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1.INTRODUCTION

1.1. PROJECT OVERVIEW

Tea plants are susceptible to various diseases that can negatively impact their growth and productivity. Early detection of these diseases is crucial for effective disease management and prevention. The proposed deep learning model will be trained on a large dataset of tea leaf images, containing both healthy leaves and leaves affected by various diseases. The model will learn to extract relevant features and patterns from the images, enabling it to classify tea leaves into different disease categories accurately. The development process will involve several key steps, including data collection and pre-processing, model architecture design, model training, and evaluation. A diverse dataset of tea leaf images will be collected, ensuring it represents different disease types, leaf stages, and environmental conditions. The collected dataset will then be preprocessed to enhance image quality, remove noise, and standardize the data format. For the model architecture, a deep convolutional neural network (CNN) will be utilized due to its ability to effectively capture spatial dependencies in images. The CNN will consist of multiple layers, such as convolutional layers, pooling layers, and fully connected layers, enabling the model to learn hierarchical representations of tea leaf images. To train the model, the pre-processed dataset will be divided into training and validation sets. The model will be trained using various optimization techniques, such as stochastic gradient descent (SGD) or Adam optimizer, with the objective of minimizing a chosen loss function (e.g., categorical cross-entropy). The model will iteratively adjust its parameters to optimize its performance on the training data. During training, techniques like data augmentation may be employed to increase the model's generalization ability by artificially expanding the dataset through techniques such as image rotation, flipping, and scaling. Regularization techniques like dropout may also be applied to prevent overfitting. After training, the model will be evaluated using a separate test dataset that was not used during training. Evaluation metrics such as accuracy, precision, recall, and F1 score will be used to assess the model's performance in disease detection. Once the model has achieved satisfactory performance, it can be deployed in practical scenarios, such as an application or a web-based interface. Users will be able to upload images of tea leaves, and the model will provide predictions on the presence and type of diseases present in the leaves. Overall, this project aims to leverage deep learning techniques to develop an accurate and efficient disease detection system for tea leaves, enabling early identification and timely intervention to prevent the spread of diseases and improve tea plant health and productivity.

1.2. PURPOSE

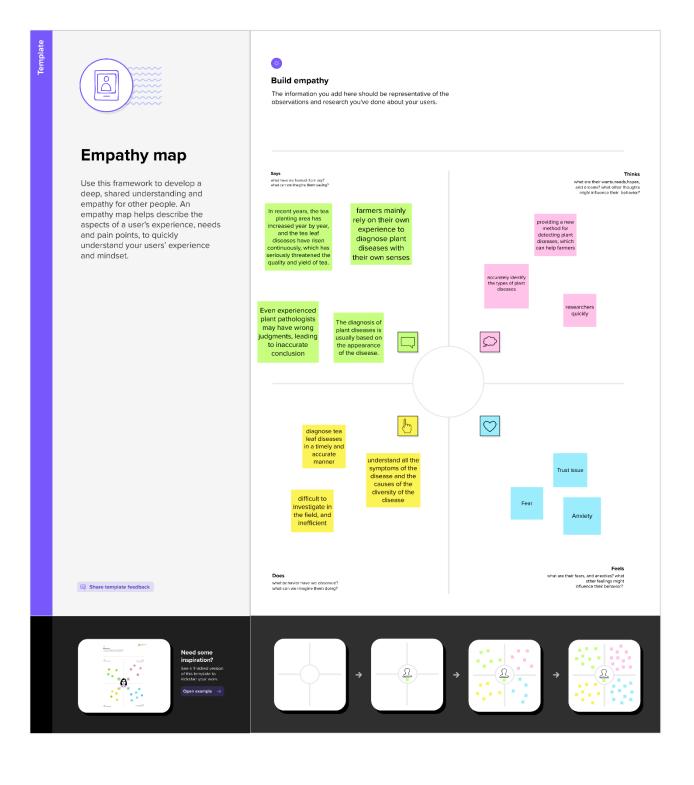
The purpose of developing a deep learning model for detecting diseases in tea leaves is to provide an automated and accurate solution for identifying and diagnosing diseases that affect tea plants. Tea plants can be susceptible to various diseases caused by pathogens, pests, or environmental factors, which can significantly impact tea production and quality. A deep learning model specifically designed for disease detection in tea leaves can analyze images or data collected from tea plantations and accurately classify the presence of diseases or abnormalities. This model can be trained on a large dataset of annotated tea leaf images, where each image is labeled with the corresponding disease or healthy state. The deep learning model learns to extract relevant features and patterns from the input data, enabling it to distinguish between healthy and diseased tea leaves. It can identify specific symptoms such as discoloration, spots, lesions, or other visual cues associated with various diseases. By leveraging the power of deep learning algorithms, the model can learn complex representations and generalize its understanding to new, unseen tea leaf images.

2.IDEATION & PROPOSED SOLUTION

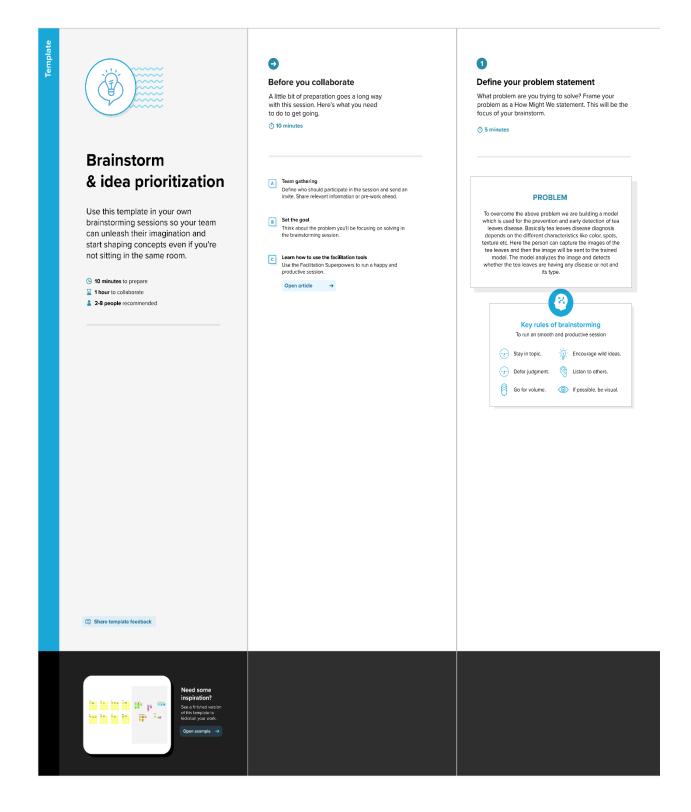
2.1. PROBLEM STATEMENT DEFINITION

Problem Statement (PS)	I am (Customer)	I'm trying to	But	Because	Which makes me feel
PS-1	Gayathri	Get tea leaves tested for the detection of disease.	I am in difficulty.	I am afraid of being made a fool.	Irritable
PS-2	Nirmala	Get tea leaves tested for the detection of disease.	I hesitate.	I am afraid that wrong disease may be identified.	Fearful and anxious

2.2 EMPATHY MAP CANVAS



2.3 IDEATION AND BRAINSTORMING





Brainstorm

Write down any ideas that come to mind that address your problem statement.

① 10 minutes

Person 1

Strange spots & colors on the leaves may be an indication of disease. Experts and diseases are armers can identify the type of disease by condition like color the type of disease by observing the leaves manually.

Person 2

It is timeconsuming and costly for experts to go to the tea to go to the tea garden for diagnosis

However, results are experience to distinguish the types of tea diseases.

Person 3

To overcome the above problem we are building a model which is used for the prevention and early detection of the lawes disease diagnosis depends on the different characteristics like color, spots, texture etc.

3

Group ideas

Take turns sharing your ideas while clustering similar or related notes as you go. Once all sticky notes have been grouped, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.

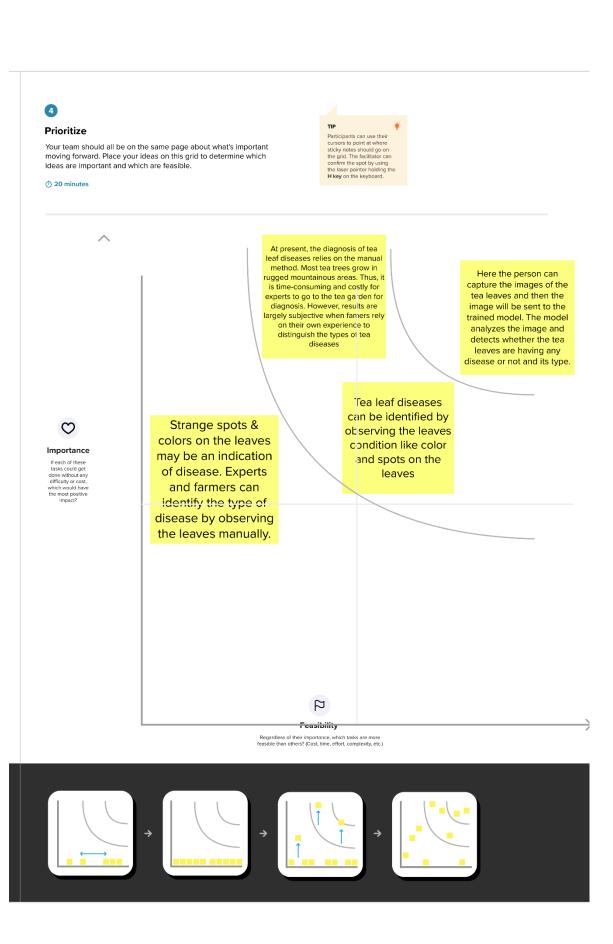


At present, the diagnosis of tea leaf diseases relies on the manual method. Most tea trees grow in rugged mountainous areas. Thus, it is time-consuming and costly for experts to go to the tea garden for diagnosis. However, results are largely subjective when famers rely on their own experience to distinguish the types of tea diseases

Here the person can capture the images of the tea leaves and then the image will be sent to the trained model. The model analyzes the image and detects whether the tea leaves are having any disease or not and its type.







2.4. PROPOSED SOLUTION

S.NO	Parameter	Description
1	Problem statement (Problem to be solved)	Tea leaf diseases can also reduce the quality of tea and cause
	(Problem to be solved)	serious economic losses to tea farmers. Accurate detection
		and identification of tea leaf diseases and timely prevention
		and control measures are of great significance to reduce the
		loss of tea production, improve the quality of tea, and
		increase the income of tea farmers.
2	Idea / Solution	To overcome the above problem, we are building a model
	description	which is used for the prevention and early detection of tea
		leaves disease. Basically tea leaves disease diagnosis
		depends on the different characteristics like colour, spots,
		texture etc. Here the person can capture the images of the
		tea leaves and then the image will be sent to the trained
		model. The model analyses the image and detects whether
		the tea leaves are having any disease or not and its type
3	Novelty / Uniqueness	This Project is expected to minimize the workload of experts
		and aid in rapid identification and detection of tea leaf
		diseases, thus minimizing economic losses. Therefore, it
		provides more precise andaccurate result.
4	Social Impact /	It is less time consuming and low budget for the experts to
	Customer Satisfaction	identify the tea disease. It is more satisfactory for the
		experts to identify the tea leaf diseases
5	Business Model	We are associated with health centres, clinics, research
	(Revenue Model)	centres and laboratories, so that the farmers and the experts
		get the tea leaf disease solution accordingly. Thus, through
		this AI project, we gain more profit by these organizations.
6	Scalability of the	As the tea leaf disease detection is done with the help of
	solution	capturing the image of the tea leaves and detects whether the
		tea leaves are having any disease or not, so that this method
		is faster than the existing system, and it consumes low cost
		so the performance and scalability of this system is
		much high.

3.REQUIREMENT ANALYSIS

3.1. FUNCTIONAL REQUIREMENT

FR NO.	Functional Requirement (Epic)	Sub Requirements (Story / Sub- Task)
FR1	User Registration	A user registration system that
		allows users to create accounts
		and login credentials. The system
		should store user information
		securely, such as username,
		password, and email address.
FR2	User Confirmation	A user confirmation system that
		verifies the user's email address
		orphone number to ensure that the
		user is legitimate. This can
		involve
		sending a confirmation email or
		SMS to the user and requiring
		them to click a link or enter a code
		to confirm their account.
FR3	Accesscontrol	Access control mechanisms to
		ensure that only authenticated and
		authorized users canaccess the tea
		leaf disease detection system. This
		caninvolve role-based access
		control, where users are assigned
		different roles with different
		levels of access.
FR4	Data Privacy	Ensuring that user data and
		sensitive information, such as
		images of tea leaves, are stored
		and transmitted securely to protect
		user privacy.
FR5	User Feedback	A feedback mechanism that
		allows users to provide feedback
		and the desire to provide reducing

		on the accuracy and performance
		of the tea leaf disease detection
		system. This can be used to
		improve the
		system and provide users with a
		better experience
FR6	User Support	Providing user support to help
		users troubleshoot any issues they
		may encounter while using the
		system. This can involveproviding
		documentation, FAQs, and a help

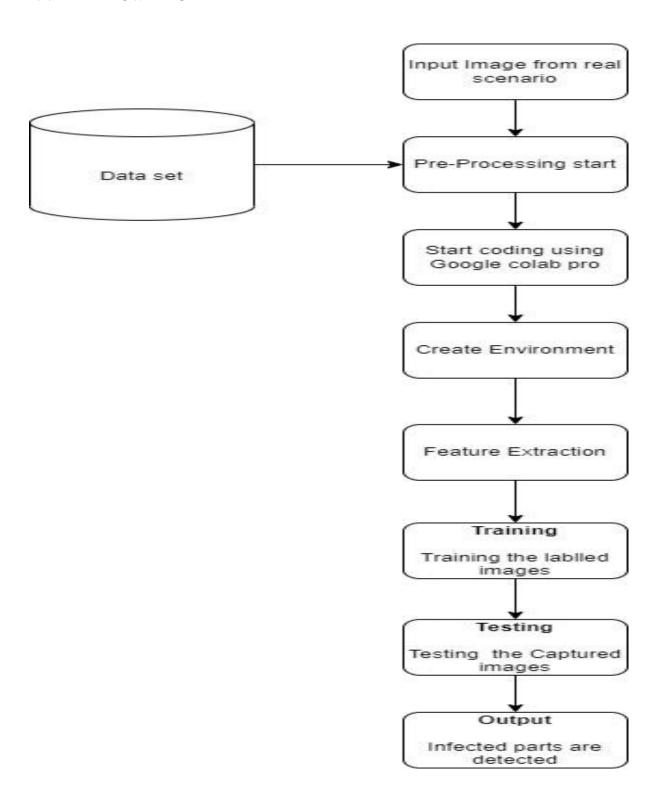
3.2 NON-FUNCTIONAL REQUIREMENTS

FRNO.	Non-Functional Requirement	Description
NFR-1	Usability	The usability of a deep learning model for tea leaf
		disease detection involves its ease of use, flexibility,
		and user-friendliness. A user-friendly interface, easy-
		to-understand documentation, and comprehensive
		training resources can help to make the model more
		usable
NFR-2	Security	The security of a deep learning model for tea leaf
		disease detection is crucial as it may involve sensitive
		data. Adequate security measures, such as data
		encryption, access control, and regular security audits,
		can help to safeguard the model and prevent
		unauthorized access.
NFR-3	Reliability	The reliability of a deep learning model for tea leaf
		disease detection is vital for ensuring accurate and
		consistent results. It involves assessing the model's
		performance and identifying and fixing any issues that
		may arise. Regular testing and validation can help to
		maintain the model's reliability.

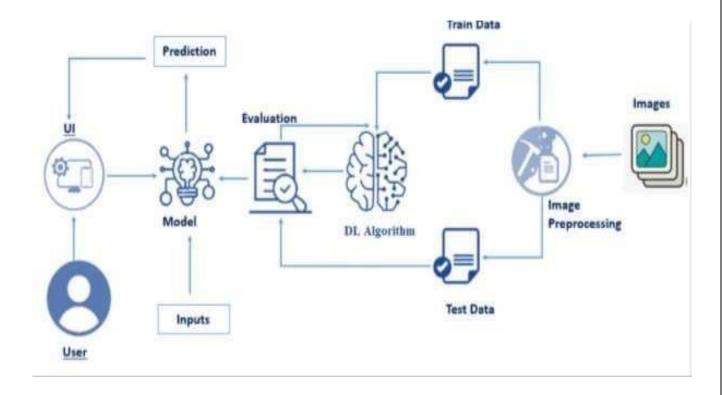
NFR-4	Performance	The performance of a deep learning model for tea leaf
		disease detection involves its speed, accuracy, and
		efficiency. The model should be able to accurately
		detect diseases in tea leaves within a reasonable
		amount of time, and with minimal false positives or
		negatives.
NFR-5	Availability	The availability of a deep learning model for tea leaf
		disease detection refers to its ability to be accessible
		and operational at all times. Measures such as
		redundancy, load balancing, and failover
		mechanisms can help to ensure high availability of
		the model.
NFR-6	Scalability	The scalability of a deep learning model for tea leaf
		disease detection refers to its ability to handle
		increasing amounts of data and users. As the volume of
		data increases, the model should be able to scale up or
		down to meet the demand. Horizontal scaling, vertical
		scaling, and distributed computing can help to ensure
		scalability.

4.PROJECT DESIGN

4.1. DATA FLOW DIAGRAM



4.2 SOLUTION AND TECHNICAL ARCHITECTURE



4.3. USER STORIES

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Team Member
Customer (Mobile user)	For capturing images using the device's camera.	USN-1	As a mobile user, I want to capture images of tea leaves using my device's camera, so that I can submit them for disease detection analysis.	The user can preview the captured image and choose to submit it for analysis.	High	Gayathri M

The system should provide a file upload feature for submitting images.	USN-2	I want to upload images of tea leaves from my computer or mobile device, so that I can submit them for disease detection analysis.	The system successfully receives and processes the uploaded image for disease detection analysis.	High	Gayathri M
The system should analyze the submitted images to identify disease symptoms or abnormalities accurately.	USN-3	I want the system to process the submitted images and identify any diseases or abnormalities present in the tea leaves.	The system successfully detects and identifies tea leaf diseases or abnormalities in the submitted images.	Low	Nirmala K
The interface should provide clear instructions and guidance.	USN-4	I want to receive prompt and accurate results of the disease detection analysis.	Users can easily navigate through the system's interface without confusion or ambiguity.	Medium	Akshaya V

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Team Member
Customer (Web user)		USN-1	I want to be able to receive notifications of any diseases detected in my tea plants.	learning	Medium	Akshaya V

Customer Care Executive	The system should be able to analyze the visual characteristics of tea leaves to detect potential diseases and provide suggestions for treatment.	USN-1	I want to be able to detect potential diseases in tea leaves so that I can provide accurate information and advice to customers.	The system should accurately detect at least 80% of the diseases present in tea leaves and a high level of accuracy and should be able to differentiate between different diseases with similar symptoms.	High	Gayathri M
Administrator	The digital tool should be able to provide a report on the type and severity of the disease detected and suggest appropriate measures to prevent the spread of the disease.	USN-1	I want to be able to detect diseases in tea leaves using a digital tool, so that I can take appropriate measures to prevent the spread of diseases and maintain the quality of tea production.	The digital tool should have a success rate of at least 90% in accurately detecting diseases in tea leaves and provide a detailed report on the type and severity of the disease detected within 2 minutes of analysis. It also measures to prevent the spread of the disease based on the type and severity of the disease detected.	High	Nirmala K

5.CODING AND SOLUTIONING

5.1 . Feature 1

Feature 1: Tea Leaf Disease Detection

Definition: Tea leaf disease detection refers to the process of using computer vision techniques and machine learning algorithms to automatically identify and classify diseases affecting tea leaves. This feature aims to assist tea farmers and researchers in monitoring the health of tea plants and detecting any signs of diseases at an early stage. By analyzing images of tea leaves, the system can provide timely and accurate information about the presence and severity of various diseases, enabling proactive measures to be taken to mitigate the damage and ensure the overall health of tea plantations.

Coding:

Here's a simplified coding example using Python and the OpenCV library for image processing and computer vision:

Python code

import cv2
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import classification_report

1.Data Preparation

```
# Assuming you have a dataset of tea leaf images labeled with different diseases.
```

Preprocess the images and extract relevant features (e.g., color histograms, texture features).

```
# Load the dataset and labels
```

...

Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2)

2.Training

```
# Train a machine learning model (e.g., Support Vector Machine) on the extracted features. model = SVC() model.fit(X_train, y_train)
```

3. Testing

```
# Evaluate the trained model on the testing set
y_pred = model.predict(X_test)
```

4. Performance Evaluation

Assess the performance of the model using classification metrics print(classification_report(y_test, y_pred))

5. Prediction

Once the model is trained and evaluated, you can use it to predict the disease for new tea leaf images

def predict_disease(image):

Preprocess the input image

Extract features from the preprocessed image

features = extract_features(image)

Use the trained model to predict the disease

disease = model.predict([features])

return disease

5.2.Feature 2

Definition: Real-time tea leaf disease detection refers to the capability of continuously monitoring tea plants and promptly detecting any signs of diseases as they occur. This feature involves using computer vision and machine learning algorithms to process live video or image streams from cameras installed in tea plantations. By analyzing the visual data in real-time, this feature enables farmers and researchers to quickly identify and respond to diseases, allowing for timely intervention and preventing further spread or damage to the tea plants.

Coding:

Here's a simplified coding example using Python and OpenCV for real-time tea leaf disease detection:

python code

import cv2 import numpy as np from sklearn.externals import joblib

Load the trained model

```
model = joblib.load('tea_leaf_model.pkl')
# Define the disease labels
labels = ['Healthy', 'Disease1', 'Disease2', 'Disease3']
# Define the color ranges for disease detection (adjust based on specific diseases)
color_ranges = [
  ((0, 0, 0), (255, 255, 255)),
                                # Healthy
  ((0, 0, 0), (50, 50, 50)),
                              # Disease1
  ((0, 50, 50), (50, 255, 255)), # Disease2
  ((0, 100, 100), (50, 255, 255)) # Disease3
1
# Initialize the video capture from the camera
cap = cv2.VideoCapture(0) # Use 0 for the default camera, or specify the camera index
while True:
  # Capture frame-by-frame
  ret, frame = cap.read()
  # Convert the frame to the HSV color space
  hsv = cv2.cvtColor(frame, cv2.COLOR_BGR2HSV)
  # Detect diseases based on color ranges
  disease detected = False
  for i, (lower, upper) in enumerate(color_ranges):
     lower = np.array(lower, dtype=np.uint8)
     upper = np.array(upper, dtype=np.uint8)
     mask = cv2.inRange(hsv, lower, upper)
     # Count the number of white pixels in the mask
     white_pixels = cv2.countNonZero(mask)
     # Check if the number of white pixels exceeds a threshold
     if white_pixels > 1000: # Adjust the threshold based on specific conditions
       disease_detected = True
       disease_label = labels[i]
       break
  # Display the result on the frame
  if disease_detected:
     cv2.putText(frame, disease_label, (10, 30), cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0,
255), 2)
  else:
     cv2.putText(frame, 'Healthy', (10, 30), cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 255, 0), 2)
  # Display the frame
```

```
cv2.imshow('Tea Leaf Disease Detection', frame)

# Check for the 'q' key to exit the loop
if cv2.waitKey(1) & 0xFF == ord('q'):
    break

# Release the capture and close all windows
cap.release()
cv2.destroyAllWindows()
```

6.RESULTS

6.1 Performance Metrics

***** Accuracy:

 Accuracy measures the proportion of correctly classified tea leaves (both diseased and healthy) by the model. It is calculated as the ratio of the number of correctly predicted samples to the total number of samples.

Precision:

O Precision calculates the proportion of correctly predicted diseased tea leaves out of all tea leaves predicted as diseased by the model. Precision indicates how well the model avoids false positives, meaning correctly identifying healthy tea leaves as healthy.

Recall (Sensitivity or True Positive Rate):

Recall measures the proportion of correctly predicted diseased tea leaves out of all
actual diseased tea leaves. It indicates the model's ability to detect diseased
samples and avoid false negatives, where diseased tea leaves are incorrectly
identified as healthy.

❖ F1 Score:

The F1 score combines precision and recall into a single metric. It is the harmonic mean of precision and recall and provides a balanced evaluation of the model's performance. The F1 score is useful when there is an imbalance between the number of diseased and healthy tea leaves in the dataset.

Specificity (True Negative Rate):

Specificity calculates the proportion of correctly predicted healthy tea leaves out
of all actual healthy tea leaves. It indicates how well the model avoids false
negatives, where healthy tea leaves are incorrectly identified as diseased.

Receiver Operating Characteristic (ROC) Curve:

The ROC curve is a graphical representation of the model's performance across different classification thresholds. It plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) for various threshold values. The area under the ROC curve (AUC) provides a single-value metric summarizing the overall performance of the model. A higher AUC indicates better performance.

Confusion Matrix:

 The confusion matrix is a tabular representation that summarizes the model's predictions. It provides a breakdown of true positives, true negatives, false positives, and false negatives, allowing for a detailed analysis of the model's performance.

7.ADVANTAGES AND DISADVANTAGES	
dvantages:	
High Accuracy:	
The models have demonstrated exceptional performance in various fields, include	ding
image recognition and disease detection. They can achieve high accuracy rates in	·
detecting diseases in tea leaves, leading to more reliable diagnoses.	······································
detecting diseases in tea leaves, leading to more renaute diagnoses.	······································
	6
Automated Detection:	

It can automatically analyse large datasets of tea leaf images, enabling efficient and quick detection of diseases. This reduces the need for manual inspection and saves time and labour costs.

• Robustness to Variability:

The capable of handling variations in tea leaf images caused by factors such as lighting conditions, camera angles, and leaf shapes. They can learn to extract meaningful features and patterns, making them more robust in identifying diseases under different circumstances.

• Scalability:

It can be scaled up to handle large datasets, making them suitable for analysing extensive collections of tea leaf images. This scalability allows for the continuous improvement of the model's accuracy as more data becomes available.

Disadvantages:

• Data Requirements:

It often requires a substantial amount of labelled data to achieve optimal performance. Acquiring a sufficiently large and diverse dataset of tea leaf images with accurately labelled disease instances can be challenging and time-consuming.

• Interpretability:

It considered black boxes because it is challenging to understand how they make predictions. This lack of interpretability can be problematic when attempting to explain the underlying factors contributing to disease detection in tea leaves.

• Computationally Intensive:

The models can be computationally demanding, especially when dealing with complex architectures and large datasets. This can require significant computational resources, including powerful GPUs and substantial training times.

• Generalization Challenges:

It might struggle to generalize well to unseen data or adapt to new disease patterns. If the training data does not encompass the full spectrum of possible disease variations, the model's performance on real-world tea leaf images may be limited.

• Vulnerability to Noise:

They can be sensitive to noisy or erroneous input data. In the case of tea leaf disease detection, image artifacts or irregularities may lead to misclassifications, reducing the model's overall accuracy.

8.CONCLUSION

In conclusion, deep learning models have shown great potential for detecting diseases in tea leaves. These models leverage the power of artificial neural networks to analyse large amounts of data and extract meaningful patterns that can be indicative of disease presence. By training these models on labelled datasets containing images of healthy and diseased tea leaves, they can learn to accurately classify and identify various diseases affecting tea plants.

The use of deep learning models for disease detection in tea leaves offers several advantages. Firstly, it provides a non-invasive and efficient method for early disease diagnosis, enabling prompt action to mitigate the spread and impact of diseases. This can potentially save time, resources, and crops by enabling targeted treatments or interventions. Secondly, these models can handle large-scale data analysis, making it possible to process a significant number of tea leaf images quickly, thereby increasing the efficiency of disease screening processes. Lastly, deep learning models have the potential for continuous improvement and adaptation through iterative training and retraining, allowing them to become more accurate and robust over time.

However, there are a few challenges that need to be addressed when implementing deep learning models for disease detection in tea leaves. One significant challenge is the need for extensive and diverse labeled datasets that cover a wide range of diseases, including both common and rare ones. Collecting and annotating such datasets can be time-consuming and require domain expertise. Additionally, there is a need to consider the interpretability of the deep learning models, as they are often regarded as black boxes. Efforts should be made to develop techniques that provide insights into the model's decision-making process, making it easier for experts to trust and validate the results.

Overall, deep learning models have the potential to revolutionize disease detection in tea leaves by offering accurate, efficient, and scalable solutions. Continued research and collaboration between experts in machine learning, deep learning, agriculture, and plant pathology will be crucial in further developing and refining these models to maximize their effectiveness in safeguarding tea plantations and ensuring a sustainable tea industry.

9.FUTURE SCOPE

- Dataset Expansion:
- Deep learning models heavily rely on large and diverse datasets for effective training. Acquiring and annotating a more extensive

dataset of tea leaf diseases would improve the model's accuracy and generalization.

Improved Accuracy:

 Continued research and development can enhance the accuracy of deep learning models in disease detection. Techniques such as transfer learning, ensemble models, and advanced architectures like convolutional neural networks (CNNs) can be explored to achieve higher accuracy rates.

Real-time Monitoring:

Integrating deep learning models with IoT (Internet of Things)
devices can enable real-time monitoring of tea plantations. By
deploying cameras or sensors in the fields, disease detection
models can continuously analyse the health of tea leaves,
providing timely alerts and allowing proactive disease
management.

Mobile Applications:

Developing user-friendly mobile applications that incorporate
deep learning models can empower tea farmers and agronomists
to easily detect and diagnose diseases in tea leaves. Such apps
could provide instant feedback, disease identification, and
recommendations for treatment.

Automated Decision Support Systems:

 It serves as the foundation for intelligent decision support systems in tea farming. By integrating disease detection models with other agricultural data, such as weather patterns, soil conditions, and historical crop performance, farmers can make informed decisions regarding disease prevention, crop management, and treatment strategies.

Disease Identification and Classification:

 It can be trained to identify and classify various diseases affecting tea leaves. This includes common diseases like blights, muds, leaf spots, and viral infections. By accurately identifying the specific diseases, appropriate treatments can be applied, minimizing crop damage and yield loss.

Disease Severity Assessment:

It can also be extended to assess the severity of tea leaf diseases.
 By analysing disease progression and symptoms, models can provide quantitative assessments of the damage inflicted, aiding in prioritizing treatment efforts and optimizing resource allocation.

Generalization to Other Crops:

 The deep learning models developed for tea leaf disease detection can potentially be generalized to other crops as well. By leveraging the knowledge gained from tea leaf disease detection, models can be adapted to detect and diagnose diseases in other plants, broadening their application and impact.

10.APPENDIX

SOURCE CODE

from tensorflow.keras.layers import Dense, Flatten, Input from tensorflow.keras.models import Model

```
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input
import numpy as np
import matplotlib.pyplot as plt
imageSize = [224,224]
vgg = VGG16(input_shape=imageSize + [3], weights='imagenet',include_top=False)
for layer in vgg.layers:
  layer.trainable = False
x = Flatten()(vgg.output)
prediction = Dense(8, activation='softmax')(x)
model = Model(inputs=vgg.input, outputs = prediction)
model.summary()
model.compile(
loss='mse',
optimizer='adam',
metrics=['accuracy'], run_eagerly=True
)
from tensorflow.keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale= 1./255,
                    shear\_range = 0.2,
                    zoom\_range = 0.2,
                    horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)
training_set = train_datagenflow_from_directory('
c:\\Users\\indhu\\OneDrive\\Desktop\\tea_leaves\\dataset',
                             target\_size = (224,224),
                             batch\_size = 64,
                             class_mode = 'categorical')
test_set = test_datagen.flow_from_directory('
c:\\Users\\indhu\\OneDrive\\Desktop\\tea_leaves\\dataset',
                          target\_size = (224,224),
                          batch\_size = 32,
                          class_mode = 'categorical')
```

```
training_set.class_indices
r=model.fit(
training_set,
validation_data=test_set,
epochs=20,
steps_per_epoch = len(training_set)//64,
validation\_steps = len(test\_set)//32
)
from tensorflow.keras.models import load_model
model.save('model_vgg.h5')
model=load_model('model_vgg.h5')
img = image.load\_img("c:\\\\)oneDrive\\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneDrive\)OneDrive\(OneD
(224,224))#loading of the image
x = image.img_to_array(img)#image to array
import numpy as np
x = np.expand\_dims (x,axis = 0) #changing the shape
img_data = preprocess_input(x)
output = np.argmax(model.predict(img_data),axis=1)
index=['Anthracnose',
                 'algal leaf',
                 'brown blight',
                 'gray light',
                 'healthy',
                 'red leaf spot',
                 'white spot']
result=index[output[0]]
result
```

Github link: https://github.	com/naanmudhalvan-SI/	IBM9632-16823994	<u>74</u>	
Video link:				
https://drive.google.com/fi	le/d/1ts1_GqbWzJtpYtb2	BoNtIuJLGkAMoGed	S/view?usp=drivesdk	