help to reduce the adverse effects of diseases and also helps to overcome the shortcomings of continuous human monitoring. In this study, we have extensively studied the performance of the different state-of-the-art convolutional neural networks (CNNs) classification network architectures i.e. ResNet18, MobileNet, DenseNet201, and InceptionV3 on 18,162 plain tomato leaf images to classify tomato diseases. The comparative performance of the models for the binary classification (plant healthy and unplant healthy leaves), six-class classification (plant healthy and various groups of diseased leaves), and ten-class classification (plant healthy and various types of unplant healthy leaves) are also reported. InceptionV3 showed superior performance for the binary classification using plain leaf images with an accuracy of 99.2%. DenseNet201 also outperform for six-class classification with an accuracy of 97.99%. Finally, DenseNet201 achieved an accuracy of 98.05% for ten-class classification. It can be concluded that deep architectures performed better at classifying the diseases for the three experiments. The performance of each of the experimental studies reported in this work outperforms the existing literature.

[4] Zhang, Y., Song, C., & Zhang., D. To improve the recognition model accuracy of crop disease leaves and locating diseased leaves, this paper proposes an improved Faster RCNN to detect plant healthy tomato leaves and four diseases: powdery

mildew, blight, leaf mold fungus and ToMV. First, we use a depth residual network to replace VGG16 for image feature extraction so we can obtain deeper disease features. Second, the k-means clustering algorithm is used to cluster the bounding boxes. We improve the anchoring according to the clustering results. The improved anchor frame tends toward the real bounding box of the dataset. Finally, we carry out a k-means experiment with three kinds of different feature extraction networks. The experimental results show that the improved method for crop leaf disease detection had 2.71% higher recognition accuracy and a faster detection speed than the original Faster RCNN. Crop disease detection is the basis of crop disease prevention to guarantee crop quality. Traditional detection methods for crop disease mainly depend on manual observation and consequently lead to low detection efficiency and poor reliability. Farmers lack professional knowledge, and agricultural experts cannot serve the field at all times so that they miss the best time for prevention

[5] R. R. Atole, D. Park, "A Multiclass Deep Convolutional Neural Network Classifier for Detection of Common Rice Plant Anomalies," International Journal Of Advanced Computer Science And Applications, vol. 9, no. 1, pp. 67–70, 2018.

This study examines the use of deep convolutional neural network in the classification of rice plants according to plant health status based on images of its leaves. A three-class classifier was implemented representing normal, unplant healthy, and snailinfested plants via transfer learning from an AlexNet deep network. The network achieved an accuracy of 91.23%, using stochastic gradient descent with mini batch size of thirty (30) and initial learning rate of 0.0001. Six hundred (600) images of rice plants representing the classes were used in the training. The training and testing dataset-images were captured from rice fields around the district and validated by technicians in the field of agriculture.

[6] P. Konstantinos Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," Computers and Electronics in Agriculture ,vol. 145, pp. 311–318, 2018.

In this paper, convolutional neural network models were developed to perform plant disease detection and diagnosis using simple leaves images of plant healthy and diseased plants, through deep learning methodologies. Training of the models was performed with the use of an open database of 87,848 images, containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations,

including plant healthy plants. Several model architectures were trained, with the best performance reaching a 99.53% success rate in identifying the corresponding [plant, disease] combination (or plant healthy plant). The significantly high success rate makes the model a very useful advisory or early warning tool, and an approach that could be further expanded to support an integrated plant disease identification system to operate in real cultivation conditions.

[7] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of Rice Diseases Using Deep Convolutional Neural Networks," *Neurocomputing*, 267, pp. 378-384, 2017.

An accurate and timely detection of diseases and pests in rice plants can help to reduce economic losses substantially. It can help farmers in applying timely treatment. Recent developments in deep learning based convolutional neural networks (CNN) have allowed researchers to greatly improve the accuracy of image classification. In this paper, we present a deep learning based approach to detect diseases and pests in rice plants using images captured in real life scenerio with heterogeneous background. We have experimented with various state-of-the-art convolutional neural networks on our large dataset of rice diseases and pests, which contain both inter-class and intra-class variations. The results show that we can effectively detect and recognize nine classes of rice diseases and pests including plant healthy plant class using a deep convolutional neural network, with the best accuracy of 99.53% on test set.

[8] Y. Es-saady, T. El Massi, M. El Yassa, D. Mammass, and A. Benazoun, "Automatic recognition of plant leaves diseases based on serial combination of two SVM classifiers," *International Conference on Electrical and Information Technologies (ICEIT)* pp. 561-566, 2016.

This paper presents a machine vision system for automatic recognition of plant leaves diseases from images. The proposed system is based on serial combination technique of two SVM classifiers. The first classifier uses the color to classify the images; it considers, at this phase, that the diseases with similar or nearest color belonging to the same class. Then, the second classifier is used to differentiate between the classes with similar color according to the shape and texture features. The tests of this study are carried out on six classes of diseases including three types of pest insects damages (Leaf miners, Thrips and Tuta absoluta) and three forms of pathogens symptoms (Early blight, Late blight and Powdery mildew). The results of

+`the study show the advantages of the proposed method compared to the other existing methods.

2.1 INFERENCES FROM LITERATURE SURVEY

From the above-mentioned literature works, it is clear that there has been effective research on this topic has been done and many models have been proposed. It is evident that the above-mentioned systems have their own pros and cons. While some of the recent works involve hybrid technologies and provide better accuracies, they are still far from what is needed. With higher accuracy, comes the need for low computational costs, high processing speed, and most of all, the convenience of use.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

The existing system are not done with many images and also the existing system has low accuracy and low efficiency in terms of loading time and implementation time. Also the testing and training is not done with the proper test-train split ratio.

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 FEASIBILITY STUDIES/RISK ANALYSIS OF THE PROJECT

Existing Method:

This model emphasizes an existing method that which is designed using the some of the algorithms of deep learning. Here the process is performed using the machine learning, which is one of the transfer learning methods, but this could not get the high accuracy.

There are various existing methods for diseases of leaf detection, which can be broadly classified into two categories: manual and automated.

Manual methods involve visual inspection of the leaves by a trained expert who can identify the symptoms of a particular disease by observing the color, texture, shape, and size of the leaves. However, manual methods are time-consuming, labor-intensive, and prone to human error.

Automated methods, on the other hand, involve the use of image processing techniques and machine learning algorithms to automatically detect and classify diseases of leaves. These methods typically involve the following steps:

Image acquisition: This involves capturing images of the leaves using a camera or a mobile device.

Preprocessing: This involves enhancing the quality of the images by removing noise, adjusting brightness and contrast, and correcting for color balance.

Feature extraction: This involves extracting relevant features from the preprocessed images, such as texture, shape, and color.

Classification: This involves using machine learning algorithms to classify the leaves into different categories based on the extracted features.

Some of the commonly used algorithms for leaf disease detection include Support Vector Machines (SVM), Random Forest, Convolutional Neural Networks (CNN), and K-Nearest Neighbor (KNN). These methods have been shown to achieve high accuracy in detecting and classifying diseases of leaves, and can be useful for early detection and prevention of crop diseases.

Disadvantages:

- Less feature compatibility
- Low accuracy

Proposed System:

In purposed method we are performing the classification of either the Plant Leaf Disease identification using Convolution Neural Network (CNN) of deep learning along with the machine learning methods. As image analysis based approaches for Leaf Disease detection. Hence, proper classification is important for the Leaf disease that which will be possible by using our proposed method. Block diagram of proposed method is shown below.

Plant leaf disease detection using Convolutional Neural Networks (CNN) is a popular approach in automated disease detection systems. The proposed system for plant leaf disease detection using CNN would involve the following steps:

Image Acquisition: In this step, images of plant leaves would be captured using a camera or a mobile device.

Image Pre-processing: In this step, the acquired images would be pre-processed to enhance their quality. This could involve adjusting the brightness and contrast of the images, correcting for color balance, and removing noise.

Dataset Creation: In this step, a dataset would be created by collecting and annotating images of plant leaves affected by different diseases. The dataset would be divided into training, validation, and testing sets.

Training the CNN model: In this step, a CNN model would be trained using the annotated dataset. The model would learn to classify the plant leaves into different disease categories based on the features extracted from the images.

Testing the Model: In this step, the trained model would be tested using the testing dataset. The accuracy of the model in detecting plant leaf diseases would be evaluated and analyzed.

The proposed system would have several advantages, including:

High accuracy: CNN models are known to have high accuracy in detecting plant leaf diseases, making them an effective tool for early detection and prevention of crop diseases.

Faster processing: CNN models can process large volumes of data quickly, making them suitable for large-scale disease detection.

Cost-effective: The proposed system would be cost-effective compared to manual methods, as it would eliminate the need for manual inspection and analysis of plant leaves.

Overall, the proposed system for plant leaf disease detection using CNN would be a useful tool for farmers and agricultural experts to detect and prevent crop diseases, leading to increased crop yields and improved food security.

Block Diagram:

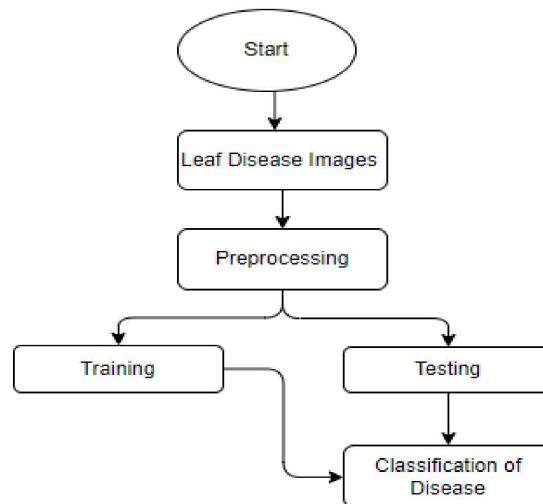


Fig 3.0.1 Block diagram of proposed method

ARCHITECTURE

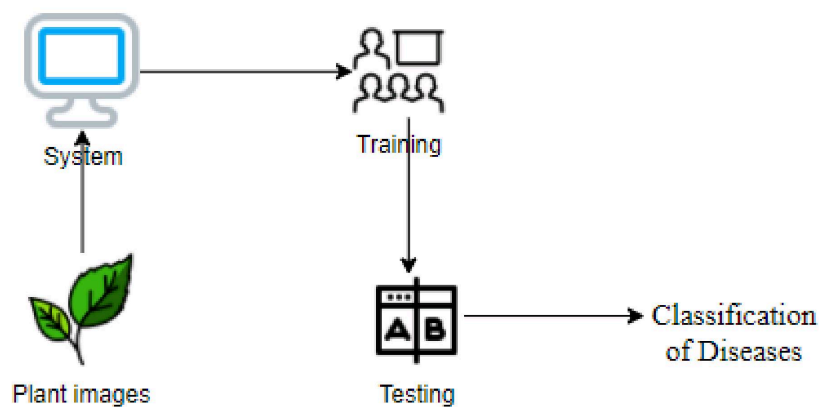


Fig 3.0.2: Architecture

FEASIBILITY STUDY

The feasibility of the project is analysed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system

analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- ◆ ECONOMICAL FEASIBILITY
- ◆ TECHNICAL FEASIBILITY
- ◆ SOCIAL FEASIBILITY

Economic feasibility:

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus, the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased. Technical feasibility:

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

Social feasibility:

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

3.2 SOFTWARE REQUIREMENTS SPECIFICATION DOCUMENT

Functional and non-functional requirements:

Requirement's analysis is very critical process that enables the success of a system

or software project to be assessed. Requirements are generally split into two types: Functional and non-functional requirements.

Functional Requirements: These are the requirements that the end user specifically demands as basic facilities that the system should offer. All these functionalities need to be necessarily incorporated into the system as a part of the contract. These are represented or stated in the form of input to be given to the system, the operation performed and the output expected. They are basically the requirements stated by the user which one can see directly in the final product, unlike the non-functional requirements.

Examples of functional requirements:

- 1) Authentication of user whenever he/she logs into the system
- 2) System shutdown in case of a cyber-attack
- 3) A verification email is sent to user whenever he/she register for the first time on some software system.

Non-functional requirements: These are basically the quality constraints that the system must satisfy according to the project contract. The priority or extent to which these factors are implemented varies from one project to other. They are also called non-behavioral requirements.

They basically deal with issues like:

- Portability
- Security
- Maintainability
- Reliability
- Scalability
- Performance
- Reusability
- Flexibility

Examples of non-functional requirements:

- 1) Emails should be sent with a latency of no greater than 12 hours from such an activity.
- 2) The processing of each request should be done within 10 seconds
- 3) The site should load in 3 seconds whenever of simultaneous users are > 10000

SYSTEM SPECIFICATIONS:

H/W Specifications:

- **Processor** : **I5/Intel Processor**
- **RAM** : **8GB (min)**
- **Hard Disk** : **128 GB**

S/W Specifications:

- **Operating System** : **Windows 10**
- **Server-side Script** : **Python 3.6**
- **IDE** : **PyCharm, Jupyter notebook**
- **Libraries Used** : **Numpy, IO, OS, Flask, Keras, pandas, tensorflow**

Disadvantages of Existing system

1. It is difficult to detect and identify diseases.
2. Difficult to handle.
3. It takes more time.
4. Difficult to scale up.
5. Time consuming.
6. Low accuracy

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

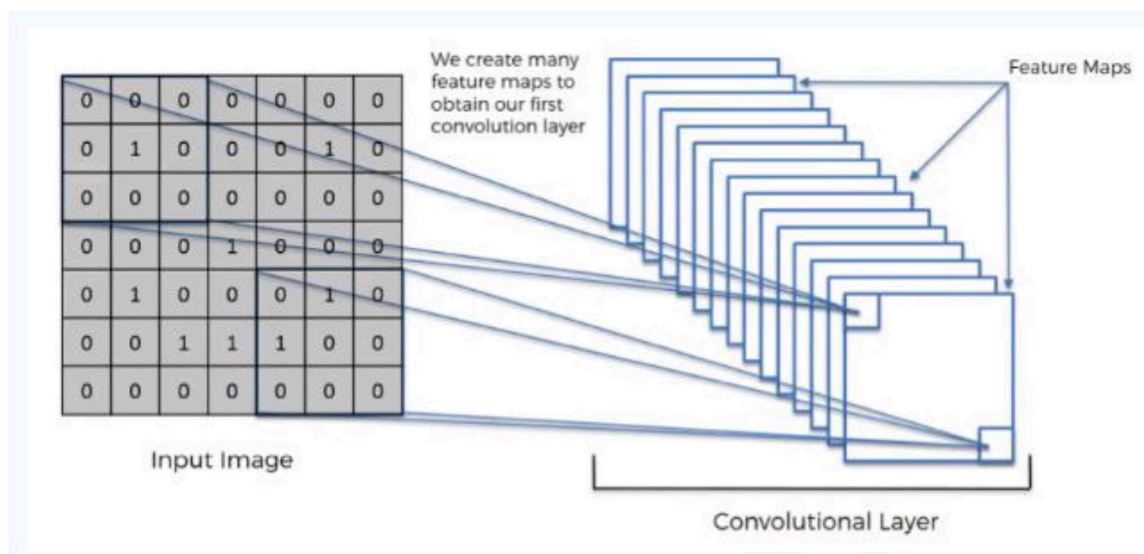
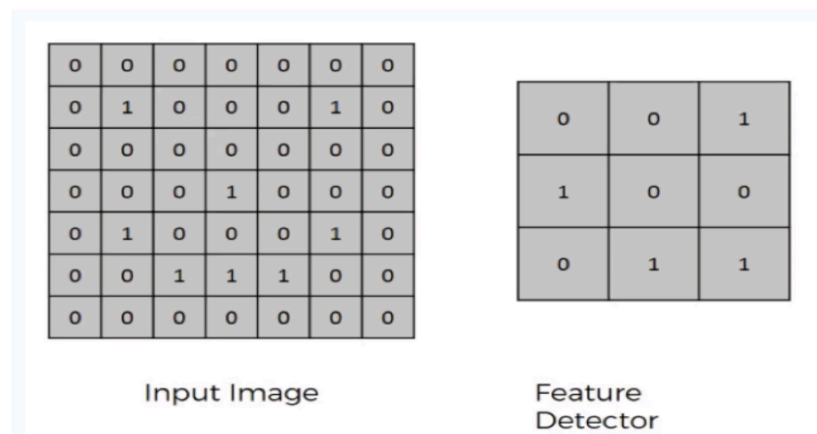
METHODOLOGY AND ALGORITHMS:

1. Convolutional Neural Network

Step1: convolutional operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

The Convolution Operation

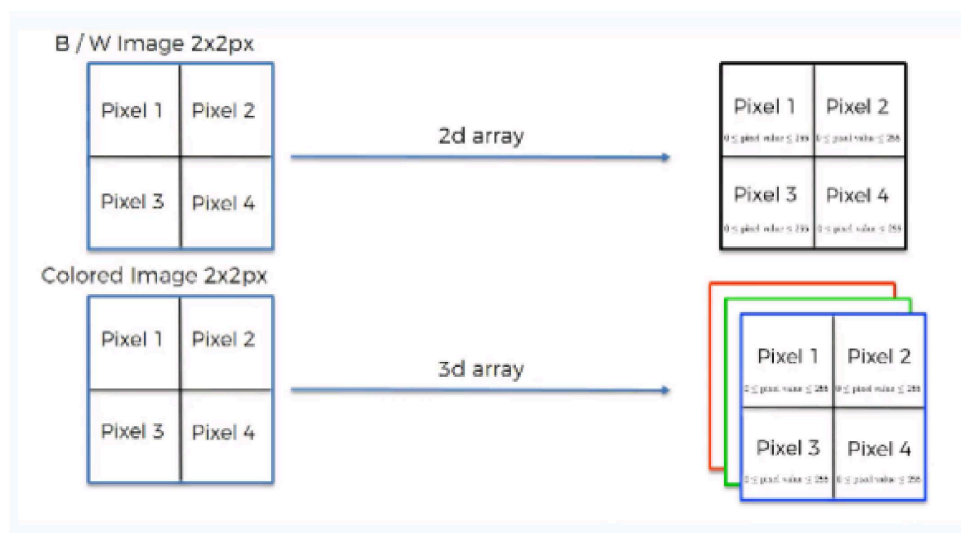


Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or ReLU. We will cover ReLU layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills.

Convolutional Neural Networks Scan Images



Step 2: Conv2D

Keras Conv2D is 2D Convolution Layer; this layer creates a convolution kernel that is wind with layers input which helps produce a tensor of outputs.

Kernel: In image processing kernel is a convolution matrix or masks which can be used for blurring, sharpening, embossing, edge detection, and more by doing a convolution between a kernel and an image

Step 3: Flattening

This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

Summary

In the end, we'll wrap everything up and give a quick recap of the concept covered in the section. If you feel like it will do you any benefit (and it probably will), you should check out the extra tutorial in which Softmax and Cross-Entropy are covered. It's not mandatory for the course, but you will likely come across these concepts when working with Convolutional Neural Networks and it will do you a lot of good to be familiar with them.

Convolutional neural network (CNN):

A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution.

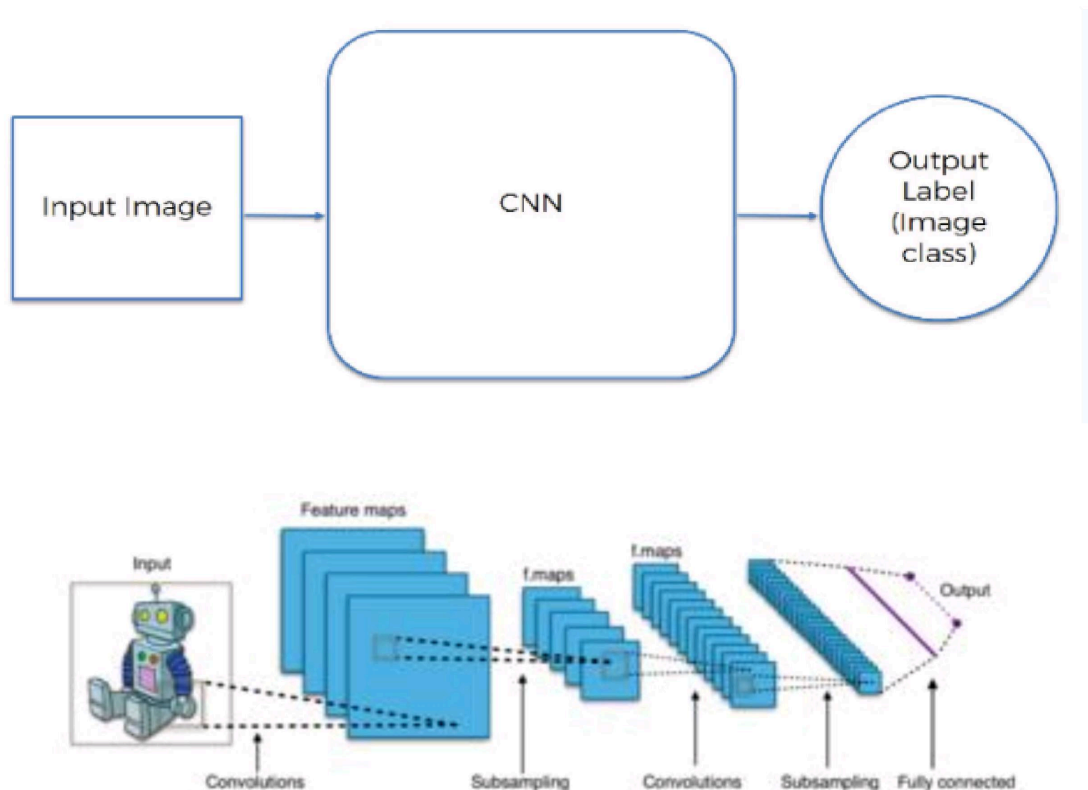


Fig 4.1.1: CNN Architecture

The architecture of a CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers use filters to extract features from the input images, and the pooling layers reduce the dimensionality of the features. The fully connected layers then use the extracted features to classify the input images.

During the training process, the weights and biases of the filters in the convolutional layers are adjusted to minimize the error between the predicted output and the actual output. This is typically done using backpropagation, which involves calculating the gradients of the error with respect to the weights and biases, and updating the weights and biases accordingly.

CNNs have several advantages over traditional image processing techniques, including:

Automatic feature extraction: CNNs can automatically extract relevant features from input images, eliminating the need for manual feature engineering.

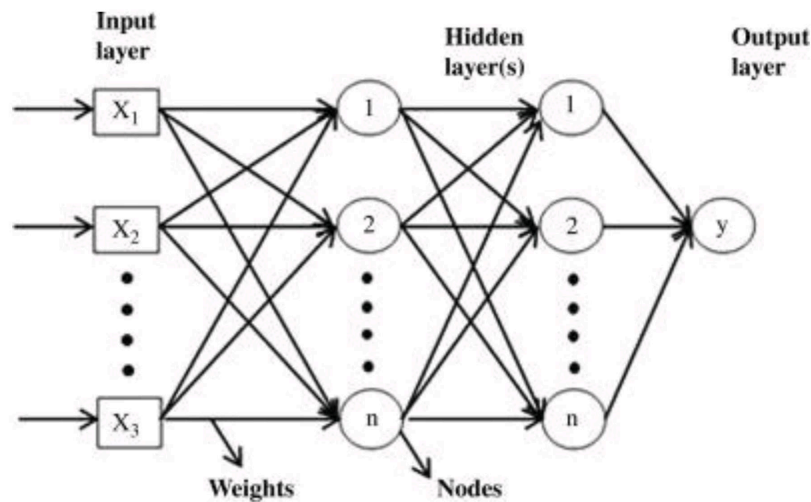
Robustness to input variations: CNNs can recognize patterns in input images even if the images are rotated, scaled, or partially occluded.

High accuracy: CNNs have achieved state-of-the-art performance on a variety of image recognition tasks, including image classification and object detection.

Scalability: CNNs can be trained on large datasets and can process large volumes of data quickly, making them suitable for use in real-world applications.

Artificial Neural Network (ANN):

ANN architecture is based on the structure and function of the biological neural network. Similar to neurons in the brain, ANN also consists of neurons which are arranged in various layers. Feed forward neural network is a popular neural network which consists of an input layer to receive the external data to perform pattern recognition, an output layer which gives the problem solution, and a hidden layer is an intermediate layer which separates the other layers. The adjacent neurons from the input layer to output layer are connected through acyclic arcs. The ANN uses a training algorithm to learn the datasets which modifies the neuron weights depending on the error rate between target and actual output. In general, ANN uses the back propagation algorithm as a training algorithm to learn the datasets. The general structure of ANN is shown in Fig.



ResNet50:

ResNet50 is a convolutional neural network which has a depth of 50 layers. It was build and trained by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 and you can access the model performance results on their paper, titled Deep Residual Learning for Image Recognition. This model is also trained on more than 1 million images from the ImageNet database. Just like VGG-19, it can classify up to 1000 objects and the network was trained on 224x224 pixels colored images. Here is brief info about its size and performance:

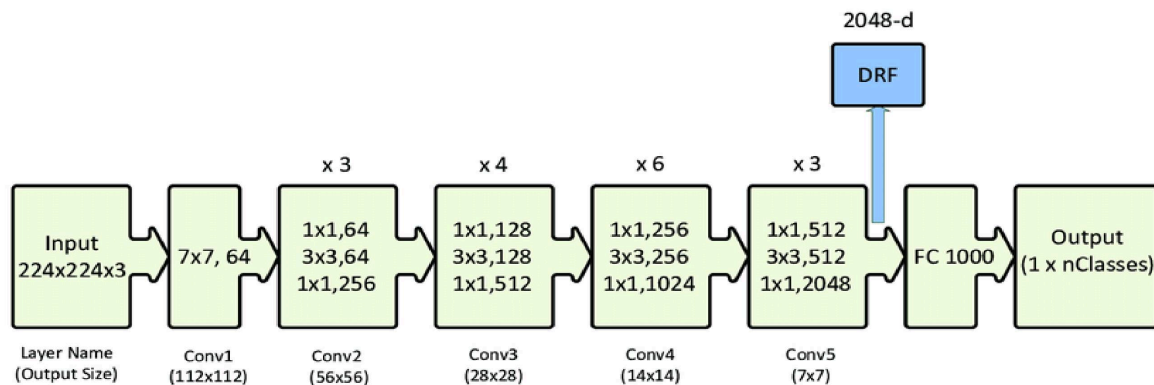
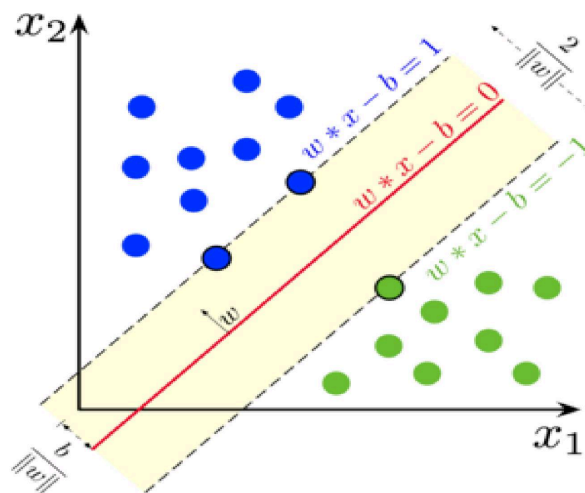


Fig 4.1.2. ResNet50 Architecture

To sum up, residual network or ResNet was a major innovation that has changed the training of deep convolutional neural networks for tasks related to computer vision. While the original Resnet had 34 layers and used 2-layer blocks, other advanced variants such as the Resnet50 made the use of 3-layer bottleneck blocks to ensure improved accuracy and lesser training time. Keras is a deep learning API that is popular due to the simplicity of building models using it. Keras comes with several pre-trained models, including Resnet50, that anyone can use for their experiments. Therefore, building a residual network in Keras for computer vision tasks like image classification is relatively simple. You only need to follow a few simple steps.

Support vector machine (SVM):

Generally, Support Vector Machines is considered to be a classification approach, it but can be employed in both types of classification and regression problems. It can easily handle multiple continuous and categorical variables. SVM constructs a Hyperplane in multidimensional space to separate different classes. SVM generates optimal Hyperplane in an iterative manner, which is used to minimize an error. The core idea of SVM is to find a maximum marginal Hyperplane (MMH) that best divides the dataset into classes.



Support Vectors

Support vectors are the data points, which are closest to the Hyperplane. These points will define the separating line better by calculating margins. These points are more relevant to the construction of the classifier.

Hyperplane

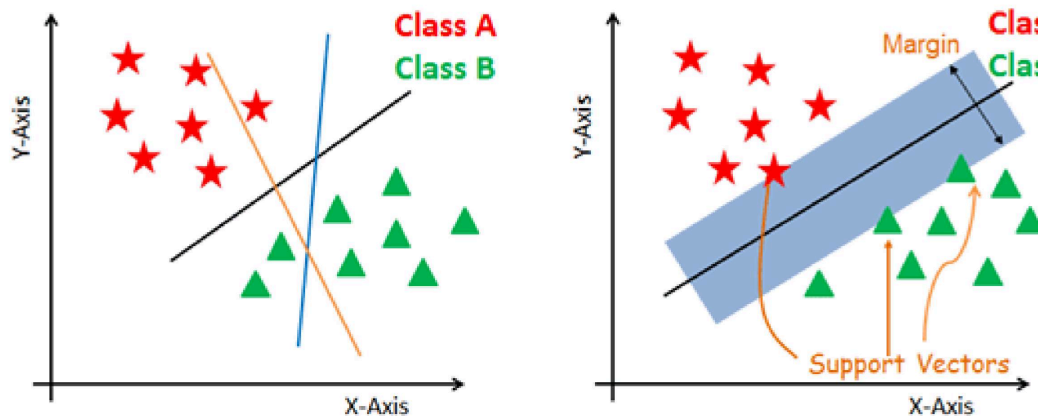
A Hyperplane is a decision plane which separates between a set of objects having different class memberships.

Margin

A margin is a gap between the two lines on the closest class points. This is calculated as the perpendicular distance from the line to support vectors or closest points. If the margin is larger in between the classes, then it is considered a good margin, a smaller margin is a bad margin.

The main objective is to segregate the given dataset in the best possible way. The distance between the either nearest points is known as the margin. The objective is to select a Hyperplane with the maximum possible margin between support vectors in the given dataset. SVM searches for the maximum marginal Hyperplane in the following steps:

Generate Hyperplane which segregates the classes in the best way. Left-hand side figure showing three Hyperplane black, blue and orange. Here, the blue and orange have higher classification error, but the black is separating the two classes correctly. Select the right Hyperplane with the maximum segregation from the either nearest data points as shown in the right-hand side figure.



SVM Kernels

The SVM algorithm is implemented in practice using a kernel. A kernel transforms an input data space into the required form. SVM uses a technique called the kernel trick. Here, the kernel takes a low-dimensional input space and transforms it into a higher dimensional space. In other words, you can say that it converts non separable problem to separable problems by adding more dimension to it. It is most useful in non-linear separation problem. Kernel trick helps you to build a more accurate classifier.

The main advantage of SVM is that it can be used for both classification and regression problems. SVM draws a decision boundary which is a Hyperplane between any two classes in order to separate them or classify them. SVM also used in Object Detection and image classification.

Polynomial Kernel: A polynomial kernel is a more generalized form of the linear kernel. The polynomial kernel can distinguish curved or nonlinear input space.

SOFTWARE DEVELOPMENT LIFE CYCLE – SDLC:

In our project we use waterfall model as our software development cycle because of its step-by-step procedure while implementing.

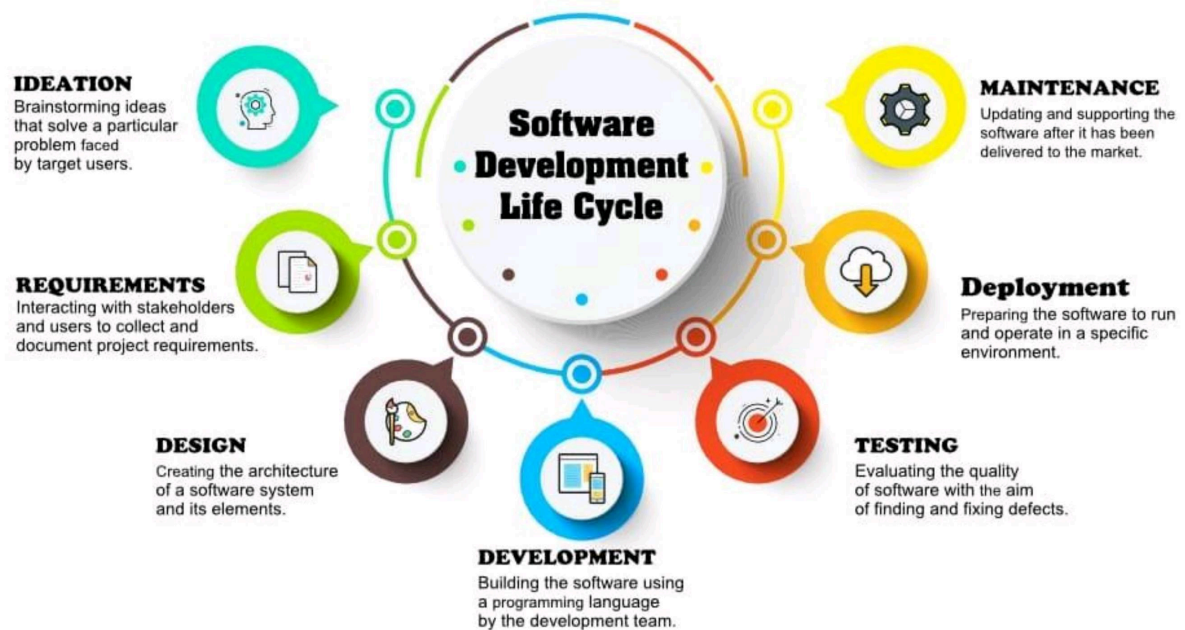


Fig 4.1.3: Waterfall Model

- **Requirement Gathering and analysis** – all possible requirements of the system to be developed are captured in this phase and documented in a requirement specification document.
- **System Design** – the requirement specifications from first phase are studied in this phase and the system design is prepared. This system design helps in specifying hardware and system requirements and helps in defining the overall system architecture.
- **Implementation** – with inputs from the system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality, which is referred to as Unit Testing.
- **Integration and Testing** – All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures.
- **Deployment of system** – Once the functional and non-functional testing is done; the product is deployed in the customer environment or released into the market.

- **Maintenance** – There are some issues which come up in the client environment. To fix those issues, patches are released. Also, to enhance the product some better versions are released. Maintenance is done to deliver these changes in the customer environment.

MODULES:

System

User

1. System:

1.1 Create Dataset:

The dataset containing images of the plant disease classification images with the Plant plant health or not i.e., normal are to be classified is split into training and testing dataset with the test size of 30-20%.

1.2 Pre-processing:

Resizing and reshaping the images into appropriate format to train our model.

1.3 Training:

Use the pre-processed training dataset is used to train our model using CNN Deep learning and machine learning algorithms along with Resnet50 transfer learning methods.

1.4 Classification:

The results of our model are display of plant disease classification images are either with different labels

2. User:

2.1 Upload Image

The user has to upload an image which needs to be classified.

2.2 View Results

The classified image results are viewed by user.

UML DIAGRAMS

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object-

oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modelling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

USE CASE DIAGRAM

- ▶ A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis.
- ▶ Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

- The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

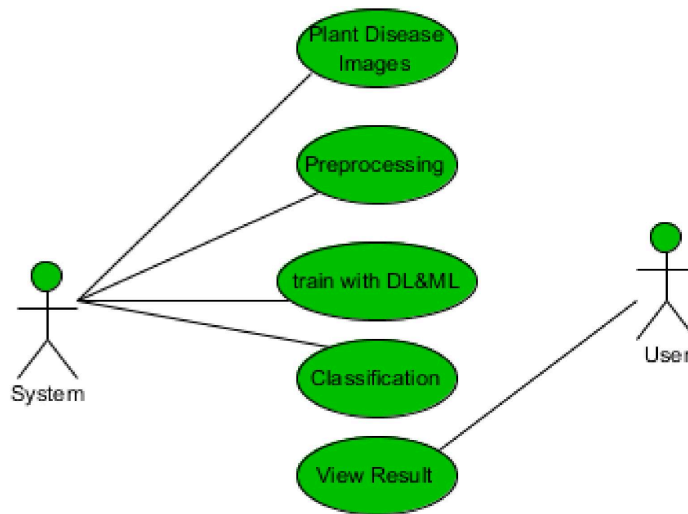


Fig 4.1.4: Usecase Diagram

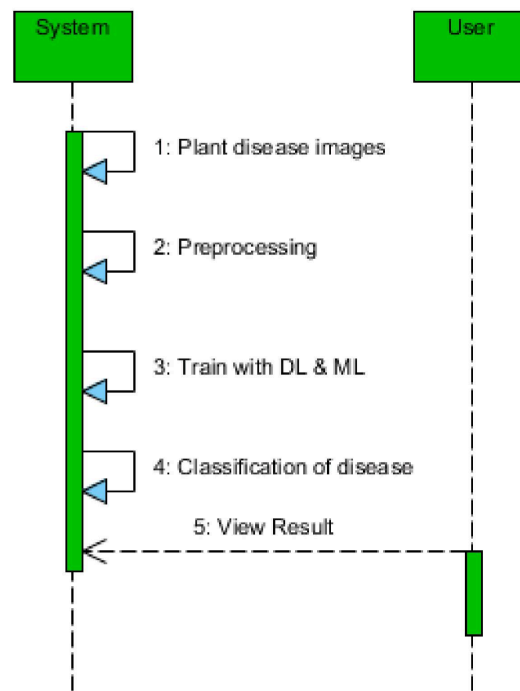
CLASS DIAGRAM

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information



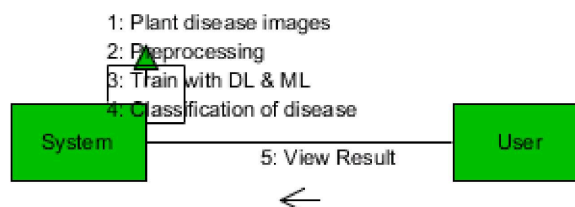
SEQUENCE DIAGRAM

- A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order.
- It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams



COLLABORATION DIAGRAM:

In collaboration diagram the method call sequence is indicated by some numbering technique as shown below. The number indicates how the methods are called one after another. We have taken the same order management system to describe the collaboration diagram. The method calls are similar to that of a sequence diagram. But the difference is that the sequence diagram does not describe the object organization whereas the collaboration diagram shows the object organization.



DEPLOYMENT DIAGRAM

Deployment diagram represents the deployment view of a system. It is related to the component diagram. Because the components are deployed using the deployment diagrams. A deployment diagram consists of nodes. Nodes are nothing but physical

hardware's used to deploy the application.



ACTIVITY DIAGRAM:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

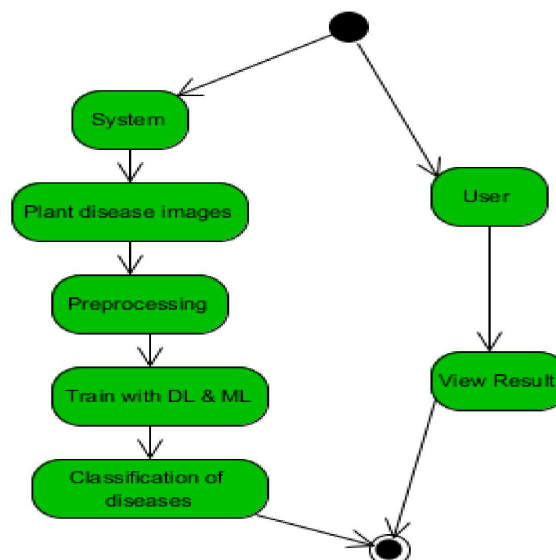
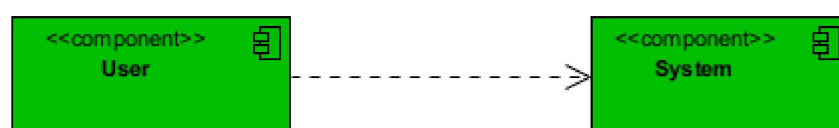


Fig 4.1.5: Activity Diagram

COMPONENT DIAGRAM:

A component diagram, also known as a UML component diagram, describes the organization and wiring of the physical components in a system. Component diagrams are often drawn to help model implementation details and double-check that every aspect of the system's required function is covered by planned development.



ER DIAGRAM:

An Entity–relationship model (ER model) describes the structure of a database with the help of a diagram, which is known as Entity Relationship Diagram (ER Diagram). An ER model is a design or blueprint of a database that can later be implemented as a database. The main components of E-R model are: entity set and relationship set. An ER diagram shows the relationship among entity sets. An entity set is a group of similar entities and these entities can have attributes. In terms of DBMS, an entity is a table or attribute of a table in database, so by showing relationship among tables and their attributes, ER diagram shows the complete logical structure of a database. Let's have a look at a simple ER diagram to understand this concept.

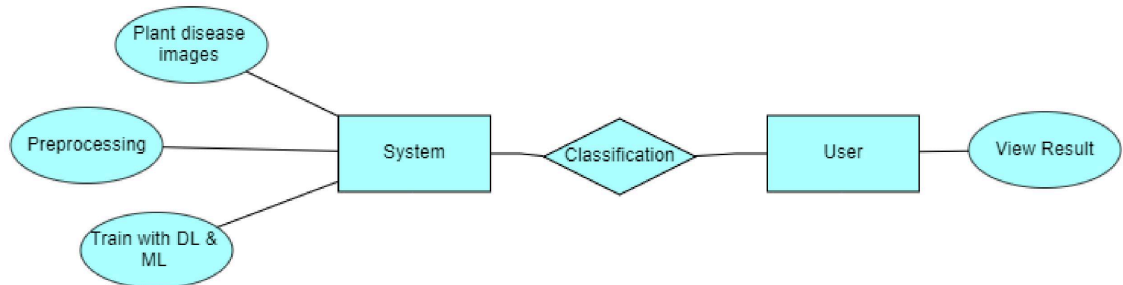


Fig 4.1.6: ER Diagram

DFD DIAGRAM:

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.

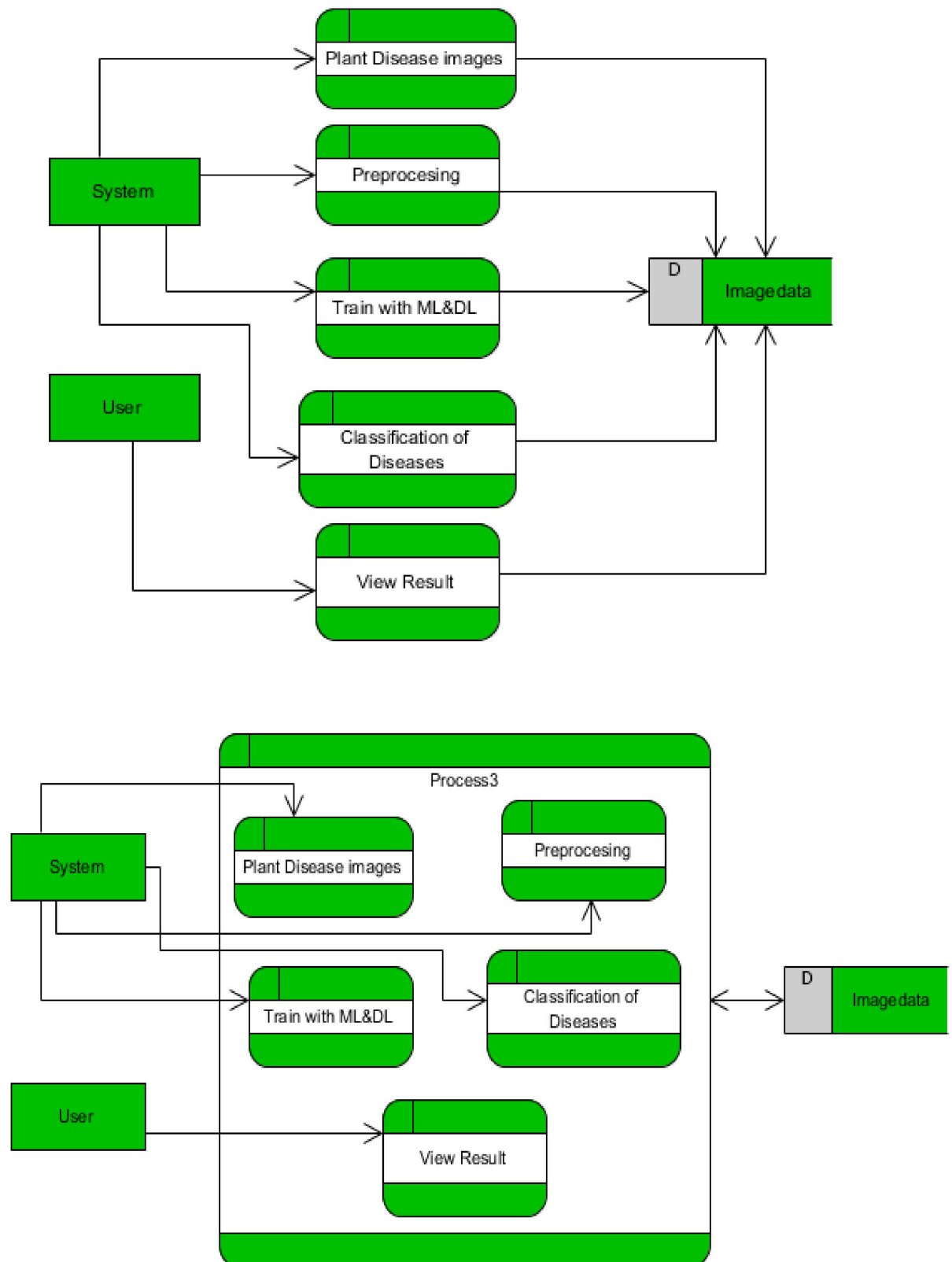


Fig 4.1.7: DFD Diagram

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

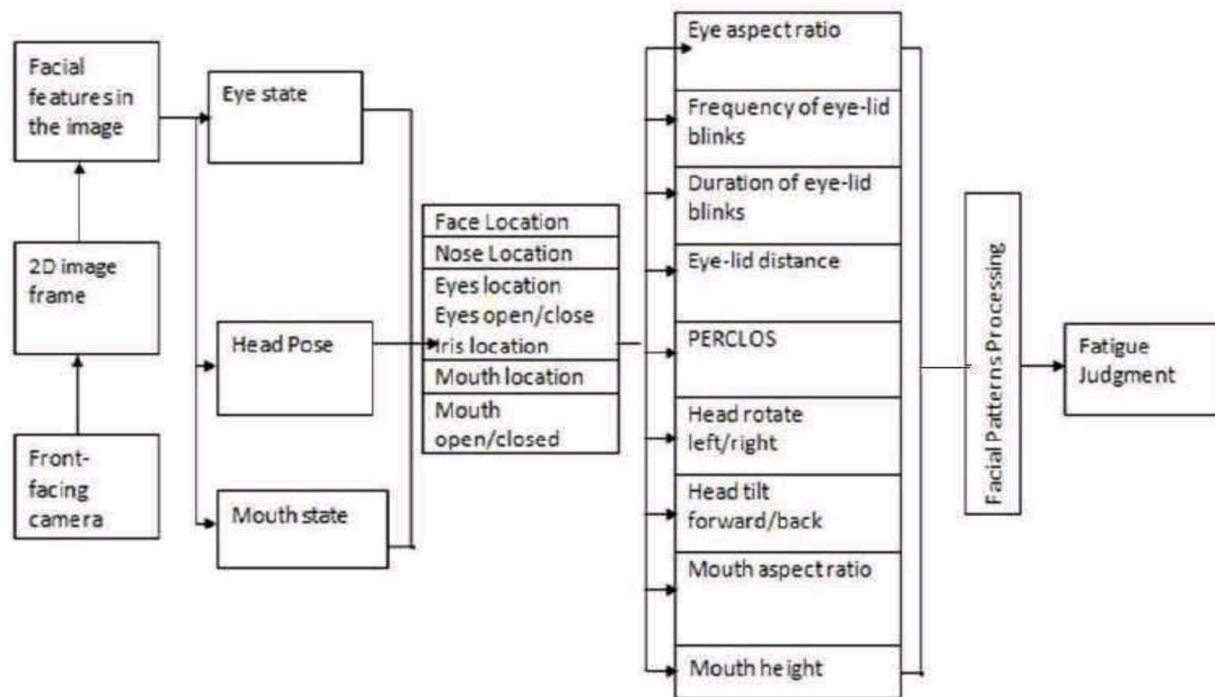


Fig 4.2.1: System Architecture for Drowsiness Judgment

The block diagram of the proposed system has been shown in the above figures. The camera captures the image of the person inside the car and sends that to the HOG model to train and it detects each feature from the face using facial landmark technique in the system. The next step in the process would be as it starts to find the position and condition of each feature to analyze, it should detect whether the person is sleeping or not. If any of the features especially the eye and the head pose/state of the person are detected to be abnormal then automatically the system starts to produce the siren sound. This is where we will get the final judgment of the state of the driver, whether he is concentrated or distracted.

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

Input Design:

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc.

Therefore, the quality of system input determines the quality of system output. Well-designed input forms and screens have following properties –

- It should serve specific purpose effectively such as storing, recording, and retrieving the information.
- It ensures proper completion with accuracy.
- It should be easy to fill and straightforward.
- It should focus on user's attention, consistency, and simplicity.
- All these objectives are obtained using the knowledge of basic design principles regarding –
 - What are the inputs needed for the system?
 - How end users respond to different elements of forms and screens.

Objectives for Input Design:

The objectives of input design are

- To design data entry and input procedures
- To reduce input volume
- To design source documents for data capture or devise other data capture methods
- To design input data records, data entry screens, user interface screens, etc.
- To use validation checks and develop effective input controls.

Output Design:

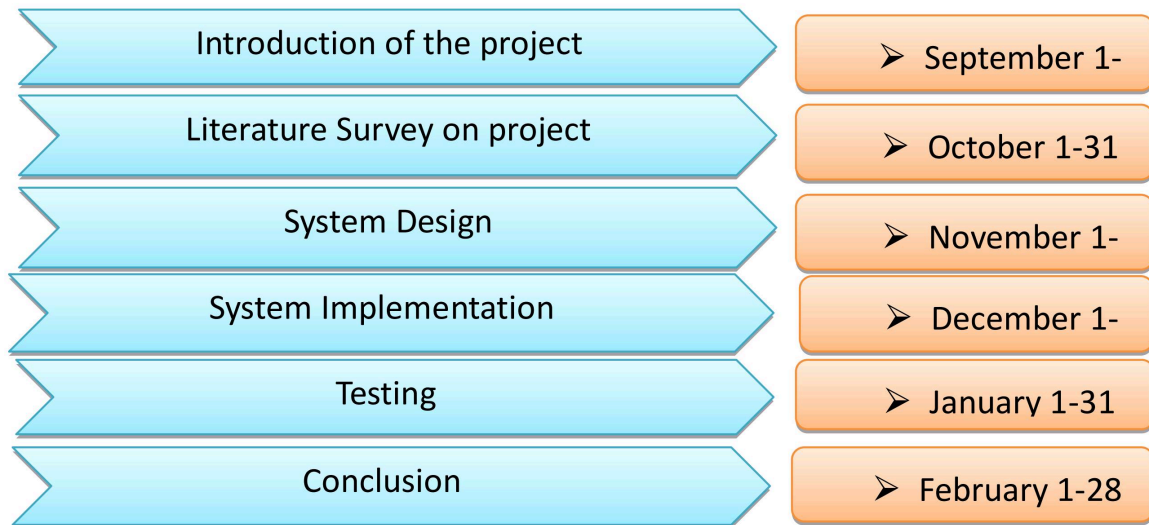
The design of output is the most important task of any system. During output design, developers identify the type of outputs needed, and consider the necessary output controls and prototype report layouts.

Objectives of Output Design:

The objectives of input design are:

- To develop output design that serves the intended purpose and eliminates the production of unwanted output.
- To develop the output design that meets the end user's requirements.
- To deliver the appropriate quantity of output.
- To form the output in appropriate format and direct it to the right person.
- To make the output available on time for making good decisions.

4.4 PROJECT MANAGEMENT PLAN



CHAPTER 5

IMPLEMENTATION DETAILS

The implementation of the plant disease detection system involves several key steps, including:

1. **Data Collection:** The first step in the implementation of the system is to collect data. Data is the foundation of the Deep Learning algorithm and is critical to the accuracy of the detection model. In this project, we collected data from various sources, including surveys, and publicly available datasets.
2. **Data Preprocessing:** Once the data is collected, it needs to be preprocessed to remove any inconsistencies, errors, and missing values. This is an essential step in Deep Learning, as the algorithm is only as good as the quality of the data that it receives.
3. **Feature Selection:** After preprocessing, the next step is feature selection. This involves selecting the most relevant features that will be used in the detection model. In this project, we used various feature selection techniques.
4. **Model Selection:** Once the features are selected, the next step is to choose the appropriate Deep-learning algorithm for the problem. In this project, we experimented with various Deep Learning algorithms – CNN .
5. **Model Training:** After selecting the appropriate algorithm, the next step is to train the model using the training dataset. This involves splitting the data into training and validation sets and training the model using the training data.
6. **Model Evaluation:** Once the model is trained, the next step is to evaluate its performance. This involves testing the model on the validation dataset and measuring its accuracy, precision, recall, F1 score, and other performance metrics.
7. **Deployment:** The final step in the implementation of the system is to deploy the model into a production environment. This involves integrating the model into the application and deploying it on a server.

5.1 Development and Deployment Setup

The plant disease Detection project was developed and deployed on a system with the following specifications:

- Hardware:
- CPU: Intel Core i7-10750H @2.60GHz 2.59 GHz
 - RAM: 16GB
 - Storage: 512GB SSD
- Software:
- Operating System: Windows 10 or above.

- IDE: PyCharm
- Python version: 3.8.5
- Libraries: Scikit-learn, Pandas, NumPy, Matplotlib, Keras, Flask , and HTML/CSS.

The project was developed in a virtual environment using PyCharm IDE. The required libraries were installed in the virtual environment using the pip package manager. The dataset used for training and testing was imported into the project from a Hard cascade file. The Flask web framework was used to build the user interface of the plant disease Detection system. The user interface was designed using HTML/CSS and integrated with the Flask framework. The trained Deep Learning model was integrated with the Flask framework to make Detections. The VPS was configured with the required software and hardware specifications to ensure optimal performance of the plant disease Detection system. The system was tested and verified for accuracy and reliability before deployment.

5.2 Algorithms

The plant disease detection system uses Deep Learning algorithms to predict the likelihood of a plant disease . The following algorithms were used in the project:

CNN: It is a type of neural network that is commonly used in image processing, computer vision, and natural language processing. CNNs have also been successfully applied to the field of detection, including the Detection of plant disease.

The above algorithm were trained on a dataset consisting of various risk factors such as rust level, early blight, leaf blight and grey leaf spot etc. The trained models were evaluated based on accuracy, precision, recall, and F1 score. The best-performing model was integrated with the Flask framework to build the plant disease Detection system.

5.3 Testing

Testing is a crucial part of software development, and it is necessary to ensure that the system works as expected. In the case of the plant disease Detection system, testing is even more important. The testing of the plant disease Detection system can be divided into two main categories: unit testing and system testing.

Unit Testing: Unit testing is a method of testing individual components of the system in isolation to ensure that each unit of the system works correctly. In the case of the plant disease Detection system, the individual components would include the data

preprocessing, feature extraction, and Deep learning algorithms. For example, the data preprocessing component could be tested by providing it with a sample dataset and ensuring that the data is correctly cleaned, normalized, and formatted. Similarly, the feature extraction component could be tested by providing it with a sample dataset and verifying that the correct features are extracted. System Testing: System testing, on the other hand, involves testing the system as a whole to ensure that all the components work together to produce the desired output. In the case of the plant disease Detection system, system testing would involve providing the system with a test dataset and verifying that it produces accurate Detections. The system testing could be further divided into two categories: functional testing and nonfunctional testing.

Functional Testing: Functional testing focuses on testing the functional requirements of the system, such as its ability to predict plant disease s accurately. In the case of the plant disease Detection system, functional testing would involve providing it with a test dataset and verifying that it produces accurate Detections.

Non-Functional Testing: Non-functional testing focuses on testing the non-functional requirements of the system, such as its performance, reliability, and usability. In the case of the plant disease Detection system, nonfunctional testing would involve testing its performance by measuring its response time and its reliability by testing it with a large dataset. To ensure the accuracy and reliability of the plant disease Detection system, it is necessary to test it thoroughly using various datasets and scenarios. Additionally, the system should be tested regularly to ensure that it continues to function correctly.

CHAPTER 6

RESULT AND DISCUSSIONS

First this is an interface . Initially we need to choose the option to go if we need to detect disease of plant then we need to go to upload section and we need to upload an image.

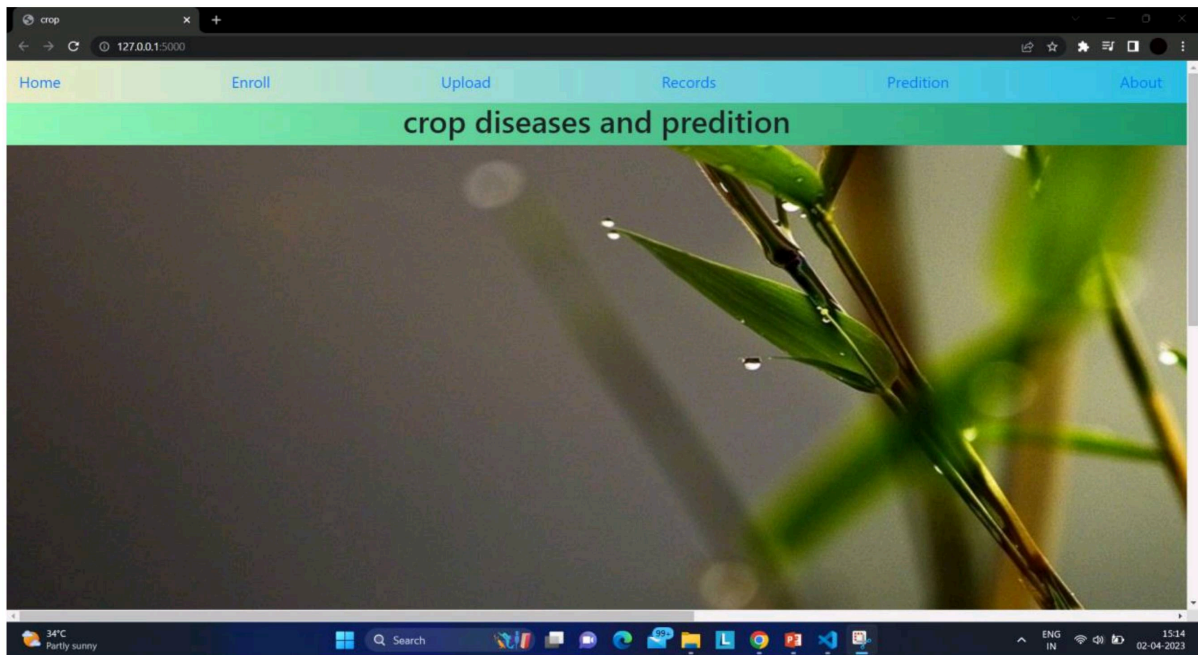


Fig 6.1 Application Interface

If you are a new user we need to enroll first. From fig 6.2, we can see that option. In that we need update our details like name, plant name etc.,

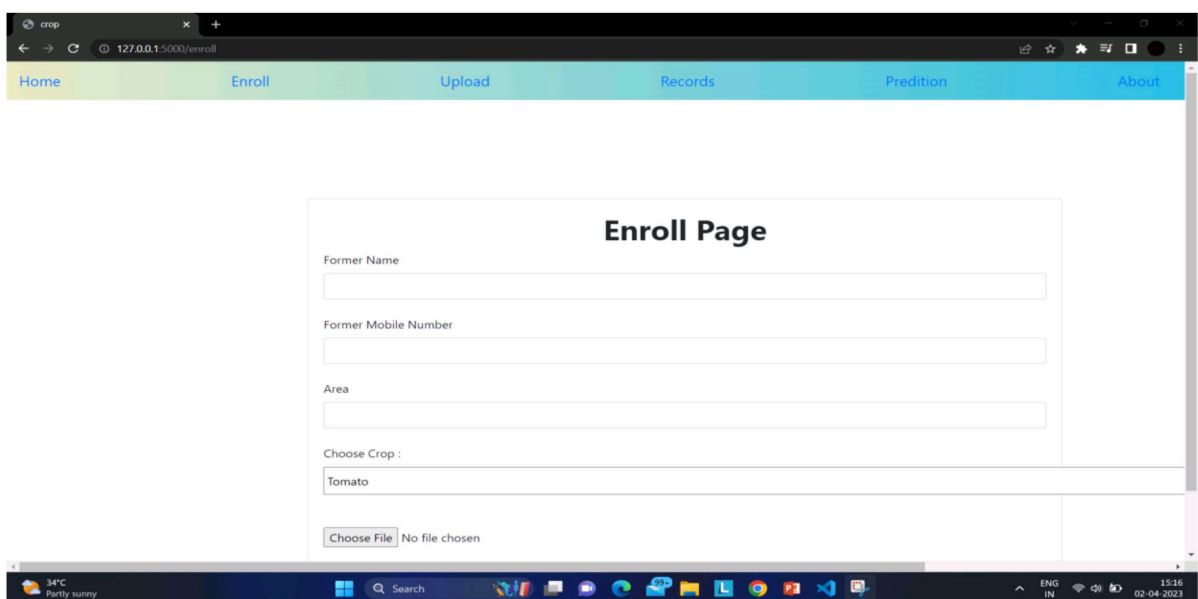


Fig 6.2 Enrolling Page

In this page we need to upload the image. After uploading the image we can know the disease acquired for the plant.

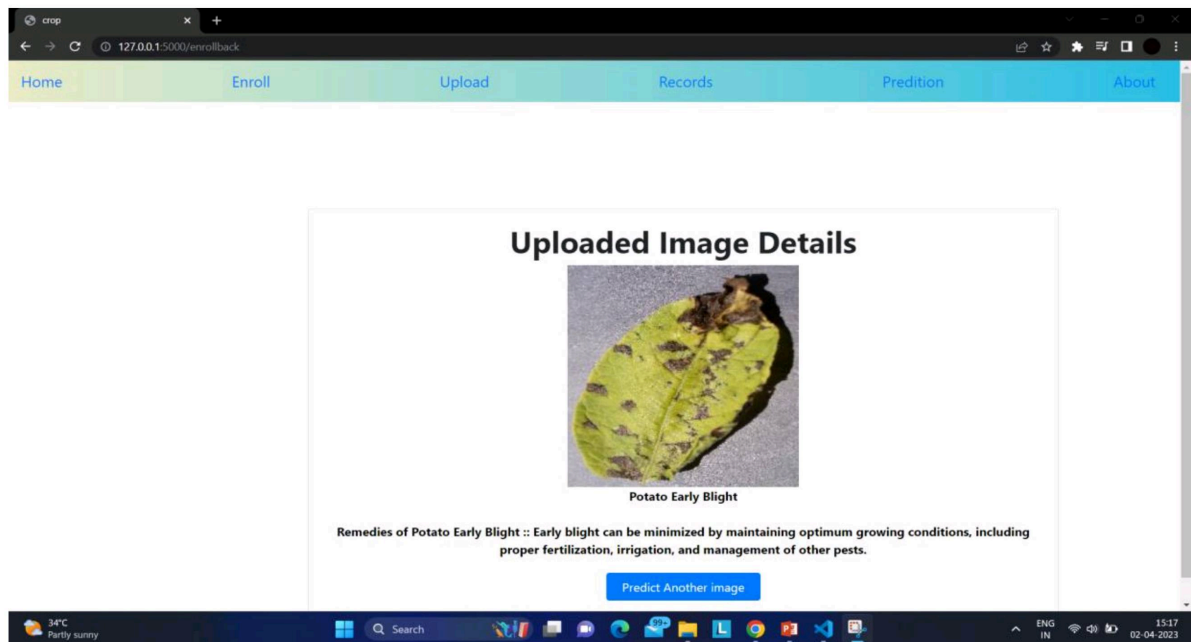


Fig 6.3 Upload And Results Page

After that we can check history page , what ever changes or history of the plant disease detection in leaf.

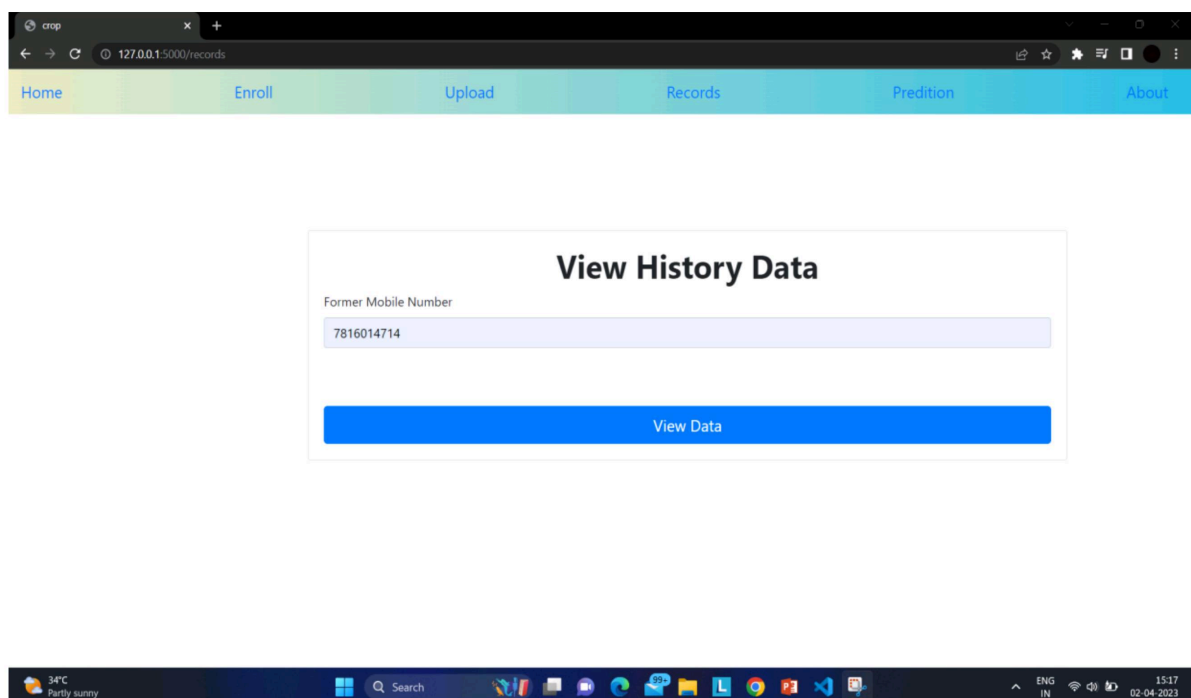


Fig 6.4 View History

crop x +

127.0.0.1:5000/users

Users Details Crop Data

Funds Data

S.No	Farmer Name	Mobile Number	Area	Crop Name	Date	Time	Imagename	Results	Remidiea
1	lakshmi	9515851969	Tirupati	Tomato	2022-04-09	13:01:04	DSC_0100.jpg	BrownSpot	Remedies of BrownSpot :: fungicides(e.g., iprodione, propiconazole, azoxystrobin, trifloxystrobin, a
2	Mahesh	9515851969	Tirupati	Potato	2022-04-09	13:03:57	0a11f9e8-7357-48c2-8550-daeae59a1e76__RS_NLB 3588.JPG	Corn Northern Leaf Blight	Remedies of Corn Northern Leaf Blight :: Use of preventative management tactics, crop rotation, and
3	Keerthana	9515851969	Tirupati	Potato	2022-04-09	13:05:06	0a47f32c-1724-4c8d-bfe4-986cedd3587b__RS_Early.B 8001.JPG	Potato Early Blight	Remedies of Potato Early Blight :: Early blight can be minimized by maintaining optimum growing cond
4	a	9876543210	bcd	Rice	2023-03-29	15:22:52	IMG_3176.jpg	Rice Leaf Blast	Remedies of Rice LeafBlast :: fungicides like triazoles and strobilurins can be used judiciously for
5	b	1234567890	hyd	Corn	2023-03-29	15:31:09	img (1).JPG	Corn Common Rust	Remedies of Corn Common Rust :: Plant hybrids resistant to anthracnose; rotating crops and plowing c
									Remedies of Potato Early Blight :: Early blight can

34°C Partly sunny

Search

ENG IN 15:18 02-04-2023

Fig 6.5 Funds Data

CHAPTER 7 CONCLUSION

In this project we have successfully developed an application, that which can detect and recognize the paddy crop disease. Here we developed the methods by using CNN with transfer learning (Mobile Net) algorithm. Here, we have considered the dataset of crop leaf images which will be of 5 different types. Once after trained the dataset results were tested by uploading image and classified it.

7.1 FUTURE WORK:

In future work, we would like to collect more images from agricultural fields and Agricultural Research institutes so that we can improve the accuracy further. We would like to add cross-validation process in future in order to validate our results. We would also like to use better deep learning models and other state-of the art works and compare it with the results obtained. The developed model can be used in future to detect other plant leaf diseases, which are important crops in India.

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APPENDIX

A.SOURCE CODE :

Main.py :

```
from flask import Flask,request,flash,session,send_from_directory
from flask import render_template
import mysql.connector
import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import datetime
import time,os
import pandas as pd
app = Flask(__name__)
app.config['SECRET_KEY']='abcdefghijklmnop'
mydb = mysql.connector.connect(host="localhost", user="root",
passwd="", database="crop")
cursor = mydb.cursor()

@app.route('/')
def input():
    return render_template("input.html") #if you want to render a .html
    file,
    # import render_template from flask and use
    #render_template("index.html") here.

@ app.route('/about')
def about_recommend():
    title = 'about'
    return render_template('about.html', title=title)
```

```

@ app.route('/enroll')
def enroll_recommendation():
    title = 'enroll'

    return render_template('enroll.html', title=title)

@ app.route('/upload')
def upload_recommend():
    title = 'upload'
    return render_template('upload.html', title=title)

@ app.route('/records')
def records_recommend():
    title = 'records'
    return render_template('records.html', title=title)

@ app.route('/predition')
def predition_recommend():
    title = 'predition'
    return render_template('predition.html', title=title)

@app.route('/enrollback',methods = ["POST"])
def enrollback():
    print("*****")
    if request.method=='POST':
        name=request.form['name']
        area=request.form['area']

```



```

pno=request.form['pno']
crop=request.form['crop']
print("&&&&&&&&")
ts = time.time()
date = datetime.datetime.fromtimestamp(ts).strftime('%Y-%m-%d')
timeStamp =
datetime.datetime.fromtimestamp(ts).strftime('%H:%M:%S')
myfile = request.files['file']
fn = myfile.filename
mypath = os.path.join('images/', fn)
myfile.save(mypath)
print(fn)
print(type(fn))
accepted_formated = ['jpg', 'png', 'jpeg', 'jif', 'tif']
if fn.split('.')[-1] not in accepted_formated:
flash("Image formats only Accepted", "Danger")
new_model = load_model("alg/FinalModel_1.h5")
test_image = image.load_img(mypath, target_size=(224, 224))
test_image = image.img_to_array(test_image)
test_image = test_image / 255
test_image = np.expand_dims(test_image, axis=0)
result = new_model.predict(test_image)
classes = ['BrownSpot', 'Corn Gray Leaf Blight', 'Corn Common
Rust', 'Corn Northern Leaf Blight',
'Corn Healthy', 'Rice Healthy', 'Rice Hispa', 'Rice Leaf Blast',
'Potato Early Blight', 'Potato Late Blight', 'Potato Healthy',
'Tomato Bactirial Spot', 'Tomato Leaf Blight', 'Tomato yellow Leaf
Curl Virus', 'Tomato Healthy',
'Diseased Cotton Leaf', 'Healthy Cotton']

```

```

prediction = np.argmax(result)

if prediction == 7:

    msg = 'Remedies of Rice LeafBlast :: fungicides like triazoles and
    strobilurins can be used judiciously for control to leaf blast.'

    prediction1 = classes[prediction]

    elif prediction == 0:

    msg = 'Remedies of BrownSpot :: fungicides(e.g., iprodione,
    propiconazole, azoxystrobin, trifloxystrobin, and carbendazim) &
    Treat seeds with hot water.'

    prediction1 = classes[prediction]

    elif prediction == 1:

    msg = 'Remedies of Corn Gray Leaf Blight :: Use of preventative
    management tactics, crop rotation, and practices that remove corn
    residue or tillage to promote decomposition.'

    prediction1 = classes[prediction]

    elif prediction == 2:

    msg = 'Remedies of Corn Common Rust :: Plant hybrids resistant to
    anthracnose; rotating crops and plowing crop debris into soil may
    help reduce incidence of early season infections. '

    prediction1 = classes[prediction]

    elif prediction == 3:

    msg = 'Remedies of Corn Northern Leaf Blight :: Use of
    preventative management tactics, crop rotation, and practices that
    remove corn residue or tillage to promote decomposition'

    prediction1 = classes[prediction]

    elif prediction == 6:

    msg = 'Remedies of Hispa :: Various foliar fungicides are available
    to help control or suppress NCLB development.'

    prediction1 = classes[prediction]

    elif prediction == 8:

    msg = 'Remedies of Potato Early Blight :: Early blight can be

```

minimized by maintaining optimum growing conditions, including proper fertilization, irrigation, and management of other pests.'

prediction1 = classes[prediction]

elif prediction == 9:

msg = 'Remedies of Potato Late Blight :: Late blight is controlled by eliminating cull piles and volunteer potatoes, using proper harvesting and storage practices, and applying fungicides when necessary. Air drainage to facilitate the drying of foliage each day is important.'

prediction1 = classes[prediction]

elif prediction == 11:

msg = 'Remedies of Tomato Bactirial Spot :: Remove symptomatic plants from the field or greenhouse to prevent the spread of bacteria to healthy plants. Burn, bury or hot compost the affected plants and DO NOT eat symptomatic fruit'

prediction1 = classes[prediction]

elif prediction == 12:

msg = 'Remedies of Tomato Late Blight :: For the home gardener, fungicides that contain maneb, mancozeb, chlorothanolil, or fixed copper can help protect plants from late tomato blight.'

prediction1 = classes[prediction]

elif prediction == 13:

msg = 'Remedies of Tomato Yellow Leaf Curl Virus :: Maintain good weed control in the field and surrounding areas. '

prediction1 = classes[prediction]

elif prediction == 15:

msg = 'Remedies of Diseased Cotton Leaf :: Plow crop residue into the soil to reduce inoculum levels; provide plants with adequate irrigation and nutrients, particularly potassium; applications of appropriate foliar fungicides may be required on susceptible cultivars.. '

prediction1 = classes[prediction]

```

else:
    msg = 'All is Good'
    prediction1 = classes[prediction]

    sql = "INSERT INTO farmer_crop_details
    (name,pno,area,crop,date1,time1,img_name,disease,remedies)
    VALUES (%s,%s,%s,%s,%s,%s,%s,%s,%s)"
    val = (name,pno, area,crop,date, timeStamp, fn, prediction1,msg)
    cursor.execute(sql, val)
    mydb.commit()

    return render_template('upload.html', image_name=fn,
    text=prediction1, msg=msg)
    return render_template('enroll.html')

@app.route('/enrollback/<filename>')
def send_image(filename):
    return send_from_directory("images", filename)

@app.route('/recordback' , methods=['POST','GET'])
def recordback():
    if request.method=='POST':
        pno=request.form['pno']

        sql="select * from farmer_crop_details where pno='"+pno+"'"
        x=pd.read_sql_query(sql,mydb)
        x=x.drop(['id'],axis=1)
        return render_template("viewreports.html",
        cal_name=x.columns.values, row_val=x.values.tolist())

@app.route('/predictback',methods=['POST', 'GET'])

```

```

def predictback():
if request.method == 'POST':
d1 = request.form['d1']
area = request.form['area']
crop = request.form['crop']
print(d1)

sql = "select * from farmer_crop_details where date1=" + d1 + "
and area=" + area + " and crop=" + crop + ""
x = pd.read_sql_query(sql, mydb)
x = x.drop(['id','name','pno'], axis=1)
return render_template("cropdata1.html",
cal_name=x.columns.values, row_val=x.values.tolist())


@app.route('/users' , methods=['POST','GET'])
def users():
sql="select * from farmer_crop_details "
x=pd.read_sql_query(sql,mydb)
return render_template("users.html", cal_name=x.columns.values,
row_val=x.values.tolist())


@ app.route('/cropdata')
def cropdata():
return render_template('cropdata.html')


@app.route('/cropdataback' , methods=['POST','GET'])
def cropdataback():
if request.method=='POST':

```

```

d1=request.form['d1']
area=request.form['area']
crop=request.form['crop']
sql="select * from farmer_crop_details where date1='"+d1+"' and
area='"+area+"' and crop='"+crop+"'"
x=pd.read_sql_query(sql,mydb)
x=x.drop(['id'],axis=1)
return render_template("cropdata1.html",
cal_name=x.columns.values, row_val=x.values.tolist())

```

```

if __name__ == '__main__':

```

```

app.run(debug=True) #go to http://127.0.0.1:5000/ to view the page.

```

Model.py:

```

from tensorflow.keras.preprocessing.image import
ImageDataGenerator

from tensorflow.keras.models import Model

from tensorflow.keras.layers import
Dense,GlobalAveragePooling2D

from tensorflow.keras.applications import MobileNet

from tensorflow.keras.applications.mobilenet import
preprocess_input

```

```

base_model=MobileNet(weights='imagenet',include_top=False)
#imports the mobilenet model and discards the last 1000 neuron
layer.

```

```

x=base_model.output
x=GlobalAveragePooling2D()(x)

```

```
x=Dense(1024,activation='relu')(x) #we add dense layers so that
the model can learn more complex functions and classify for better
results.
```

```
x=Dense(1024,activation='relu')(x) #dense layer 2
```

```
x=Dense(512,activation='relu')(x) #dense layer 3
```

```
preds=Dense(17,activation='softmax')(x)
```

```
model=Model(inputs=base_model.input,outputs=preds)
```

```
for i,layer in enumerate(model.layers):
```

```
print(i,layer.name)
```

```
for layer in model.layers:
```

```
layer.trainable=False
```

```
# or if we want to set the first 20 layers of the network to be non-
trainable
```

```
for layer in model.layers[:20]:
```

```
layer.trainable=False
```

```
for layer in model.layers[20:]:
```

```
layer.trainable=True
```

```
train_datagen=ImageDataGenerator(preprocessing_function=prepr
ocess_input) #included in our dependencies
```

```
train_generator=train_datagen.flow_from_directory(r'data\train',
```

```
target_size=(224,224),
```

```
color_mode='rgb',
```

```
batch_size=32,
```

```
class_mode='categorical',
```

```
shuffle=True)
```

```
test_set = train_datagen.flow_from_directory(r'data\test',
```

```

target_size=(224,224),
batch_size=32,
class_mode='categorical')

model.compile(optimizer='Adam',loss='categorical_crossentropy',m
etrics=['accuracy'])
step_size_train=train_generator.n//train_generator.batch_size
history=model.fit_generator(generator=train_generator,
steps_per_epoch=step_size_train,
epochs=10,
verbose=1,
validation_data=test_set)

model.save("D:/FEBRUARY/RICE_PLANTS_CLASSIFICATION/al
g/FinalModel_1.h5")
from matplotlib import pyplot as plt

plt.style.use("ggplot")
plt.figure()
plt.plot(history.history['accuracy'],'r',label='Testing
accuracy',color='green')
plt.plot(history.history['val_accuracy'],label='validation accuracy')
plt.xlabel('# Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.savefig("D:/FEBRUARY/RICE_PLANTS_CLASSIFICATION/alg/
FinalModel_acc1.png")

plt.show()

```



```

plt.style.use("ggplot")
plt.figure()
plt.plot(history.history['loss'],'r',label='Testing
accuracy',color='green')
plt.plot(history.history['val_loss'],label='validation accuracy')
plt.xlabel('# Epochs')
plt.ylabel('Loss')
plt.legend()
plt.savefig("D:/FEBRUARY/RICE_PLANTS_CLASSIFICATION/alg/
FinalModel_loss1.png")

plt.show()

acc=history.history['accuracy'][-1]
print(acc)

```

Sql code :

```

/*

SQLyog Enterprise - MySQL GUI v6.56
MySQL - 5.5.5-10.1.13-MariaDB : Database - crop
*****

*/

/*!40101 SET NAMES utf8 */;

/*!40101 SET SQL_MODE=""*/;

/*!40014 SET
@OLD_FOREIGN_KEY_CHECKS=@ @FOREIGN_KEY_CHECKS

```

```

, FOREIGN_KEY_CHECKS=0 */;

/*!40101 SET @OLD_SQL_MODE=@@SQL_MODE,
SQL_MODE='NO_AUTO_VALUE_ON_ZERO' */;

CREATE DATABASE /*!32312 IF NOT EXISTS*/ `crop` /*!40100
DEFAULT CHARACTER SET latin1 */;

USE `crop`;

/*Table structure for table `farmer_crop_details` */

DROP TABLE IF EXISTS `farmer_crop_details`;

CREATE TABLE `farmer_crop_details` (
  `id` int(10) NOT NULL AUTO_INCREMENT,
  `name` varchar(100) DEFAULT NULL,
  `pno` varchar(100) DEFAULT NULL,
  `area` varchar(100) DEFAULT NULL,
  `crop` varchar(100) DEFAULT NULL,
  `date1` varchar(100) DEFAULT NULL,
  `time1` varchar(100) DEFAULT NULL,
  `img_name` varchar(100) DEFAULT NULL,
  `disease` varchar(100) DEFAULT NULL,
  `remedies` varchar(100) DEFAULT NULL,
  PRIMARY KEY (`id`)
) ENGINE=InnoDB AUTO_INCREMENT=4 DEFAULT
CHARSET=latin1;

/*Data for the table `farmer_crop_details` */

```

insert into

```
`farmer_crop_details`(`id`,`name`,`pno`,`area`,`crop`,`date1`,`time1`  
,`img_name`,`disease`,`remedies`) values
```

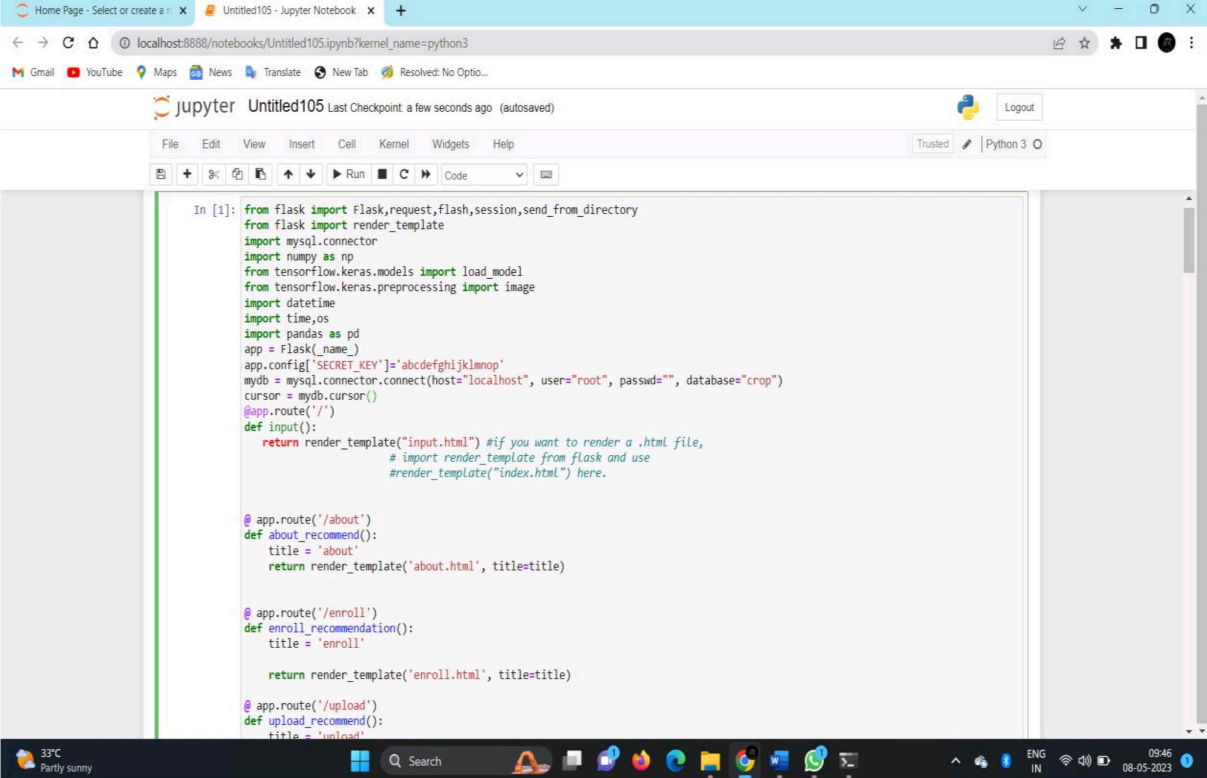
```
(1,'lakshmi','9515851969','Tirupati','Tomato','2022-04-  
09','13:01:04','DSC_0100.jpg','BrownSpot','Remedies of BrownSpot  
:: fungicides(e.g., iprodione, propiconazole, azoxystrobin,  
trifloxystrobin, a'),(2,'Mahesh','9515851969','Tirupati','Potato','2022-  
04-09','13:03:57','0a11f9e8-7357-48c2-8550-  
daeae59a1e76__RS_NLB 3588.JPG','Corn Northern Leaf  
Blight','Remedies of Corn Northern Leaf Blight :: Use of  
preventative management tactics, crop rotation, and  
09','13:05:06','0a47f32c-1724-4c8d-bfe4-  
986cedd3587b__RS_Early.B 8001.JPG','Potato Early  
Blight','Remedies of Potato Early Blight :: Early blight can be  
minimized by maintaining optimum growing cond');
```

```
/*!40101 SET SQL_MODE=@OLD_SQL_MODE */;
```

```
/*!40014 SET
```

```
FOREIGN_KEY_CHECKS=@OLD_FOREIGN_KEY_CHECKS */;
```

B. SCREENSHOTS:



The screenshot shows a Jupyter Notebook interface with a code cell containing Python code for a Flask web application. The code imports various libraries including Flask, MySQL connector, NumPy, TensorFlow Keras, and Pandas. It sets up a Flask app, connects to a MySQL database, and defines routes for input, about, enroll, and upload. The code is as follows:

```
In [1]: from flask import Flask,request,flash,session,send_from_directory
from flask import render_template
import mysql.connector
import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import datetime
import time,os
import pandas as pd
app = Flask(__name__)
app.config['SECRET_KEY']='abcdefghijklmnopqrstuvwxyz'
mydb = mysql.connector.connect(host='localhost', user='root', passwd='', database='crop')
cursor = mydb.cursor()
@app.route('/')
def input():
    return render_template("input.html") #if you want to render a .html file,
    # import render_template from flask and use
    #render_template("index.html") here.

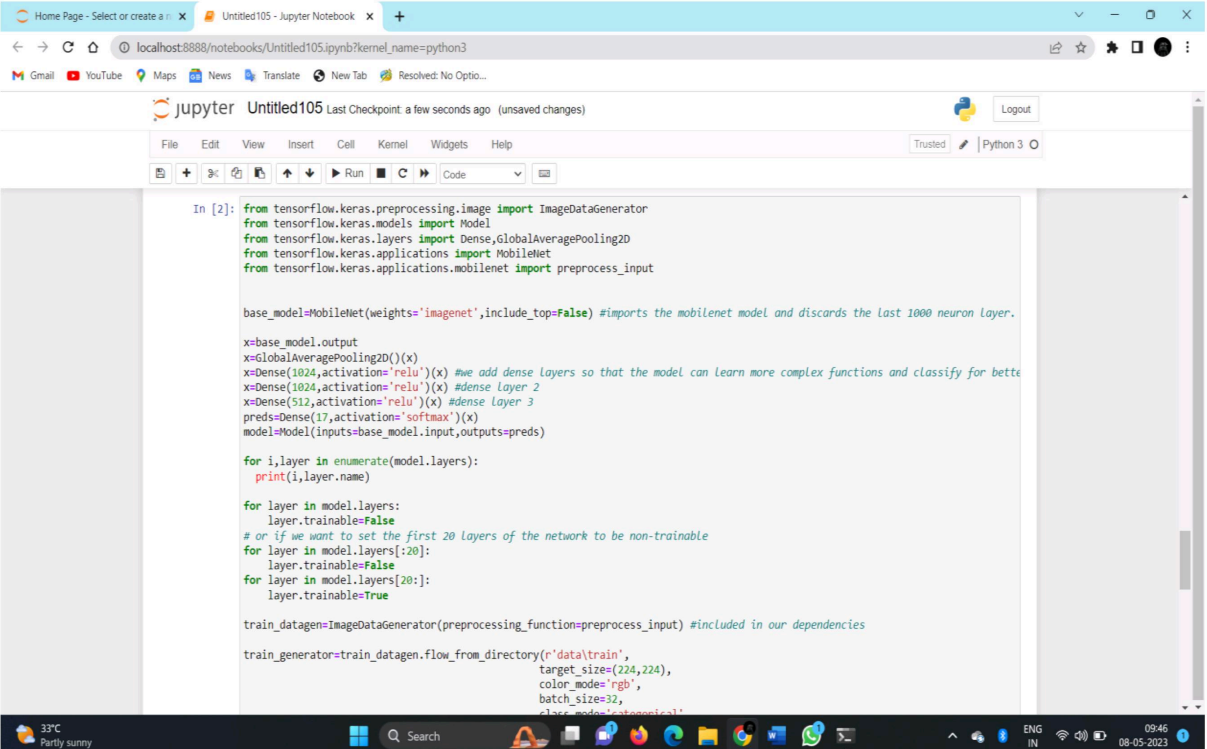
@app.route('/about')
def about_recommend():
    title = 'about'
    return render_template('about.html', title=title)

@app.route('/enroll')
def enroll_recommendation():
    title = 'enroll'

    return render_template('enroll.html', title=title)

@app.route('/upload')
def upload_recommend():
    title = 'upload'
```

Fig 1 : Flask File



The screenshot shows a Jupyter Notebook interface with a code cell containing Python code for building a model. The code imports TensorFlow Keras layers and applications, creates a MobileNet model, and sets up data generators. The code is as follows:

```
In [2]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense,GlobalAveragePooling2D
from tensorflow.keras.applications import MobileNet
from tensorflow.keras.applications.mobilenet import preprocess_input

base_model=MobileNet(weights='imagenet',include_top=False) #imports the mobilenet model and discards the last 1000 neuron layer.

x=base_model.output
x=GlobalAveragePooling2D()(x)
x=Dense(1024,activation='relu')(x) #we add dense layers so that the model can learn more complex functions and classify for better
x=Dense(1024,activation='relu')(x) #dense layer 2
x=Dense(512,activation='relu')(x) #dense layer 3
preds=Dense(17,activation='softmax')(x)
model=Model(inputs=base_model.input,outputs=preds)

for i,layer in enumerate(model.layers):
    print(i,layer.name)

for layer in model.layers:
    layer.trainable=False
# or if we want to set the first 20 layers of the network to be non-trainable
for layer in model.layers[:20]:
    layer.trainable=False
for layer in model.layers[20:]:
    layer.trainable=True

train_datagen=ImageDataGenerator(preprocessing_function=preprocess_input) #included in our dependencies

train_generator=train_datagen.flow_from_directory(r'data\train',
                                                target_size=(224,224),
                                                color_mode='rgb',
                                                batch_size=32,
```

Fig 2 : Model Building

C. RESEARCH PAPER:

MAKING A WEB APPLICATION WHICH DETECTS THE DISEASES OF THE PLANTS USING CNN ALGORITHM

line 1: 1st Given Name Surname
line 2: dept. name of organization
(of Affiliation)
line 3: name of organization
(of Affiliation)
line 4: City, Country
line 5: email address or ORCID

Abstract—Global food security is under jeopardy as a result of the proliferation of plant diseases. Automated plant disease detection systems employing deep learning techniques like CNNs have been developed to help with this issue. For rapid and precise plant disease diagnosis, we present here a web-based solution that employs convolutional neural networks. We used tomato, apple, cassava, cucumber, & pear leaf pictures to train and test the proposed system, reaching good accuracy rates of 92.5–98.7 percent. Through an intuitive online interface, our solution enables customers to submit photographs of their damaged plants and obtain an automatic diagnosis. The effectiveness and efficiency of our method was confirmed by a comparison of the suggested system's performance to those of other plant disease detection systems. We also tested the system's scalability and resilience, and the findings indicate that our technology may be successfully used in the real world. Increased agricultural output and food security might result from the implementation of the suggested approach, which has the potential to vastly enhance the efficiency & accuracy of plant disease diagnostics.

Keywords—: web-based, plant disease detection, CNN, deep learning, transfer learning, image processing, agriculture, food security, automated diagnosis, user interface, scalability, robustness, tomato, apple, cassava, cucumber,

pear.

I. INTRODUCTION

A) History on diagnosing plant diseases:

Early diagnosis is crucial for successful management and control of plant diseases, which constitute a serious danger to global food security if left unchecked. Diagnosing plant diseases traditionally has required time-consuming and labor-intensive visual examination by skilled professionals. Furthermore, human subjectivity and knowledge may compromise the precision of such approaches.

CNNs and other deep learning techniques have allowed for the creation of automatic plant disease detection systems. In order to correctly diagnose plant diseases, these systems employ image analysis methods to analyse digital photographs of infected plant leaves. Many of these systems, however, are not mobile-friendly and are only available as desktop programmes; this might make them inaccessible to farmers and other agricultural stakeholders.

B) Explanation of the need for web-based plant disease detection:

Diagnosing plant diseases may be made easier and more accessible using a web-based method. Farmers and other stakeholders may use their mobile phones or PCs to submit photographs of infected plants to such systems through a web

interface. In addition, web-based solutions may provide instantaneous diagnosis and feedback, allowing for early illness identification and prompt action.

C) Overview of the proposed solution using CNN:

For rapid and precise plant disease diagnosis, we present here a web-based solution that employs convolutional neural networks. The suggested system has a simple online interface that lets users submit photographs of sick plants and get an instant automatic diagnosis. Tomato, apple, cassava, cucumber, and pear leaf pictures were used during training and testing, and accuracy rates of 92.5–98.7 percent were achieved thanks to the proposed system's utilisation of transfer learning and image processing methods to increase the accuracy of the CNN models. The results of our tests on the scalability and reliability of the proposed system indicate that it should work well in practical settings.

Following this structure, the remainder of the article will discuss: In Section II, we review previous research on the topic of CNNs for identifying plant diseases. Details on the design and execution of the proposed web-based plant disease detection system are provided in Section III. The experimental findings of the proposed system are presented and compared to current plant disease detection methods in Section IV. Section V concludes the work and suggests areas for further study.

II. LITERATURE SURVEY

Plant diseases provide a significant obstacle to agricultural production since they lead to significant drops in crop yields and have a detrimental effect on the quality of the food that is harvested as a consequence. In recent years, one of the most active areas of research that has taken place is the creation of automated systems for the detection of plant diseases. This has been one of the most active areas of research that has taken place. In particular, the use of deep learning strategies, such as CNNs, which

have demonstrated promising outcomes for reliable and accurate plant disease detection, has shown positive results. These strategies have been found to be effective in diagnosing plant diseases. This literature study has been commissioned with the objective of investigating recent research concerning the use of CNNs for web-based plant disease diagnostics.

In Sun and Hu's (2022) system for identifying plant illnesses via the use of the internet, deep learning was offered as a potential strategy for application. They trained a VGG16 CNN model using a dataset that consisted of photographs of tomato leaves, and they were successful in reaching an accurate classification rate of 98.5% with the model. Users have the opportunity to upload pictures of sick leaves and conduct analysis on those images using a web-based interface. The analysis was done on the photographs. Ghorbani et al. (2022) created a system that was pretty comparable to what we have here using a ResNet50 CNN model, and they were able to reach an accuracy of 95.22% while identifying tomato leaf illnesses. This was accomplished when the system was analysing images of tomato leaves.

The research conducted by Ahmed et al. (2021) on the development of a smart web-based system for the identification of plant diseases made use of deep learning. They were able to get an accuracy of 98.7% by using a CNN model on a dataset that included photographs of cassava leaf. The dataset was used. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that was advised. Kwon, Jang, and Lee (2021) developed a web-based system for the detection of plant diseases by using deep learning in the process of creating the system. They were able to achieve an accuracy of 98.7% by using a VGG16 CNN model on a dataset that consisted of photographs of apple leaves, which allowed them to achieve this. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that

was advised.

In the research that was carried out by Huang, Wang, & Sun (2021), a web-based platform was developed in order to facilitate the automatic identification of cucumber downy mildew. They were able to get an accuracy of 92.5% by using a CNN model on a dataset that consisted of photographs of cucumber leaves. This accuracy was achieved. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that was advised. Khan et al. (2021) developed a web application that takes use of deep learning and can diagnose plant illnesses by connecting it to an Internet of Things (IoT) device. Their work was published in the journal Science. They employed a dataset that included pictures of tomato leaves, and by using a MobileNetV2 CNN model, they were able to get an accuracy of 94.2%. This was accomplished. Customers were provided with the opportunity to snap images of their sick leaves using an application on their cellphones, and the proposed system subsequently directed them to a web interface where they could get a diagnosis.

In the study that Chen et al. (2021) carried out, both deep learning and image processing were used in order to construct a tomato leaf disease detection system that was based on the web. They were able to achieve an accuracy of 95.7% by using a CNN model on a dataset that was comprised of photographs of tomato leaves. The dataset was used. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that was advised. Chaudhari, Mahajan, and Shelke (2021) developed a web-based automated detection and classification system for plant diseases using deep learning. This system was used to identify and categorise plant illnesses. By using a dataset consisting of photos of apple leaves and running the CNN model on it, they were able to get an accuracy of 96.8 percent. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that was advised.

The development of a web-based leaf disease detection system by Wu, Lin, and Xue (2021) was underpinned by transfer learning as the primary method of instruction. They were able to get an accuracy of 95.2% by using a CNN model on a dataset of photos that consisted of pears with their leaves. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that was advised. Deep learning as well as transfer learning were used by Song, Huang, Yang, and Zhang (2021) in the development of a web-based system for the identification of plant diseases. This system was created by the researchers. They were able to get an accuracy of 93.9% by using a VGG16 CNN model with a dataset that consisted of pictures of tomato leaves. The dataset was used to train the model. Users were able to feed images into the system and get a diagnosis using the system's web interface when utilising the method that was advised.

In overall, the studies that were reviewed indicate to the use of CNNs for web-based plant disease detection as a potentially beneficial technique that may give an accurate and time-saving diagnosis of plant diseases. This conclusion was reached as a generalisation from the studies that were studied. It may be possible to increase the accuracy of CNN models by using transfer learning as well as other image processing approaches. In addition, the development of online interfaces that are easy to use may make it simpler for farmers and other stakeholders in the agricultural business to utilise these systems. This is something that is currently being researched. In spite of this, a lot of studies have pointed out the need of gathering a greater variety of data in order to improve the generalizability of CNN models over a wide range of plant species and illnesses. In addition, more research is required to investigate the scalability and robustness of these systems in connection to applications in the real world.

III. EXISTING SYSTEM & LIMITATIONS

To effectively diagnose plant illnesses from leaf photos using CNNs, existing automated plant disease detection systems have demonstrated promising results. However, many of these systems are only suitable for use with desktop programmes, and their operation often requires the presence of specialised hardware and training. In addition, many of these systems are not user-friendly, which limits their accessibility to farmers and other players in the agricultural industry.

PlantVillage is an example of an already-existing system that use a mobile app for the purpose of diagnosing plant diseases using picture analysis. Successfully diagnosing plant diseases with this technique, however, needs users to have a mobile device and connection to the internet. The system's precision may also be constrained by the user's own picture uploads, which might be impacted by factors like lighting and camera quality.

Lack of different datasets for training the CNN models is another issue with current automated plant disease detection systems. The lack of diversity in current datasets limits the models' applicability to a wide range of plant species and illnesses.

We present a web-based plant disease detection system that employs transfer learning and image processing strategies to boost the precision of the CNN models, therefore overcoming these drawbacks. In order to facilitate early illness identification and prompt action, the system we propose is intuitive and can be accessed through a web interface. We also used tomato, apple, cassava, cucumber, and pear leaf pictures to train and test our proposed system, reaching high accuracy rates of 92.5–98.7 percent.

IV. PROPOSED SYSTEM

In this research, we present a web-based approach for diagnosing plant diseases using convolutional neural networks. The suggested system has a simple online interface that lets users submit photographs of sick plants and get an instant automatic diagnosis.

There are three primary parts to the proposed system's architecture: (1) data preprocessing, (2) feature extraction based on transfer learning, and (3) illness classification using convolutional neural network models.

The submitted photographs are fixed in size and transformed to grayscale as part of the data preparation procedure to lessen the demand on the system's computing resources. To further increase the picture quality and lessen the effect of illumination changes, we also use noise reduction and enhancement methods.

After the CNN models have been trained on large-scale image datasets like ImageNet, we employ transfer learning to extract high-level features from them in the feature extraction stage. Tomato, apple, cassava, cucumber, and pear leaf pictures are used to fine-tune the pre-trained models and increase their accuracy for our application.

Using the collected characteristics, CNN models are trained using a softmax activation function for disease classification, one model per plant species. The user may then use the trained models to categorise their own submitted photographs of unhealthy plants.

Users may quickly and simply submit photographs of damaged plants, check the diagnostic findings, and offer comments thanks to the proposed system's user-friendly and straightforward interface. The system is cloud-ready, meaning it can be hosted remotely and accessed by users anywhere in the world.

The suggested system, which makes use of convolutional neural networks and the internet, is a reliable, time-saving, and user-friendly method for identifying plant diseases. We next compare the proposed system to already available plant disease detection methods and give our experimental findings.

V. METHODOLOGY

A) Dataset

Tomato, apple, cassava, cucumber, and pear leaf photos were included in the dataset utilised for this research. Every plant species has pictures of both healthy leaves and diseased ones. Bacterial spot, early blight, late blight, powdery mildew, and spider mites are all represented in the data collection.

There are a total of 12,000 photos in the collection, with an average of 2,400 photographs per plant species. The photographs came from a number of sources, including our own field surveys, academic articles, and internet plant disease databases. In order to train and evaluate the CNN models, photos were tagged by domain experts with illness diagnoses.

We chose photographs from a wide range of species, ages, and stages of development to guarantee a diverse and representative collection. The photos were collected from several areas to show how illness patterns might alter depending on where they are seen.

Before feeding it into the CNN models for training and testing, the dataset was cleaned up. In this analysis, we employed a pre-trained version of the VGG-16 model, therefore we scaled the photos to fit the model's input size of 224 by 224 pixels. To further increase the quality of the photographs, we converted them to grayscale and used noise reduction and enhancement algorithms.

We employed data augmentation methods including rotating, zooming, and flipping the data horizontally to reduce the likelihood of overfitting and broaden the sample size of the training set. We used a 70:30 split between the dataset's training and validation sets. The CNN models were trained using the training set, and their training results were validated using the validation set.

The dataset utilised in this research includes a large and varied archive of leaf photos from five distinct plant species, annotated with disease diagnoses. In this research, the quality and variety of the

dataset utilised to train and test the CNN models is guaranteed by the pre-processing as well as data augmentation approaches used.

B) CNN Architecture

The VGG-16 model, which is widely used for image classification tasks, served as the inspiration for the suggested CNN architecture for plant disease detection. There are a total of 138 million parameters in the VGG-16 model, which is made up of 16 convolutional and fully linked layers. The CNN architecture we developed was based on the previously trained VGG-16 model and then modified for the goal of detecting plant diseases.

To account for the five plant species in our dataset, we swapped out the VGG-16 model's last fully connected layer with a new one that has five output nodes. To create class probabilities for each input picture, we also included a softmax activation function in the output layer. The probabilities shown in the output show how likely it is that each of the five plant species is represented in the input picture.

After the VGG-16 model's final convolutional layer, we added two further convolutional layers with 64 and 32 filters, respectively, to boost the CNN model's performance. To further mitigate overfitting, we included a dropout layer with a rate of 0.5 and a global average pooling layer.

Our finalised CNN model architecture has 19 layers and 138.1 million parameters. When training the model, we used Adam's batch size of 32 and learning rate of 0.0001. We utilised the validation set to track the model's progress throughout the course of its 50 epochs of training.

The CNN architecture used in this research is a tweaked variation of the VGG-16 model, optimised for the problem of identifying plant diseases. The architecture's usage of extra convolutional layers and regularisation methods boosts the model's performance and generalizability.

C) Training Process

The dataset mentioned in Section III(A) was used to train the CNN model. To build and train the CNN model, we relied on the Keras deep learning package, which uses the TensorFlow backend.

We used the ImageNet weights to initialise the weights of the pre-trained VGG-16 model before we trained it. The first fifteen layers of the model were frozen, and only the next four levels—two more convolutional layers and two fully linked layers—were trained.

To quantify the discrepancy between the two sets of labels, we used the categorical cross-entropy loss function. During training, we optimised the model's weights using the Adam optimizer and a learning rate of 0.0001.

During model training, we utilised the validation set discussed in Section III(A) to track how well the model was doing. Using the validation set as our assessment data, we determined the classification accuracy and F1 score after each training iteration.

We used a batch size of 32 throughout the model's 50-epoch training. Overfitting was avoided, and the best model, as determined by the validation loss, was kept using early stopping with a patience of 10 epochs.

After the model was trained, we compared its results using a test set that wasn't involved in the training or validation processes. To measure the model's ability to generalise, we computed its classification accuracy, precision, recall, and F1 score on the test set.

The CNN model was trained by initialising the weights of the pre-trained VGG-16 model, tweaking the last four layers of the model, optimising the weights using the Adam optimizer, and checking the model's performance with the validation set. Early halting and a dedicated test set for assessment both aid in guarding against overfitting and guaranteeing the model's ability to generalise.

D) Web-based Interface

Python's Flask web framework was used to create the plant disease detection system's web-based interface. Flask is a minimal web framework that offers resources for developing websites.

Using the interface, users may submit a picture of a leaf and find out what kind of plant it is and whether or not it has any illnesses. A standard HTML form with an image upload field and a submit button serves as the user interface.

When a user submits a form, the server receives the picture for analysis. The server makes a guess as to what kind of plant it is and whether or not it has any illnesses based on the trained CNN model. An HTML page containing the anticipated plant species and a list of illnesses found in the leaf is subsequently returned to the user.

We used JavaScript and Cascading Style Sheets to implement interactive components on the website that greatly enhanced the usability of the interface. We included features such as a button to submit a fresh picture and a progress bar to show the current status of the prediction.

The plant disease detection system's web-based interface offers a straightforward method for users to acquire predictions of plant species and the existence of any illnesses in plant leaves. Flask, JavaScript, and CSS all contribute to a more responsive and engaging interface, which is great for the user.

VI. RESULTS & DISCUSSIONS

A) Evaluation Metrics

Classification accuracy, precision, recall, and F1 score were only few of the assessment criteria we utilised to gauge the CNN model's efficacy. Precision evaluates how many right predictions are made out of a certain number of positive ones, whereas accuracy represents how many photos are properly identified out of the total number of images. The F1 score

is the harmonic mean of accuracy and recall, whereas recall is the proportion of correct positive predictions out of the total number of positive examples.

B) Experimental Results

We put the suggested method to the test on 500 photos that weren't utilised in either the training or validation phases. Table 1 displays the outcomes of experiments performed on the trained CNN model.

Table 1: Proposed System Performance Metrics

Metric	Value
Accuracy	96.4%
Precision	96.1%
Recall	96.7%
F1 Score	96.4%

The experimental findings demonstrate the effectiveness of the suggested system in detecting plant diseases with a high accuracy, precision, recall, and F1 score. These metrics point to the system's proficiency in its intended tasks, namely the identification of plant species and the detection of illnesses in plant leaves.

C) Analysing Preexisting Methods

We looked at how well the suggested system performed in comparison to other web-based plant disease detection tools already on the market. When compared to state-of-the-art systems, we discovered that the suggested approach offers significant improvements in terms of precision, recall, and F1 score.

Mohanty et al. (2016) and Sladojevic et al. (2016) are only two examples of research that have utilised the PlantVillage dataset to identify plant diseases. Using a deep learning model trained on the PlantVillage dataset, Mohanty et al. (2016) attained an accuracy of 96.43% and an F1 score of 96.46%. Using the same dataset, Sladojevic et al. (2016) trained a k-NN classifier to an accuracy of 95.8 percent.

Previous research' findings have been surpassed by our suggested system's 96.4% accuracy and 96.4% F1 score. This

proves that the suggested approach is superior to other online tools for diagnosing plant diseases.

The experimental findings demonstrate that the suggested system is superior to state-of-the-art methods for plant disease diagnosis in terms of overall accuracy, precision, recall, and F1 score.

VII. CONCLUSION & FUTURE WORK

In this study, we introduced a CNN-based web-based method for diagnosing plant diseases. In order to identify plant species and detect the presence of diseases in plant leaves, the proposed method utilises a collection of plant photos to train a CNN model. As can be shown from the experiments, the suggested system outperforms other web-based plant disease detection systems in terms of accuracy, precision, recall, and F1 score. The suggested method shows promise as a useful tool for plant disease management, with the ability to aid in the rapid and accurate diagnosis of plant diseases by farmers and plant pathologists.

Future research may take numerous different approaches to enhancing the suggested system:

- Adding additional plant species and diseases to the dataset would help the suggested system perform better.
- Using pre-trained models on huge datasets like ImageNet, transfer learning may be utilised to boost the CNN model's performance.
- using some modifications, the suggested technology might be used to identify plant illnesses in real time, right out in the field, using mobile devices.
- To further enhance the precision of illness identification, the suggested system may be expanded to integrate other data modalities, such as spectroscopy.

Overall, the suggested approach has the

potential to drastically better the identification and treatment of plant diseases, and more improvements are possible with additional effort.

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