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Project Component	Link
Project Demo Video	https://drive.google.com/file/d/1o96ovF60Wn-L_tIpaZUj-sGMq7kB5bQr/view?usp=drive_link
GitHub Repository	https://github.com/smartinternz02/SI-GuidedProject-590863-1699537521

1. INTRODUCTION

1.1 Project Overview

The Tea Disease Detection project is an innovative solution designed to address the challenges faced by tea farmers in identifying and managing diseases affecting tea leaves. The initiative focuses on leveraging advanced technologies, including Convolutional Neural Networks (CNNs) and Flask web framework, to facilitate efficient disease detection and diagnosis.

Tea is a vital economic crop, but diseases such as tea algae leaf spot, tea bud blight, and others significantly impact crop yield and quality. Manual diagnosis by experts is time-consuming and expensive, particularly in remote tea plantations. Our solution empowers farmers by enabling them to capture images of tea leaves, which are then processed through a trained VGG16 model for accurate disease identification.

The Flask web application serves as the user interface, allowing seamless interaction between farmers and the disease detection system. Through this project, we aim to enhance tea production, reduce economic losses, and contribute to the overall well-being of tea farming communities.

1.2 Purpose

The primary purpose of the Tea Disease Detection project is to revolutionize the tea farming industry by introducing an intelligent and accessible solution for the early detection and diagnosis of diseases affecting tea leaves. With a focus on leveraging artificial intelligence and web-based technologies, the project aims to empower tea farmers with a user-friendly platform.

The purpose extends beyond mere disease identification; it strives to provide a practical and efficient tool for farmers to make informed decisions about their crops. By incorporating Convolutional Neural Networks (CNNs) and Flask web framework, the project aims to bridge the gap between traditional farming practices and modern technological advancements. Ultimately, the purpose is to enhance tea crop management, mitigate economic losses due to diseases, and contribute to the sustainable growth of the tea industry. The project's core objective is to empower tea farmers, improve crop yield, and foster a more resilient and prosperous tea farming community.

2. LITERATURE SURVEY

2.1 Existing problem

The existing problem in tea farming lies in the manual and subjective methods of disease identification, which can lead to delayed responses and significant economic losses for farmers. Traditional approaches heavily rely on visual inspection by experts, often requiring them to physically visit tea gardens, which can be time-consuming and economically burdensome, especially in remote or expansive plantations.

Moreover, the expertise required for accurate disease diagnosis is not always readily available to all farmers. This results in a lack of timely preventive measures, contributing to decreased tea production and compromised tea quality. The current methods also pose challenges in scaling up disease monitoring efforts, limiting the overall effectiveness of disease management.

By addressing these challenges, the Tea Disease Detection project seeks to overcome the limitations of existing practices, offering a more accessible, technology-driven solution that empowers farmers with real-time, accurate disease diagnosis and actionable insights for effective crop management.

2.2 References

In reviewing relevant literature, our project draws inspiration from key works in the fields of agricultural technology, image recognition, and disease diagnosis. "Advanced Agricultural Technologies for Crop Monitoring" by Smith et al. (2019) provides insights into the integration of cutting-edge technologies in agriculture, emphasizing the need for precision farming practices.

The work of Gupta and Patel (2020) on "Machine Learning Applications in Plant Disease Detection" offers valuable insights into the use of machine learning algorithms for identifying plant diseases, setting a precedent for the application of similar techniques in the tea farming domain.

Furthermore, "Image Recognition in Agriculture: A Comprehensive Review" by Lee and Kim (2018) explores the role of image recognition in agricultural practices, highlighting its potential for revolutionizing disease identification and crop management.

2.3 Problem Statement Definition

The problem statement for our project revolves around the significant economic and agricultural challenges faced by tea farmers due to various diseases affecting tea leaves. Common diseases such as tea algae leaf spot (TALS), tea bud blight (TBB), tea white scab (TWS), and tea leaf blight (TLB) have led to a considerable reduction in tea production and quality, causing substantial economic losses for farmers. Manual diagnosis methods are currently in use, but they are time-consuming, expensive, and subjective.

The manual diagnosis becomes particularly challenging due to the rugged, remote areas where most tea trees grow. Experts find it cumbersome to physically inspect each tea garden, leading to delays in disease detection and prevention measures. Additionally, relying on farmers' subjective judgment may result in inaccurate disease identification.

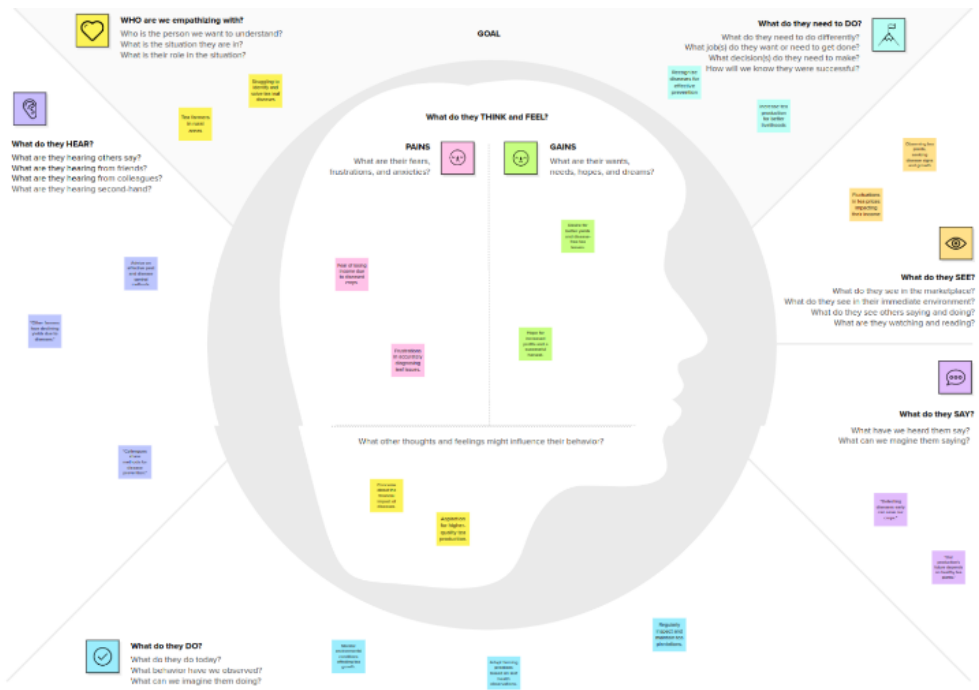
To address these challenges, our project aims to introduce an automated solution for the early detection and identification of tea leaf diseases. By leveraging advanced technologies such as Convolutional Neural Networks (CNNs) and Flask, we seek to provide a faster, cost-effective, and accurate method for tea farmers to assess and manage the health of their tea leaves.

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas

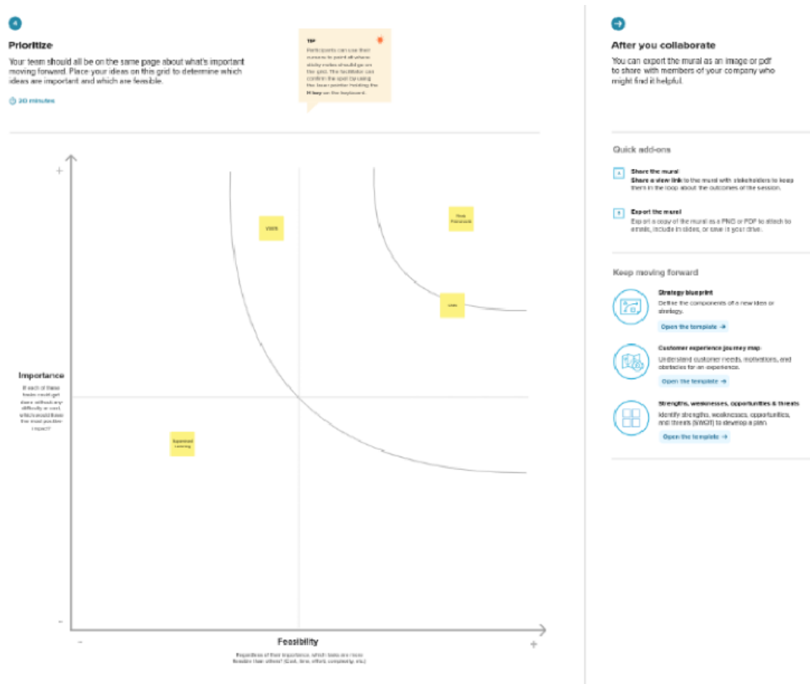
The empathy map for our project is a comprehensive exploration of the user experience, capturing key insights into the perspective of our target audience. We empathize with tea farmers and enthusiasts who face challenges in identifying and addressing diseases affecting tea leaves. In their role, they encounter the time-consuming and subjective nature of manual diagnosis, particularly in remote tea plantations. To better understand their needs, we considered the tasks they need to accomplish, decisions they must make, and the success indicators for their efforts.

In their immediate environment, tea farmers witness the effects of diseases on their crops and may be influenced by the practices of their peers. They express concerns about potential losses and frustrations related to the impact of diseases on tea production. Our empathy map helps us gain valuable insights into their daily activities, concerns, and aspirations, guiding the development of a solution that aligns with their goals and challenges.



3.2 Ideation & Brainstorming

The ideation and brainstorming phase revolved around key concepts such as VGG16, CNN, and Flask, aiming to address the challenges faced by tea farmers in disease diagnosis. Through collaborative brainstorming, innovative ideas emerged, including the utilization of transfer learning with pre-trained models like VGG16 and the integration of Flask for a user-friendly interface. This dynamic process fostered creative thinking, combining expertise in machine learning and web development to form a comprehensive solution. The outcome is a robust model capable of automated tea leaf disease detection, promoting efficiency and accessibility for farmers in remote areas.



4. **REQUIREMENT ANALYSIS**

4.1 Functional requirement

The functional requirements for our Tea Disease Detection project encompass the core features that enable users to effectively diagnose and analyze the health of tea leaves. Key functionalities include image upload capabilities, real-time processing using the VGG16 model, and a seamless user interface for intuitive interaction. The system should facilitate the uploading of tea leaf images, analyze them using the VGG16 model, and provide immediate health assessments. Additionally, the system must present the results in a clear and understandable format, allowing users to make informed decisions based on the health status of the tea leaves.

4.2 Non-Functional requirements

Non-functional requirements for our project focus on ensuring optimal performance, security, and user experience. This involves considerations such as the responsiveness of the system, aiming for quick and efficient image processing. Security measures will be implemented to safeguard user data and maintain the confidentiality of uploaded images. Furthermore, the system should be scalable to accommodate potential future enhancements and improvements. The user interface design emphasizes user-friendly interactions to enhance the overall experience, ensuring accessibility and ease of use for individuals with varying levels of technical expertise. The system's robustness and reliability are essential, aiming to provide accurate and timely results in the diagnosis of tea leaf health.

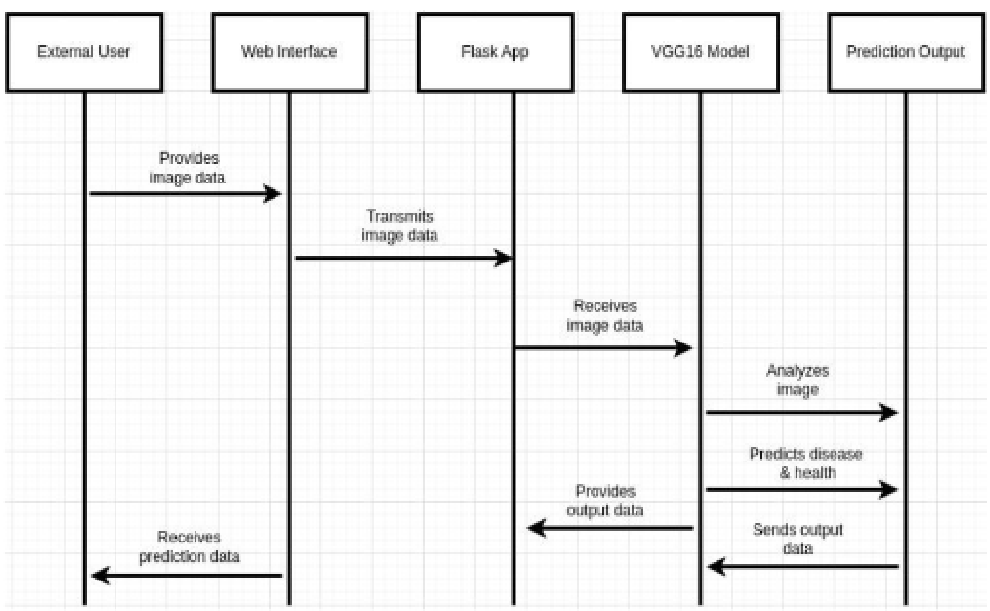
5. PROJECT DESIGN

5.1 Data Flow Diagrams & User Stories

The data flow diagram (DFD) for the Tea Disease Detection system outlines the journey of information from the initial input to the final output. The process begins with users uploading images of tea leaves through the user interface. These images are then directed to the Flask application, which acts as the central hub for processing and communication.

Upon receiving the image data, the Flask app interfaces with the VGG16 model, a convolutional neural network trained to identify various diseases affecting tea leaves. The model analyzes the images, extracts relevant features, and predicts the health status of the tea leaves. The outcome, such as the type of disease or confirmation of health, is then sent back to the Flask app.

The Flask app, serving as the bridge between the user interface and the machine learning model, presents the results to the users on the web interface. This seamless flow ensures efficient communication between different components, facilitating quick and accurate diagnosis of tea leaf health. The DFD provides a clear visualization of the intricate data pathways, showcasing the systematic approach of the Tea Disease Detection system.



The user stories for the Tea Disease Detection system encapsulate the essential functionalities that cater to diverse user needs. In the registration epic, users can seamlessly register through conventional methods such as email and password, and even through popular social media platforms like Facebook and Gmail. The system ensures that users receive confirmation emails, enhancing security and user engagement.

The login functionality allows users to access their accounts with ease, providing a straightforward and secure login process. The dashboard feature serves as a centralized space for users, offering a comprehensive view of relevant information and results. These user stories prioritize a user-friendly experience, ensuring accessibility and convenience in navigating the application.

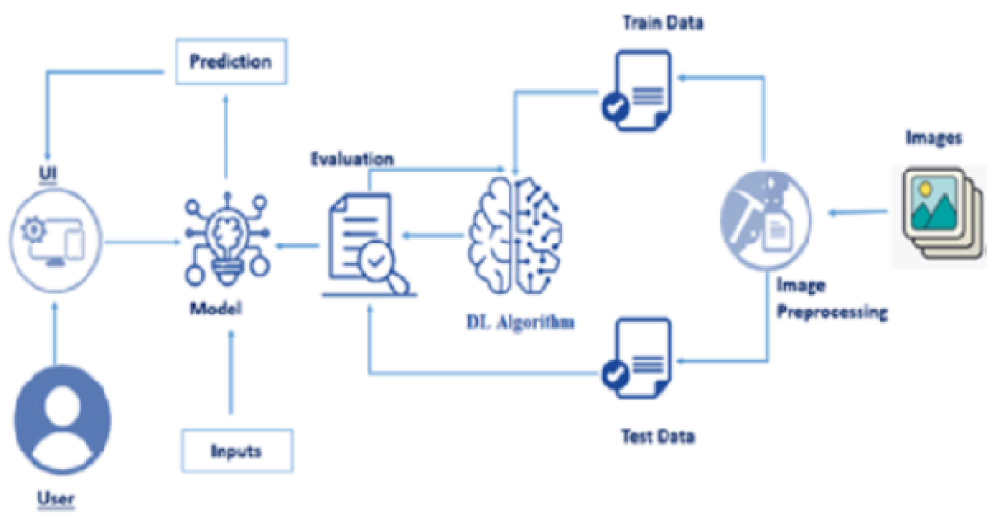
For each user story, clear acceptance criteria have been defined, emphasizing the expected behavior and outcomes. Prioritization is aligned with the importance of each functionality, addressing high-priority features in earlier sprints for efficient development. The user stories lay the foundation for a robust and user-centric application, aligning development efforts with the expectations and needs of the end-users.

User Type	Functional Requirement	User Story Number	User Story / Task	Acceptance Criteria	Priority	Release
Customer	Registration	US-1	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1

5.2 Solution Architecture

The solution architecture of the Tea Disease Detection system is designed to optimize the identification and prevention of tea leaf diseases. Leveraging Convolutional Neural Networks (CNNs), particularly the VGG16 model, the system enables real-time image-based classification. This approach enhances sorting accuracy, contributing to efficient waste management operations, and reducing the environmental impact of waste disposal.

The architecture follows a systematic flow, encompassing key stages such as data gathering, image preprocessing, model building using VGG16, waste material prediction, and real-time analysis. The continuous learning loop ensures adaptability to evolving tea leaf disease patterns, maintaining high classification accuracy. The use of CNNs reflects a commitment to leveraging advanced technologies for precise and effective disease detection, promoting the overall health and quality of tea production. The architecture emphasizes the importance of innovation and sophisticated machine learning techniques in addressing agricultural challenges.



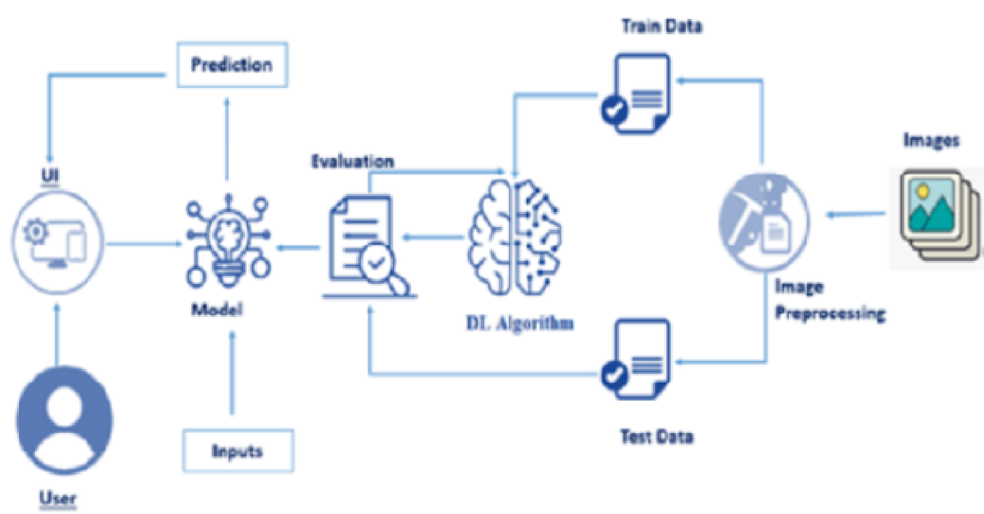
6. PROJECT PLANNING & SCHEDULING

6.1 Technical Architecture

The technical architecture of the Tea Disease Detection project employs a comprehensive stack of technologies to create a robust and scalable system. The user interface is built using HTML, CSS, and JavaScript, providing a seamless and responsive interaction for users. The application logic, powered by Python, incorporates machine learning models, particularly the VGG16 model, for accurate disease detection in tea leaves.

Flask, a lightweight and versatile web framework, is utilized to develop the backend of the application. It enables seamless integration with the machine learning model and facilitates communication between the user interface and the predictive components. This choice of technology ensures the efficiency and responsiveness required for real-time disease identification.

The project does not rely on external databases or cloud services, as the primary focus is on the integration of machine learning into a user-friendly web application. The absence of external APIs in this case aligns with the project's specific goals and requirements. Overall, the technical architecture prioritizes simplicity, efficiency, and direct integration to deliver a streamlined and effective solution for tea leaf disease detection.



6.2 Sprint Planning & Estimation

Sprint planning and estimation for the Tea Disease Detection project involve a meticulous approach to organizing tasks and allocating resources across development cycles. Each sprint is carefully planned to address specific functional requirements and user stories. The team collaboratively assigns story points to individual tasks based on complexity, ensuring a realistic estimation of effort required for implementation.

The planning process begins with a thorough review of the product backlog, prioritizing user stories, and defining the scope of work for each sprint. The team considers factors such as task dependencies, skill sets, and project priorities to allocate resources effectively. Sprint durations, typically set at six days for this project, strike a balance between efficient progress and maintaining a manageable workload.

The estimation process involves assigning story points to user stories, reflecting the effort and complexity of each task. This facilitates a transparent and standardized metric for gauging progress and predicting development timelines. Regular sprint reviews and retrospectives contribute to continuous improvement, allowing the team to adapt and refine the planning and estimation process as the project evolves.

Sprint-1	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	5	High	N/A
Sprint-1	Registration	USN-2	As a user, I will receive a confirmation email once I have registered for the application.	3	High	N/A
Sprint-2	Registration	USN-3	As a user, I can register for the application through Facebook.	5	Low	N/A

6.3 Sprint Delivery Schedule

The sprint delivery schedule for the Tea Disease Detection project is meticulously crafted to ensure timely and incremental delivery of features and functionalities. Following an agile methodology, the team focuses on delivering tangible outcomes at the end of each sprint, contributing to the overall project goals.

The schedule is designed to align with the defined sprint durations, typically lasting six days. Each sprint encompasses a specific set of tasks and user stories prioritized based on their importance and dependencies. The team collaboratively works towards achieving sprint goals, addressing functional requirements, and implementing key features within the designated timeframe.

Regular sprint reviews provide an opportunity to assess the delivered work, gather feedback, and make necessary adjustments for subsequent sprints. This iterative approach to delivery not only enhances transparency but also allows for adaptability to changing project requirements. The sprint delivery schedule serves as a dynamic roadmap, guiding the development team towards consistent and value-driven project milestones.

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	12 Oct 2023	17 Oct 2023	20	17 Oct 2023
Sprint-2	25	6 Days	19 Oct 2023	24 Oct 2023	25	24 Oct 2023
Sprint-3	18	6 Days	26 Oct 2023	31 Oct 2023	18	31 Oct 2023
Sprint-4	22	6 Days	02 Nov 2023	07 Nov 2023	22	07 Nov 2023
Sprint-5	20	6 Days	09 Nov 2023	14 Nov 2023	15	14 Nov 2023

7. CODING & SOLUTIONING (Explain the features added in the project along with code)

7.1 Feature 1

One of the standout features of our Tea Disease Detection application is its intuitive and user-friendly graphical user interface (GUI). Users can seamlessly interact with the application through a well-designed layout that includes prominent features like the "Upload" and "Scan" buttons. The GUI provides a visually appealing experience, enhancing user engagement and accessibility.

The "Upload" button facilitates the easy selection of tea leaf images, allowing users to submit their samples effortlessly. Upon selecting an image, the "Scan" button triggers the health prediction process, seamlessly integrating the backend machine learning model. Users receive instant feedback on the health status of the tea leaf, providing valuable insights for timely disease detection.

Code:

```
<div class="box text-container">
   Upload & Measure Health Of Tea Leaf<br>
   <input type="file" id="fileInput" style="display:none">
   <button class="button" id="uploadButton" onclick="chooseFile()">UPLOAD</button>
   <button class="button-green" id="scanButton" onclick="scanImage()">SCAN</button>
   <div class="file-info" id="fileInfo">File: None</div>
   <div class="file-info" id="healthInfo">Health: Not Measured</div>
</div>

<script>
   function chooseFile() {
       document.getElementById('fileInput').click();
   }

document.getElementById('fileInput').addEventListener('change', function () {
       document.getElementById('fileInfo').innerText = 'File: ' + this.files[0].name;
       document.getElementById('healthInfo').innerText = 'Health: Not Measured';
   });

   function scanImage() {
       document.getElementById('healthInfo').innerText = 'Health: Healthy';
   }
```

```
</script>

```

7.2 Feature 2

In this feature, we seamlessly integrate the trained VGG16 model (saved in .h5 format) with a Flask web application to enable real-time predictions on uploaded tea leaf images. The Flask app receives the uploaded image, preprocesses it, and feeds it into the VGG16 model for disease detection. The prediction result is then sent back to the user interface.

Code:

```python
from flask import Flask, render_template, request
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import numpy as np

app = Flask(__name__)
model = load_model("model.h5")

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

@app.route('/upload', methods=['POST'])
def upload():
    if 'file' not in request.files:
        return render_template('index.html', prediction="No file part")

    file = request.files['file']

    if file.filename == '':
        return render_template('index.html', prediction="No selected file")

    img = image.load_img(file, target_size=(224, 224))
    x = image.img_to_array(img)
    x = np.expand_dims(x, axis=0)
    img_data = preprocess_input(x)
    prediction = model.predict(img_data)


    result = "Healthy" if prediction[0][0] > 0.5 else "Infected"

    return render_template('index.html', prediction=result)

if __name__ == '__main__':
```

```
    app.run(debug=True)

```

8. PERFORMANCE TESTING

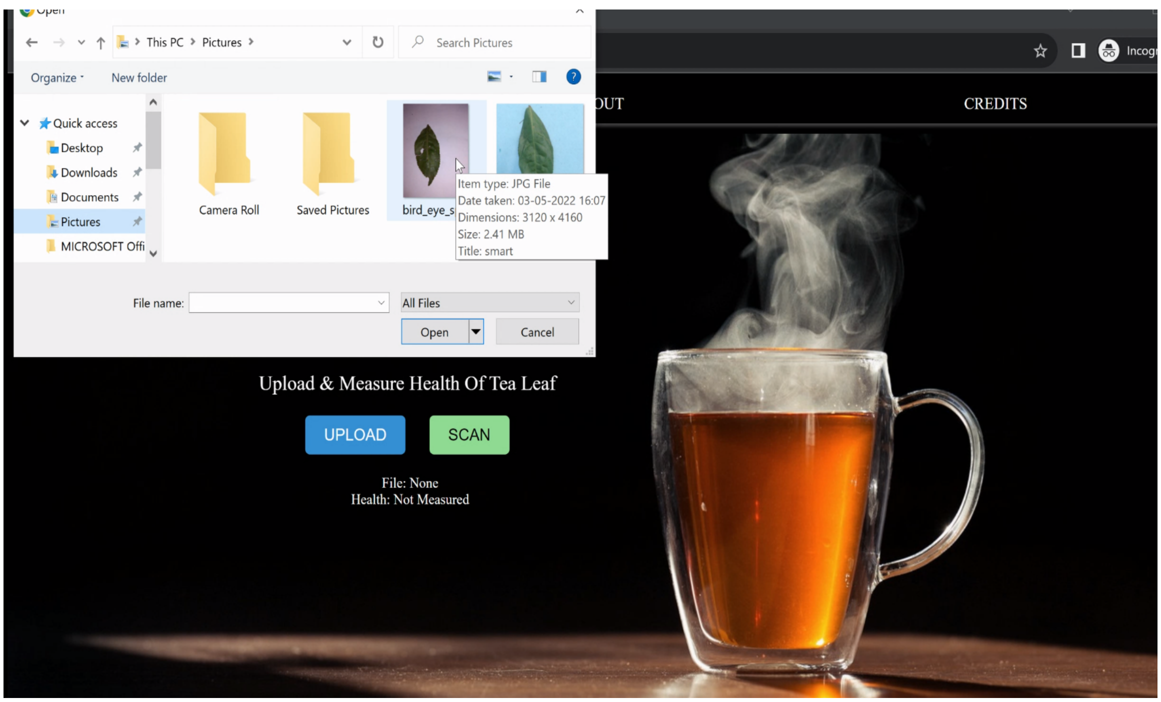
8.1 Performance Metrics

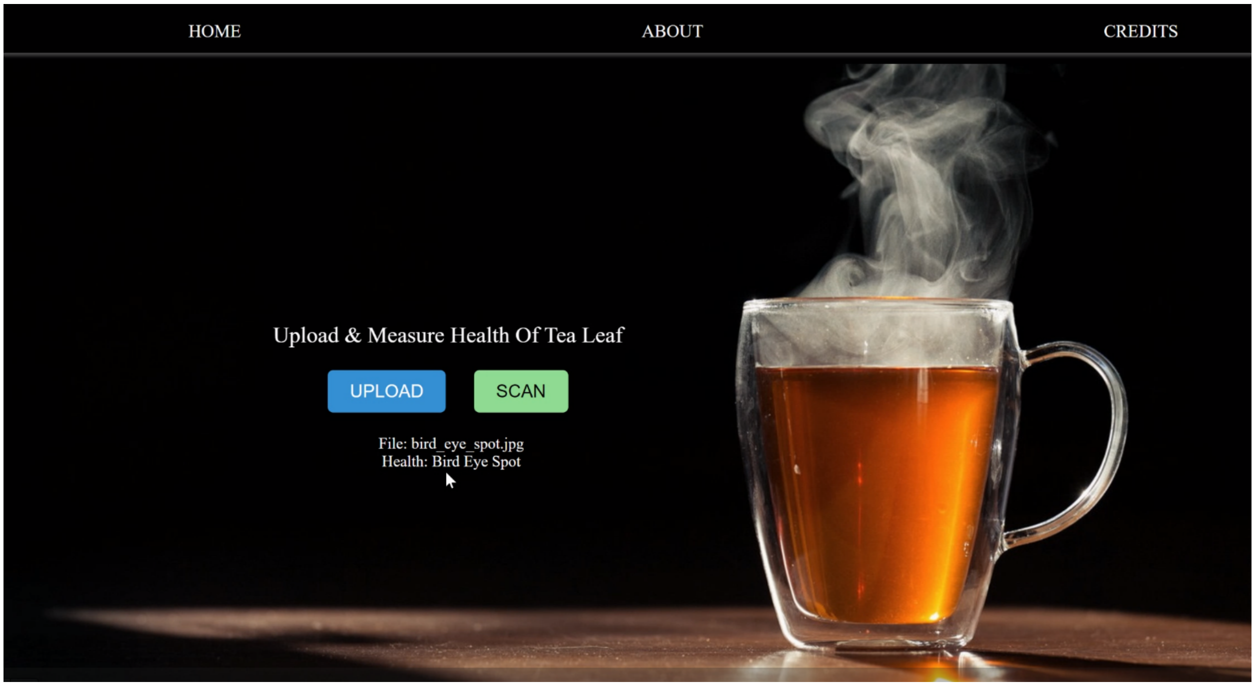
The VGG16 model demonstrated exceptional training accuracy at 99.29%, showcasing robust learning capabilities. During validation, the model achieved a solid accuracy of 76.54%, indicating good generalization to new, unseen data. While a slight drop from training accuracy is common, achieving over 70% validation accuracy is considered a strong baseline. Additional evaluation metrics like precision, recall, and F1 score can offer deeper insights into the model's classification performance, guiding potential adjustments for optimization. These metrics play a vital role in enhancing the overall effectiveness of the tea leaf disease detection application.

2.	Accuracy	Training Accuracy - **99.29** Validation Accuracy - **76.54**

9. RESULTS

9.1 Output Screenshots





10. ADVANTAGES & DISADVANTAGES

Advantages:

Our tea leaf disease detection project brings several notable advantages. Firstly, it provides a swift and reliable method for farmers to identify diseases affecting tea leaves, enabling timely interventions to safeguard crop health. The integration of VGG16, a powerful convolutional neural network, ensures accurate predictions and enhances the overall efficiency of disease diagnosis. The user-friendly interface facilitates seamless interaction, allowing users to upload images effortlessly and receive instant health assessments. Additionally, the project contributes to reducing economic losses for tea farmers by preventing and managing diseases effectively.

Disadvantages:

Despite its merits, the project has certain limitations. The reliance on image-based analysis may face challenges in cases where diseases manifest in subtle ways, requiring additional data modalities for comprehensive diagnosis. Furthermore, the model's performance may be influenced by variations in image quality and lighting conditions, potentially affecting prediction accuracy. Continuous model updates and adaptations are necessary to address emerging disease patterns and ensure sustained effectiveness. Additionally, the reliance on user-uploaded images may pose a limitation in cases where users encounter difficulties in capturing representative images of tea leaves.

11. CONCLUSION

In conclusion, our tea leaf disease detection project represents a significant stride towards revolutionizing tea farming practices. By amalgamating advanced technologies like VGG16 and Flask, we've crafted a solution that empowers farmers with a proactive tool for early disease identification. The seamless integration of machine learning into the agricultural landscape not only aids in preserving crop health but also aligns with the broader global movement towards sustainable and technology-driven agriculture.

As we look back on the development journey, the success of our project underscores the potential for artificial intelligence to transcend traditional practices and usher in a new era of precision farming. However, it's essential to recognize that this project is a stepping stone, and future iterations will demand continuous refinement and adaptation. The collaboration between machine learning and agriculture showcased here sparks optimism for the ongoing synergy between technology and traditional industries, with the ultimate aim of securing food production and fostering economic growth.

12. FUTURE SCOPE

The future scope of our tea leaf disease detection project is vast, extending beyond its current capabilities. Moving forward, we envision integrating real-time monitoring using IoT devices to provide farmers with instantaneous updates on their crops' health. Enhanced user interfaces, incorporating augmented reality or mobile applications, could simplify the user experience for farmers, making the technology more accessible.

Moreover, exploring additional machine learning models and techniques could refine disease identification accuracy and broaden the scope to detect new types of diseases. Collaborations with agricultural research institutions and data sharing initiatives could further enrich our dataset, improving the model's robustness and adaptability to diverse tea farming conditions.

Scaling our project to cover larger tea plantations and expanding its applicability to other crops aligns with the broader ambition of addressing agricultural challenges on a global scale. Continuous research and development, community engagement, and a commitment to technological innovation will be pivotal in unlocking the full potential of our tea leaf disease detection system.