

SMART INDIA HACKATHON 2024



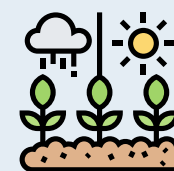
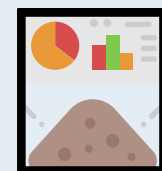
- **Problem Statement ID-** 1638
- **Problem Statement Title-** AI-Driven Crop Disease Prediction and Management System
- **Theme-** Agriculture, FoodTech & Rural Development
- **PS Category-** Software
- **Team ID-**
- **Team Name-** Lunatic Coders



Problem Statement

Escalating
Crop DiseaseNo Reliable AI system
for early detectionUnpredictable
WeatherLow Food
SecurityLimited Sources
for yieldPoor Financials
of farmers

Novelty/Uniqueness

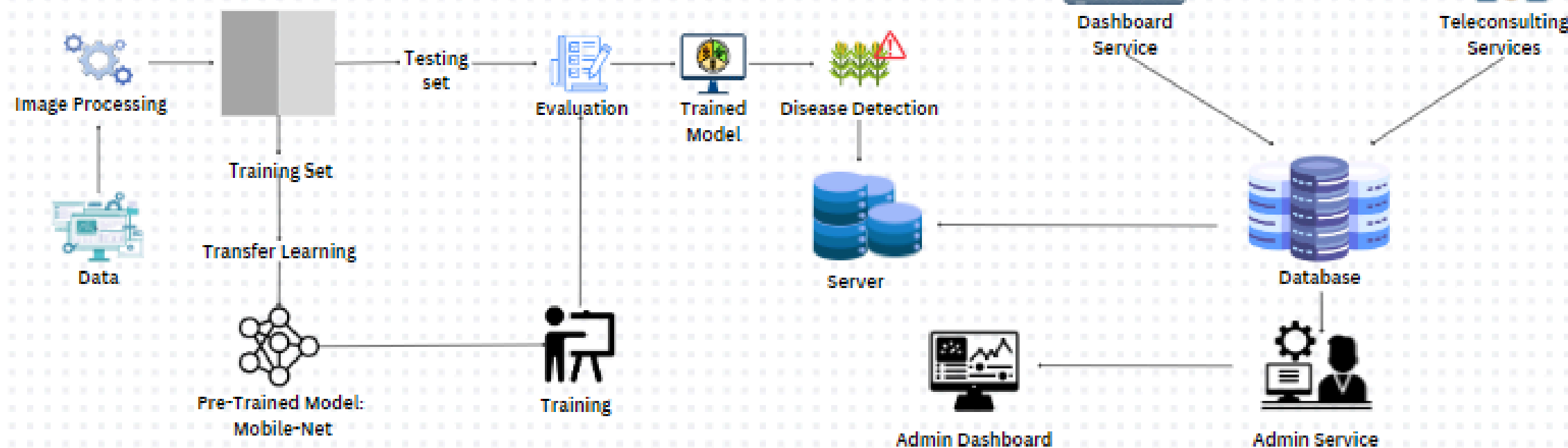
Automated diagnosis,
treatment, prevention
recommendationsTargeted and
precise weed
controlIntegrating
weather, humidity,
CO2 and soil dataAdvanced CNN networks
to process imagesRetrained
model on
regional data

Proposed Solution

- Crops worldwide face a **significant yield loss of 20-40%** due to pests and diseases. Early detection and preventive measures are crucial to mitigate these losses.
- Integrating technologies like **ML** and **Computer Vision** into farming can greatly improve crop disease prediction and boost agricultural productivity.
- Advanced **CNN** architectures like **MobileNets**, **AlexNets**, and **VGGNet** are particularly effective in analyzing crop images and identifying disease patterns.
- Farmers can simply **upload images** of suspected diseased crops to our platform. Our AI system will then provide a **detailed report**, including disease diagnosis, treatment recommendations, and preventive measures.
- Model can accurately predict crop diseases early on, allowing for **timely implementation** of preventive measures and suggest **new age pesticide solutions**.
- Environmental conditions play a significant role in crop health. By monitoring factors like **temperature, humidity, CO2 levels and other conditions**, we can predict **disease susceptibility** and proactively address potential risks.
- Users will receive **real-time alerts** about abrupt weather changes, allowing them to take timely action to **prevent potential crop damage**.
- AI-powered weed detection uses **image analysis** to identify and locate weeds in fields, enabling **targeted herbicide application** instead of blanket spraying.

Techstack

Purpose	Technology used
Frontend	React, Tailwind CSS
Backend	Express.js, Node.js
Data Collection	Selenium webdriver and Tensorflow datasets
Image preprocessing	OpenCV
Model development	PyTorch, DL models(MobileNet)
Database	MongoDB
Hosting and deployment	Vercel



Methodology

- Images and data are collected from various sources.
- Collected images are processed and prepared for training.
- Pre-trained **MobileNet** model is fine-tuned with new data.
- Model is trained and evaluated with a testing set.
- Trained models predict diseases from uploaded crop images.
- Farmers interact via **mobile/web** apps to upload images, receive farming, and weather conditions.
- **HTTP requests** send data to a dashboard, connecting farmers to real-time insights.
- **Multi-lingual** and **audio support** enhance farmer accessibility.
- Experts provide remote advice via **Web RTC**.
- All data is stored in a **database**, monitored by an admin dashboard for system management.

Analysis of Feasibility

- **Multi-lingual feature** allows farmers to switch to their regional language for better communication
- **Audio-support** feature enables text-to-speech communication
- A **streamlined, intuitive UI** for easy navigation of farmers
- Implementation of an **online mode which syncs with the browser in presence of internet** permits the user to access the existing data in remote areas as well
- Using AWS or Google cloud to host the application provides the option of **scalable infrastructure** thus enabling easy resource maintenance

Potential Challenges and Risks



AI model might overfit the training data



Location specificness of data



Lack of trust in AI



Lack of good internet connection in rural areas



Weather and climate challenges

Strategies to overcome the drawback

Usage of **transfer learning** (pre-trained models, cross-validation and regularization)

Scalable architecture to accommodate additional crops and diseases by retraining with localized datasets

Consulting services with experts for reconfirmation and further assistance if the model has predicted a disease positive

Use low bandwidth gap to compress images and enabling **offline functionality** (system syncs when online)

Real time **weather data** with adaptive learning which can adjust to changing patterns over time

Potential Impacts



Early pest detection can **reduce crop damage**, improving overall productivity for farmers.



Reduces the need for manual pest monitoring and costly pest control measures.



Provides less-educated farmers with easy-to-use tools, **improving decision-making and self-sufficiency**.



Promotes **targeted pest control**, reducing excessive pesticide use and environmental harm.



Enhances agricultural efficiency, potentially boosting rural economies through improved crop success.

Economic Benefits

Early pest detection minimizes crop loss, leading to **higher yields and profitability**.

Reduces the need for extensive pesticide use, **cutting input costs** for farmers.

Improved crop quality can lead to **better market prices** and opportunities for farmers.

Social Benefits

Provides easy access to advanced pest detection tools, improving **farmer self-reliance**.

Early pest detection leads to healthier crops, contributing to more **stable food supplies**.

Offers **real-time insights**, helping farmers improve their knowledge of **pest management** and crop health.

Environmental Benefits

Targeted pest control **minimizes overuse of chemicals**, promoting healthier ecosystems.

Encourages more **eco-friendly agriculture** by identifying pest threats early, reducing the need for harsh interventions.

Helps **protect non-target species and maintain ecological balance** by minimizing indiscriminate pesticide application.



Research Paper by, EPFL, Switzerland:
<https://arxiv.org/pdf/1604.03169v2>
Short Literature Review

- The study demonstrates the strong performance of CNNs like **GoogLeNet**, and **MobileNet** for plant disease detection using the **PlantVillage dataset**, with **accuracies** ranging from 85.53% to **99.34%**. **Transfer learning**, particularly with GoogLeNet and MobileNet, consistently **outperforms** models trained from scratch. Transfer learning enhances performance by leveraging **pre-trained models**, especially with color images, achieving **higher accuracy** and **faster convergence**.
- The study also highlights the **superior results** with **colored and segmented images** over grayscale. While controlled environment tests show high accuracy, **real-world** tests drop to 31.4%, indicating the need for more **diverse data for real-world application**.



Research Paper by IIT Gandhinagar:
<https://arxiv.org/pdf/1911.10317v1>
Short Literature Review

- The study highlights **MobileNet's efficiency** in plant disease detection. Despite its lower mean Average Precision (mAP) compared to Faster R-CNN with InceptionResNetV2, MobileNet excels in **real-time mobile applications** due to its **reduced complexity**.
- MobileNet's design, which **balances accuracy** and **computational efficiency**, makes it particularly suited for mobile environments where real-time processing is crucial.

Research Paper from researchgate.net:

https://www.researchgate.net/publication/371417735_55_Major_Insect_Pests_in_Paddy_Crop_and_Their_Management

For researching about crop diseases and their management solutions.

Dataset Source: <https://data.mendeley.com/datasets/tywbtsjrjv/1>