SCTR's Pune Institute of Computer Technology
Dhankawadi, Pune

AN INTERNSHIP REPORT ON

Title:
"AI-Based Crop Disease Detection and Location-Specific Remedies Using Deep Learning and Weather Data"

SUBMITTED BY

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Under the guidance of
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DEPARTMENT OF INFORMATION TECHNOLOGY
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DEPARTMENT OF INFORMATION TECHNOLOGY

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CERTIFICATE

This is to certify that the SPPU Curriculum-based internship report entitled
"Inhouse Internship on Crop Disease Detection and Remdies"

Submitted by
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has satisfactorily completed the curriculum-based internship under the guidanceof Mrs. Sayali Gaikwad towards the partial fulfillment of third year Information Technology Semester VI, Academic Year 2024-25 of Savitribai PhulePune University.

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Date:

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Contents

"AI-Based Crop Disease Detection and Location-Specific Remedies Using Deep Learning and Weather Data"

Introduction:

Crop diseases pose a significant threat to global food production, especially in regions where agriculture is a primary livelihood. The early and accurate identification of plant diseases is crucial to minimizing yield loss and maintaining crop quality. However, traditional methods of disease detection rely heavily on manual inspection, which is not only time-consuming and labour-intensive but also often inaccessible to smallholder farmers in remote areas. These limitations highlight the need for an automated, scalable, and intelligent system that can support farmers by providing timely and accurate disease diagnosis without the need for expert supervision.

This project introduces an AI-based system designed to detect crop diseases and recommend location-specific remedies using deep learning and real-time weather data. The core of the system is built upon EfficientNet, a high-performance convolutional neural network architecture known for its ability to balance accuracy and computational efficiency. To further enhance the model's ability to focus on relevant features in plant images, we incorporate the Convolutional Block Attention Module (CBAM), which improves the network's attention to disease-relevant spatial and channel-wise details. The system is trained on disease datasets for four major crops: tomato, cashew, cassava, and maize. These crops are selected due to their agricultural importance and their susceptibility to a wide range of diseases that can be visually diagnosed through symptoms on leaves, stems, or fruits.

To provide more intelligent and context-aware outputs, the system integrates real-time weather data—including temperature, humidity, and rainfall—retrieved from external APIs based on the user's location. Environmental conditions play a vital role in the occurrence and spread of many plant diseases, and incorporating this data allows the system to tailor its recommendations more effectively. Once the disease is detected and relevant weather conditions are analysed, the system uses the Gemini API, a large language model, to generate customized remedy suggestions. These recommendations consider both the diagnosed disease and the local climate context, offering farmers practical, location-specific actions to mitigate crop damage. This fusion of deep learning, weather intelligence, and natural language generation forms a comprehensive tool for early disease detection and precision agriculture support.

Looking ahead, the proposed system has the potential to scale across different regions and crop types, providing a foundation for more inclusive and intelligent agricultural tools. By reducing dependency on expert intervention and enabling farmers to make informed decisions directly from their mobile devices or field cameras, this solution can help bridge the technological gap in rural farming communities. It also opens the door for future integration with additional data sources such as soil health metrics, satellite imagery, and multilingual support, making it a stepping stone toward a fully AI-driven ecosystem for sustainable and smart farming.

Problem Statement:

Farmers face challenges in quickly and accurately identifying crop diseases, often relying on slow, manual methods. Existing solutions lack integration with environmental factors like weather, which are crucial for effective disease management. There is a need for an automated system that can detect diseases from images and provide location-specific remedies based on real-time weather data.

4. Objectives and Scope

4.1 Objectives

The primary objectives of this project are:

1. **Disease Detection:** Develop a deep learning model using EfficientNet and CBAM to accurately detect diseases in crops such as tomato, cashew, cassava, and maize from images.

2. **Context-Aware Remedies:** Integrate real-time weather data to provide location-specific remedies based on the detected disease and environmental conditions.

3. **Scalability:** Design the system to be scalable across different crops and regions, making it accessible to farmers in both developed and developing areas.

4. **User-Friendly Interface:** Create an easy-to-use platform that allows farmers to upload crop images and receive immediate, actionable insights for disease management.

5. **Precision Agriculture:** Enhance the precision of agricultural decision-making by combining AI-powered disease detection with weather data to reduce crop losses.

4.2 Scope

The scope of this project includes:

1. **Crop Types:** Focus on four major crops—tomato, cashew, cassava, and maize—that are commonly affected by various diseases and widely cultivated across different regions.

2. **Disease Detection:** The system will cover a range of common diseases in the selected crops, which can be diagnosed through visible symptoms on the plant.

3. **Weather Data Integration:** Utilize external weather APIs to collect and incorporate relevant environmental data, such as temperature, humidity, and rainfall, to improve the accuracy of disease predictions and remedy suggestions.

4. **Geographical Context:** Provide location-specific recommendations, leveraging geospatial data to tailor the output to local conditions and climate factors.

Methodological Details

5.1 Data Collection and Processing

- **Image Sourcing & Labeling:**
  We leverage the CCMT dataset (Cashew, Cassava, Maize, Tomato) introduced by Mensah *et al.* (2023) – a curated collection of **24 ,881 raw images** covering multiple disease classes plus healthy samples. Each image was captured under varied backgrounds and orientations, then annotated by a team of plant virologists and pathologists who reached consensus on labels and discarded any ambiguous instances to ensure a high-quality ground truth.

- **Balanced Class Representation:**
  To prevent bias toward overrepresented classes, the raw CCMT images were expanded through geometric transformations (rotations, flips) and photometric adjustments (color and contrast jitter). This augmentation elevated per-crop representation to roughly 25 – 30 % each, producing a balanced dataset that enhances model robustness across all classes.

- **Uniform Input Size:**
  All images are resized to **224 × 224 pixels**, matching the input dimensions expected by EfficientNet-B3. This standardization guarantees consistent tensor shapes for batch processing and allows seamless transfer learning from ImageNet-pretrained weights.

- **Normalization:**
  Pixel values are normalized to zero mean and unit variance using the same channel-wise statistics as ImageNet. This alignment reduces the domain gap between the CCMT images and the pre-trained backbone, accelerating convergence during fine-tuning.

- **On-the-Fly Augmentation for Robustness:**
  During training, further augmentations—random brightness, contrast, and hue shifts—are applied in real time. These simulate diverse field conditions (e.g., variable lighting, shadowing) and help the model learn invariant features of disease symptoms, improving performance on unseen environments.

Figure 1 Dataset Source

5.2 Model Architecture & Training

- **EfficientNet-B3 Backbone**
  Adopt EfficientNet-B3 for its compound scaling of depth, width, and resolution, delivering top-tier accuracy with a moderate parameter count. This backbone offers a strong feature extractor for subtle leaf and fruit symptom patterns.
- **Convolutional Block Attention Module (CBAM)**
  Integrate CBAM after key EfficientNet blocks:
  - Channel Attention recalibrates feature-map importance, spotlighting color/texture channels indicative of infection.
  - Spatial Attention masks out background clutter, directing focus to symptomatic regions on leaves or stems.
- **Optimization & Regularization**
  Use a categorical cross-entropy loss with label smoothing to mitigate over-confidence. Optimize with AdamW (weight decay) and apply a cosine-annealing learning-rate schedule. Incorporate early stopping based on validation F1-score to prevent overfitting.
- **Evaluation Metrics**
  Go beyond plain accuracy by monitoring per-class precision, recall, and F1-scores. Confusion matrices help identify commonly confused disease pairs, guiding further data collection or architectural tweaks.

Figure 2 EfficientNet b3 Architecture

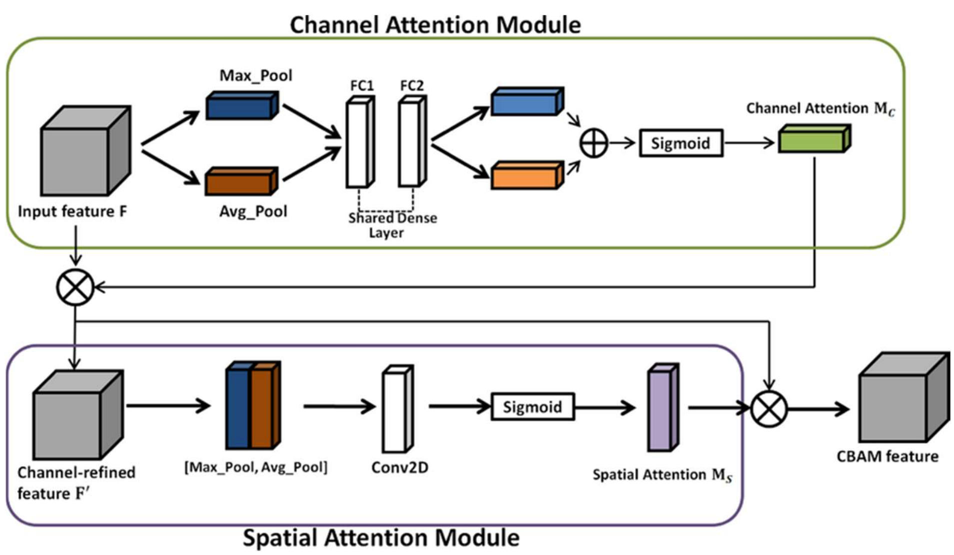


Figure 3 CBAM Architecture

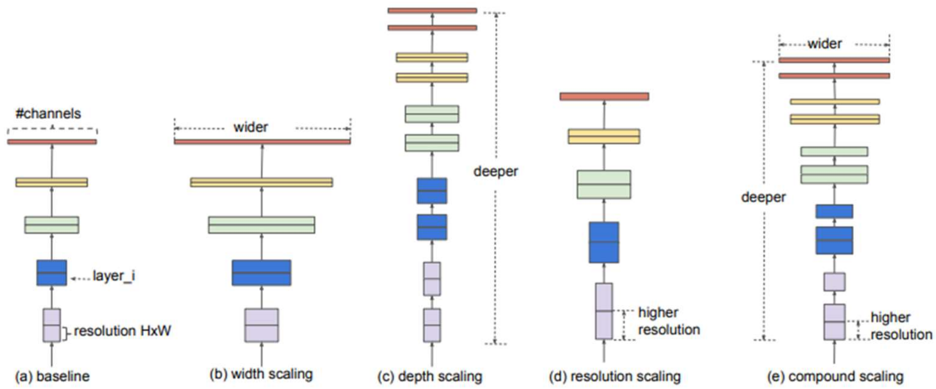


Figure 4 Compound Scaling of EfficientNet Model

5.3 Weather Data Integration

- OpenWeather API Usage
  Instead of EXIF metadata, the system prompts the user for a location (e.g., nearest city or GPS coordinates). This location is sent to the OpenWeather API, retrieving current values for temperature, humidity, and rainfall.
- Feature Engineering
  Normalize the raw weather variables and, if desired, compute simple aggregates (e.g., 3-day rolling average) to smooth out anomalies. These weather features are concatenated with the visual embeddings just before the classification/remedy stage, allowing the model logic to consider environmental context alongside image symptoms.
- Contextual Decision-Making
  Weather inputs help disambiguate visually similar diseases—for example, two fungal infections that present alike but only one thrives under high humidity. By fusing these features, the system raises or lowers confidence scores appropriately.

5.4 Remedy Generation via Gemini Flask 1.5

- Model Selection
  Use the Gemini Flask 1.5 LLM, deployed as a lightweight microservice via Flask. This model version balances speed and generative quality for on-device or edge deployment.
- Prompt Engineering
  Craft prompts that embed (a) detected crop and disease, (b) the fetched OpenWeather stats, and (c) any user-specified preferences (organic vs. chemical, local regulations).
  Example structure:

"For cassava mosaic virus at 28 °C, 85% humidity, and 5 mm recent rain, recommend three practical treatments…"

- Dynamic, Safe Recommendations
  The response generator outputs multiple remedy options—dosages, application timings, and safety notes. A lightweight ruleset filters out any suggestions that conflict with extreme weather (e.g., no foliar sprays if rain is imminent).
- Extensibility for Localization
  While currently in one language, this Flask service can be extended with translation modules or regional knowledge bases to support local guidelines and languages.

Modern Engineering Tools Used

- **PyTorch**
  PyTorch is the foundational deep learning library used for designing and training the image classification model. Its dynamic computation graph makes it highly flexible for experimenting with new architectures like EfficientNet integrated with attention modules. PyTorch also provides robust support for GPU acceleration, enabling faster training on high-resolution image datasets. Built-in libraries such as torch.nn (for neural networks), torch.optim (for optimizers), and torch.utils.data (for data loading and preprocessing) streamline the entire training pipeline.

- **EfficientNet-B3 with CBAM (Convolutional Block Attention Module)**
  EfficientNet-B3 is a modern convolutional neural network that scales depth, width, and input resolution in a balanced manner. It is chosen for its ability to provide high accuracy with relatively fewer parameters, which is important for real-world applications with limited computational resources. The CBAM module is added to further refine feature learning by applying attention mechanisms. CBAM works by first identifying important channels (e.g., color tones related to infection) and then focusing spatially on specific regions (e.g., leaf spots or lesions), thereby guiding the model's attention to critical patterns for accurate disease classification.

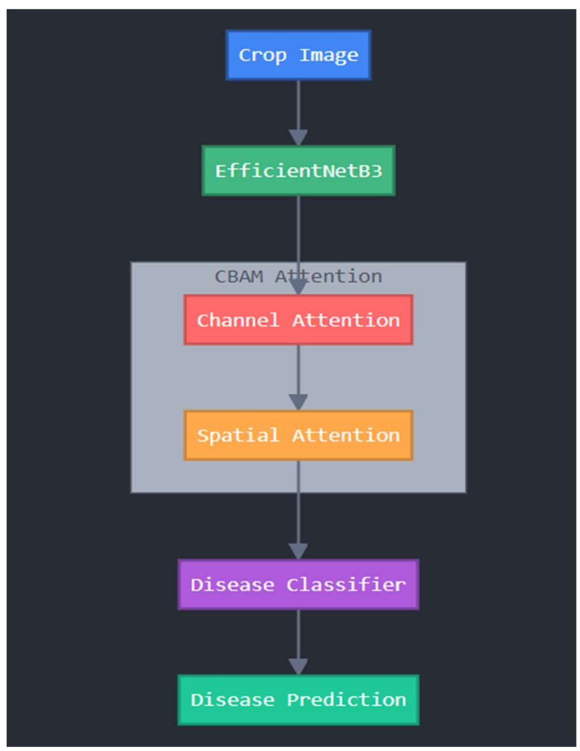


Figure 5 Disease Prediction

- **Torchvision**
  Torchvision is used for handling image preprocessing tasks such as resizing, normalization, and basic augmentations like flipping and rotation. These transformations prepare raw input images to meet the input requirements of the EfficientNet-B3 model. Additionally, Torchvision’s ImageFolder and dataset loaders make it easier to organize and batch images during training and evaluation, ensuring efficient memory management and smoother training on larger datasets.

- **Albumentations**
  Albumentations is an advanced augmentation library used to create synthetic variations of training images. Unlike basic transformations, Albumentations allows for realistic changes like motion blur, random shadows, noise, and occlusion. These augmentations are important in making the model robust to diverse and unpredictable field conditions, helping it generalize better on real-world inputs such as leaves photographed under poor lighting or partial coverage.

- **Gemini Flask 1.5 API**
  Gemini Flask 1.5 is a lightweight, locally hosted large language model used for remedy generation. Once a crop disease is detected, relevant data (like the disease name, crop type, and current weather conditions) are passed to the Gemini model. It then generates a customized set of actionable recommendations in natural language. This dynamic remedy generation approach eliminates the need for static lookup tables, providing flexible, real-time suggestions tailored to the farmer’s local situation and preferences.

- **OpenWeather API**
  The OpenWeather API is used to fetch real-time weather data such as temperature, humidity, and rainfall based on the user's location input. These environmental conditions are critical because they influence disease spread, severity, and treatment effectiveness. For instance, some fungal diseases are more active in high humidity, while certain pesticides may lose effectiveness if it rains shortly after application. Integrating weather data ensures that both disease detection and treatment advice are context-aware and relevant.

- **Jupyter Notebook**
  Jupyter Notebook is used for development, experimentation, and analysis. Its interactive coding environment allows for modular execution of code blocks, immediate visualization of results, and seamless debugging. It’s particularly helpful when testing model architectures, comparing training metrics, or visualizing class-wise performance. Jupyter supports markdown and inline plotting, making it ideal for combining code, documentation, and results in a single, readable format.

Any Achievement

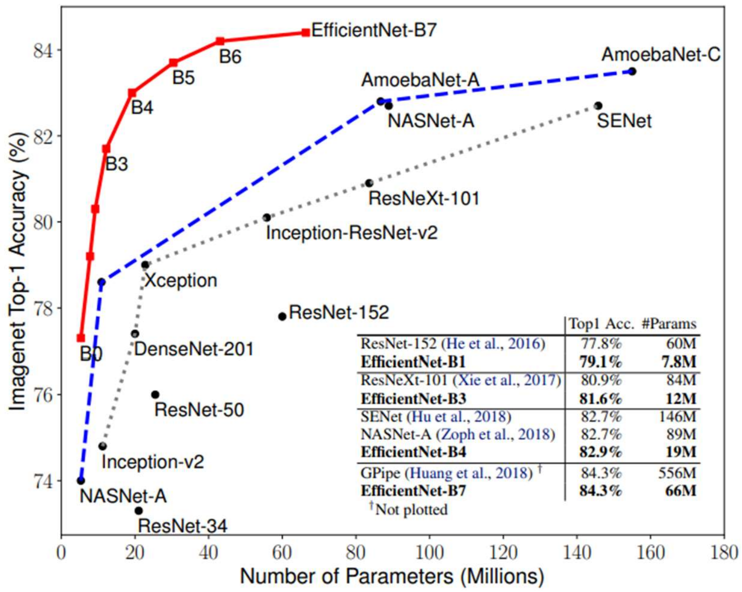
This project has not only advanced technical learning in the domain of artificial intelligence and agriculture but also opened several professional and academic opportunities. Through the application of advanced deep learning techniques and integration with real-world data (weather APIs, large language models), this work attracted strong attention in academic review forums and institutional showcases.

- **Research Publication Opportunity:**
  The project demonstrates a novel combination of EfficientNet-B3 with CBAM for crop disease detection, along with context-aware remedy generation using LLMs and weather data. Due to its technical novelty and societal relevance, it has strong potential for submission to conferences or journals in domains like agricultural informatics, machine learning applications, or precision farming.

- **Portfolio Enhancement and Placement Readiness:**
  This project stands out in the portfolio due to its end-to-end system integration—from computer vision to API handling to LLM-driven decision support. It demonstrates both domain depth and practical deployment experience, which strengthens candidacy for roles in AI, machine learning engineering, or data science. The integration of multiple technologies shows a clear capacity for solving real-world problems using modern tools.

Outcome/Results

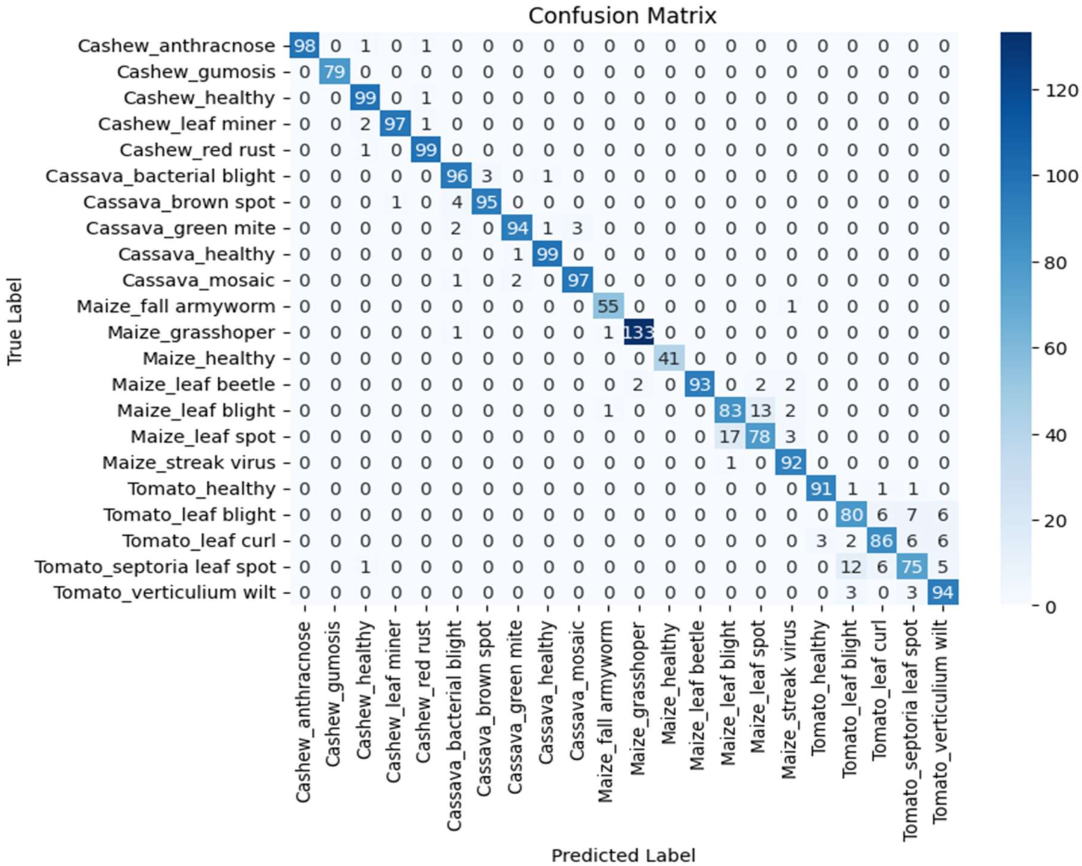
1. Comparison of EfficientNet with other Models (*source: "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks"*)



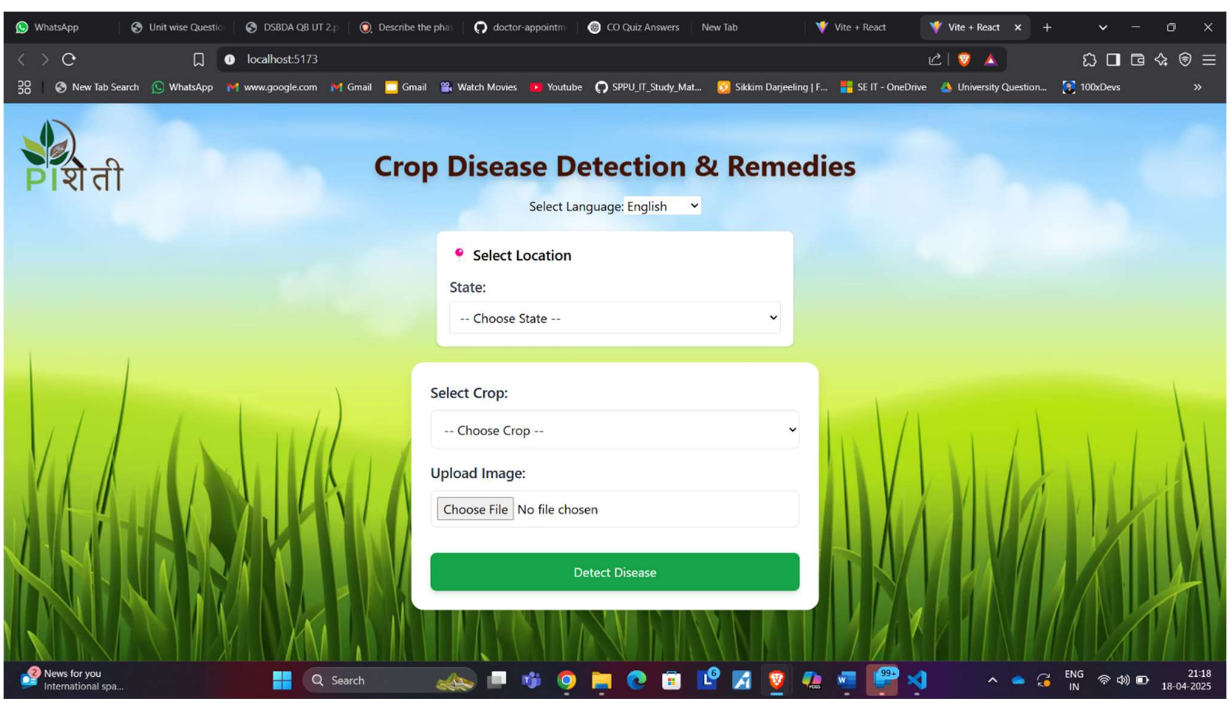
2. Evaluation metrics of model (EfficientNet + CBAM)

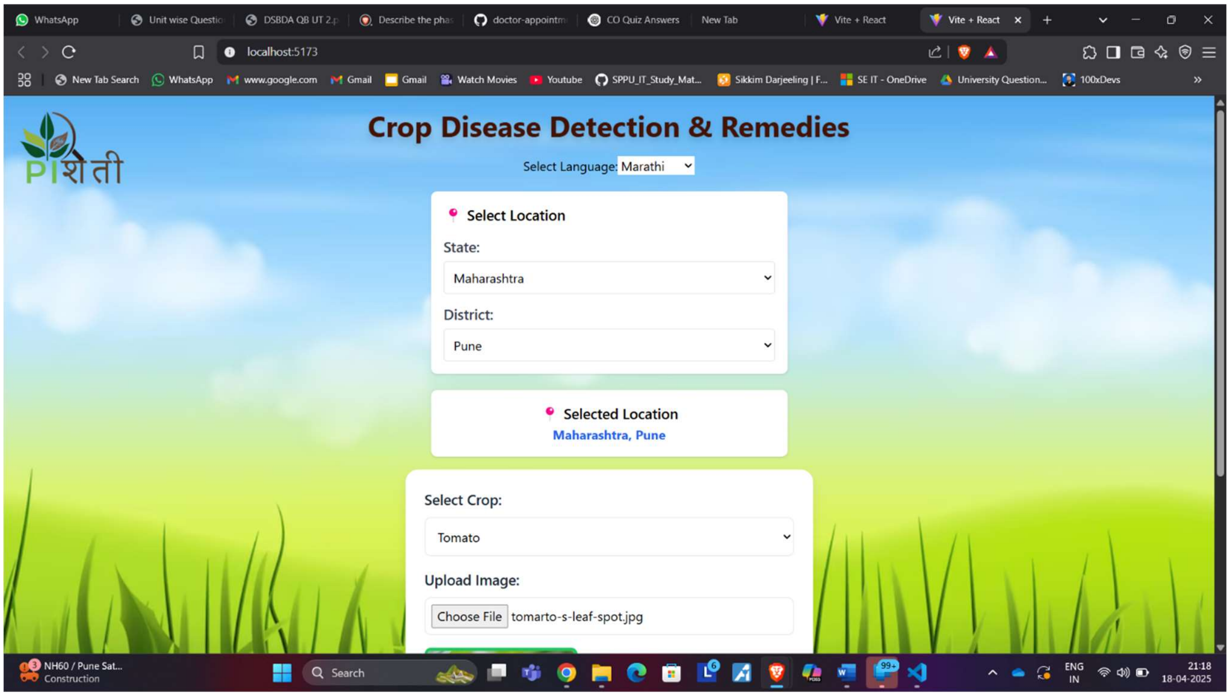
```
Accuracy: 0.93
Precision: 0.93
Recall: 0.93
F1 Score: 0.93

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99       100
           1       1.00      1.00      1.00        79
           2       0.95      0.99      0.97       100
           3       0.99      0.97      0.98       100
           4       0.97      0.99      0.98       100
           5       0.92      0.96      0.94       100
           6       0.97      0.95      0.96       100
           7       0.97      0.94      0.95       100
           8       0.98      0.99      0.99       100
           9       0.97      0.97      0.97       100
          10       0.96      0.98      0.97        56
          11       0.99      0.99      0.99       135
          12       1.00      1.00      1.00        41
          13       1.00      0.94      0.97        99
          14       0.82      0.84      0.83        99
          15       0.84      0.80      0.82        98
          16       0.92      0.99      0.95        93
...
    accuracy                           0.93      2095
   macro avg       0.93      0.94      0.93      2095
weighted avg       0.93      0.93      0.93      2095
```

3. Confusion Matrix of Individual Classes

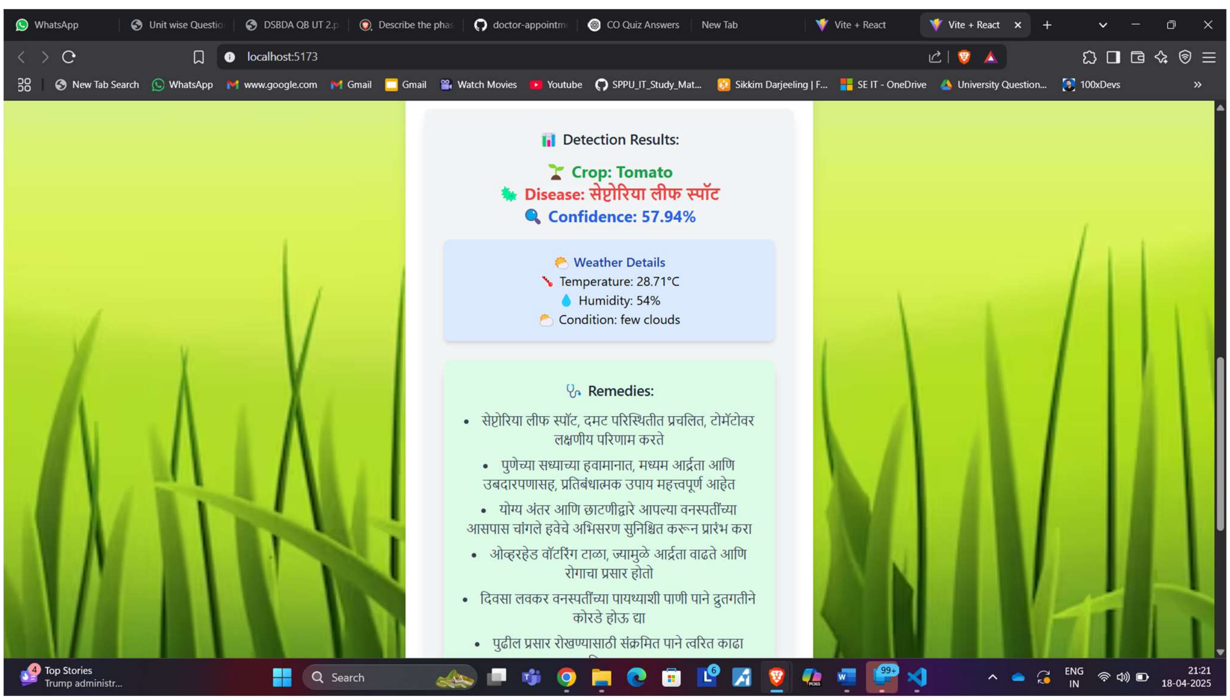


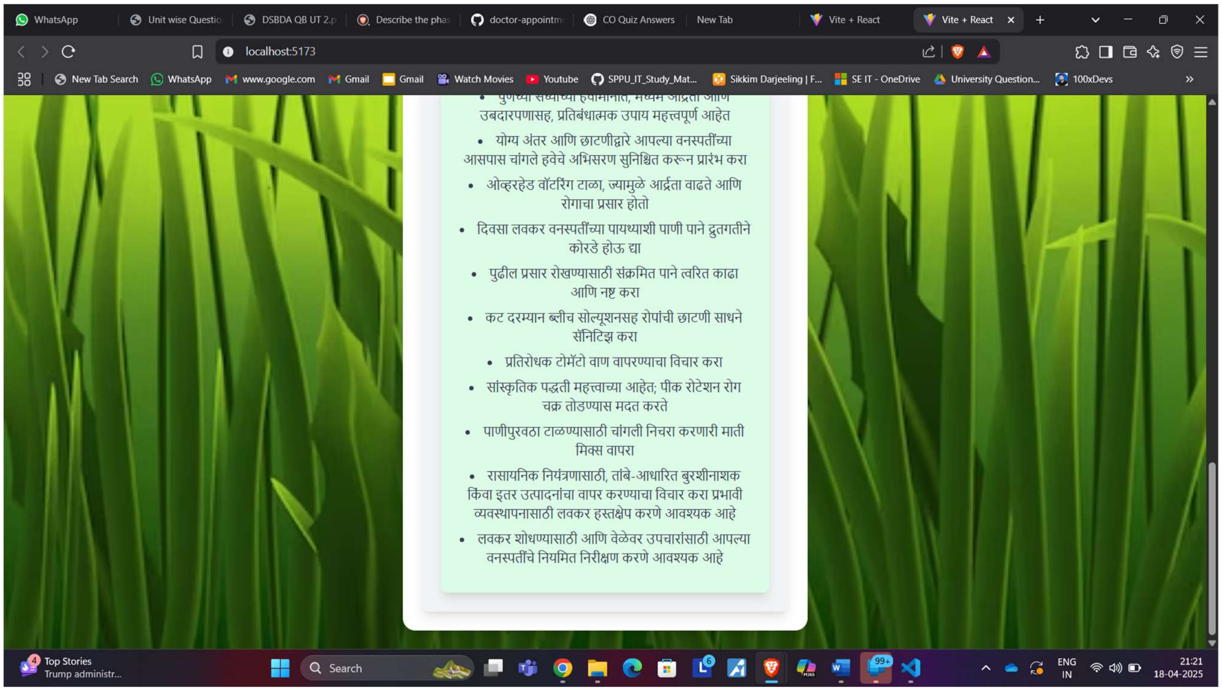
4. Snapshot of Website




localhost:5173
Crop Disease Detection & Remedies
Select Language: Marathi
Select Location
State:
Maharashtra
District:
Pune
Selected Location
Maharashtra, Pune
Select Crop:
Tomato
Upload Image:
Choose File tomarto-s-leaf-spot.jpg

5. Results:


localhost:5173
Detection Results:
Crop: Tomato
Disease: सेप्टोरिया लीफ स्पॉट
Confidence: 57.94%
Weather Details
Temperature: 28.71°C
Humidity: 54%
Condition: few clouds
Remedies:
सेप्टोरिया लीफ स्पॉट, दमट परिस्थितीत प्रचलित, टोमॅटोवर लक्षणीय परिणाम करते
पुणेच्या सध्याच्या हवामानात, मध्यम आर्द्रता आणि उबदारपणासह, प्रतिबंधात्मक उपाय महत्त्वपूर्ण आहेत
योग्य अंतर आणि छाटणीद्वारे आपल्या वनस्पतींच्या आसपास चांगले हवेचे अभिसरण सुनिश्चित करून प्रारंभ करा
ओव्हरहेड वॉटरिंग टाळा, ज्यामुळे आर्द्रता वाढते आणि रोगाचा प्रसार होतो
दिवसा लवकर वनस्पतींच्या पायथ्याशी पाणी पाने द्रुतगतीने कोरडे होऊ द्या
पुढील प्रसार रोखण्यासाठी संक्रमित पाने त्वरित काढा


उबदारपणासह, प्रतिबंधात्मक उपाय महत्त्वपूर्ण आहेत
योग्य अंतर आणि छाटणीद्वारे आपल्या वनस्पतींच्या आसपास चांगले हवेचे अभिसरण सुनिश्चित करून प्रारंभ करा
ओव्हरहेड वॉटरिंग टाळा, ज्यामुळे आर्द्रता वाढते आणि रोगाचा प्रसार होतो
दिवसा लवकर वनस्पतींच्या पायथ्याशी पाणी पाने द्रुतगतीने कोरडे होऊ द्या
पुढील प्रसार रोखण्यासाठी संक्रमित पाने त्वरित काढा आणि नष्ट करा
कट दरम्यान ब्लीच सोल्यूशनसह रोपांची छाटणी साधने सॅनिटिझ करा
प्रतिरोधक टोमॅटो वाण वापरण्याचा विचार करा
सांस्कृतिक पद्धती महत्त्वाच्या आहेत; पीक रोटेशन रोग चक्र तोडण्यास मदत करते
पाणीपुरवठा टाळण्यासाठी चांगली निचरा करणारी माती मिक्स वापरा
रासायनिक नियंत्रणासाठी, तांबे-आधारित बुरशीनाशक किंवा इतर उत्पादनांचा वापर करण्याचा विचार करा प्रभावी व्यवस्थापनासाठी लवकर हस्तक्षेप करणे आवश्यक आहे
लवकर शोधण्यासाठी आणि वेळेवर उपचारांसाठी आपल्या वनस्पतींचे नियमित निरीक्षण करणे आवश्यक आहे