PROJECT-3

Agri Guardian

PROTECTING CROPS, EMPOWERING FARMERS

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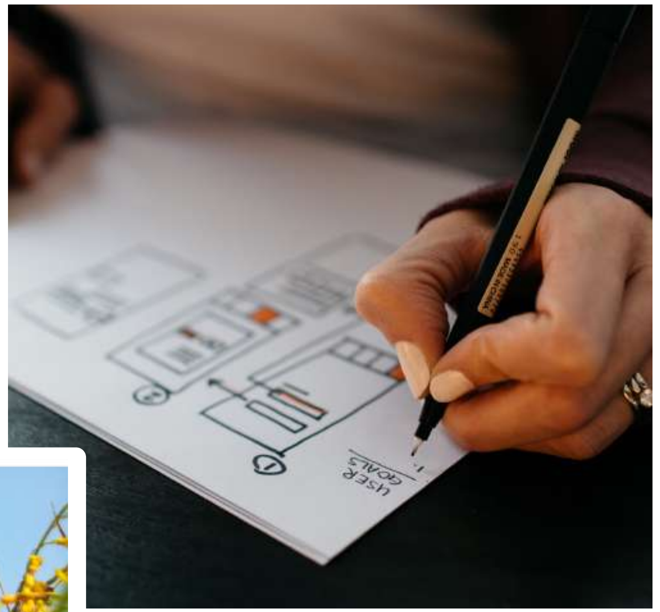
AGENDA

1. INTRODUCTION

2. METHODOLOGY

3.RESULTS

4.DEMONSTRATION



5. FUTURE SCOPE

Introduction

- Leaf diseases are a major threat to global food security, impacting crop health and productivity.
- Traditional detection methods are time taking process, relying on manual inspection.
- The Agri Guardian application which is integrated with deep learning techniques, detect the leaf diseases through the camera feed.
- This approach addresses the urgent need for timely diagnosis, enhancing agricultural sustainability and food production.

MAIN OBJECTIVE : AN APPLICATION FOCUSING ON DETECTING RICE LEAF DISEASES USING DEEP LEARNING TECHNIQUES

DATASET

This dataset contains images of disease-infected rice leaves in jpg format. The images are grouped into 6 classes based on the type of disease in the train and validation folder. There are 450+ images in each class.

Classes:

1. bacterial_leaf_blight
2. brown_spot
3. healthy
4. leaf_blast
5. leaf_scald
6. narrow_brown_spot

LITERATURE REVIEW

1. **Latif, G.; Abdelhamid, S.E.; Mallouhy, R.E.; Alghazo, J.; Kazimi, Z.A. Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model. Plants 2022, 11, 2230. https://doi.org/10.3390/plants11172230**

- Rice is a crucial crop feeding billions, but it's prone to diseases causing significant yield loss. Detecting these diseases early is vital, but it is challenging for farmers to monitor vast fields daily.
- Using machine learning and drones can help.
- The authors suggested a method using **Deep Convolutional Neural Networks (DCNN)** for accurate disease detection in rice leaves.
- Their approach, based on modified **VGG19** transfer learning, can identify three types of diseases with high accuracy, up to 96.08%.
- This method outperforms previous approaches, offering better precision, recall, specificity, and F1 score.

LITERATURE REVIEW

2. **Udayananda, G.K.V.L., Shyalika, C. & Kumara, P.P.N.V. Rice plant disease diagnosing using machine learning techniques: a comprehensive review. *SN Appl. Sci.* 4, 311 (2022). https://doi.org/10.1007/s42452-022-05194-7**

- The researchers looked at different CNN models for spotting diseases in rice plants.
- The authors tested models like **VGG16**, **VGG19**, **MobileNet, LeNet5, and ResNet50. VGG19, LeNet5**, and **MobileNet-V2** showed accuracies of around 77%. VGG16 and VGG19 did particularly well.
- They also tried a hybrid model that was efficient and accurate.
- However, the **R-CNN** model was the best, with 96% accuracy for blast diseases, 95% for Brown Spot disease, and 94.5% for Sheath blight disease, making it the top choice for detecting rice plant diseases.

LITERATURE REVIEW

3. **Trinh, D.C.; Mac, A.T.; Dang, K.G.; Nguyen, H.T.; Nguyen, H.T.; Bui, T.D. Alpha-EIOU-YOLOv8: An Improved Algorithm for Rice Leaf Disease Detection. *AgriEngineering* 2024, *6*, 302-317. https://doi.org/10.3390/agriengineering6010018**

- The authors compared their new method with **YOLOv7 and YOLOv5** and found their model was more accurate, reaching 89.9% accuracy compared to 62%, 80.7%, and 82.8% in other studies on a dataset of 3175 images.
- By using the Y**OLOv8n model and alpha-EIoU loss function**, they improved the accuracy compared to previous studies.
- Their system quickly alerts farmers when it detects diseases, helping them respond faster.
- They made their model work on affordable hardware for practical use. They also created a new dataset of common rice leaf diseases in Vietnam, which could save time and money for future research.
- Overall, their modified YOLOv8 framework performed better than other methods.

LITERATURE REVIEW

4. **Yang, H.; Deng, X.; Shen, H.; Lei, Q.; Zhang, S.; Liu, N. Disease Detection and Identification of Rice Leaf Based on Improved Detection Transformer. *Agriculture* 2023, *13*, 1361. https://doi.org/10.3390/agriculture13071361**

- The authors conducted research and found out that recent advancements integrate the Dense Higher-Level Composition Feature Pyramid Network (**DHLC-FPN)** into the **Detection Transformer (DETR)** to improve plant affliction diagnosis through image classification.
- This method addresses challenges with multiple ailments in one plant and effectively detects three rice leaf diseases: sheath blight, rice blast, and flax spot.
- By replacing DETR's backbone with **DHLC-FPN**, leveraging **Res2Net** and high-density rank hybrid sampling, the model achieves a significant 17.3% improvement in **mean Average Precision (mAP)**, notably excelling in small target detection with a 9.5% boost.

LITERATURE REVIEW

5. **R. R. Patil and S. Kumar, "Rice Transformer: A Novel Integrated Management System for Controlling Rice Diseases," in *IEEE Access*, vol. 10, pp. 87698-87714, 2022, https://ieeexplore.ieee.org/document/9864182**

- The research reveals that the Rice Transformer model merges 4200 sensor inputs and images, achieving a high accuracy of 97.38% in identifying rice diseases.
- Splitting the data into 80% for training and 20% for testing, the model integrates attention-based cross-attention modules, surpassing both unimodal and multimodal fusion techniques.
- Utilizing separate streams for agro-meteorological data and rice images, the model employs self-attention encoders and a cross-attention decoder module to extract interactive features.
- The model's training involves combining features from **CNN and MLP** architectures, followed by processing through additional layers for final classification, generating crop advisories based on predictions.

METHODOLOGY

Data
Collection

Data
Preprocessing

Model
Selection &
Development

Model Training
& Validation

Model
Evaluation

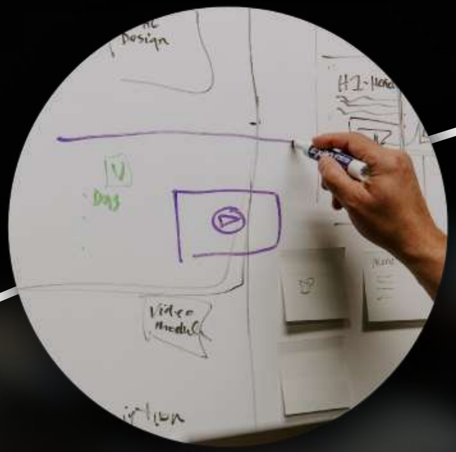
User
Application

APP METHODOLOGY

User Requirement

Feature Identification

Design phase in Figma



App Development

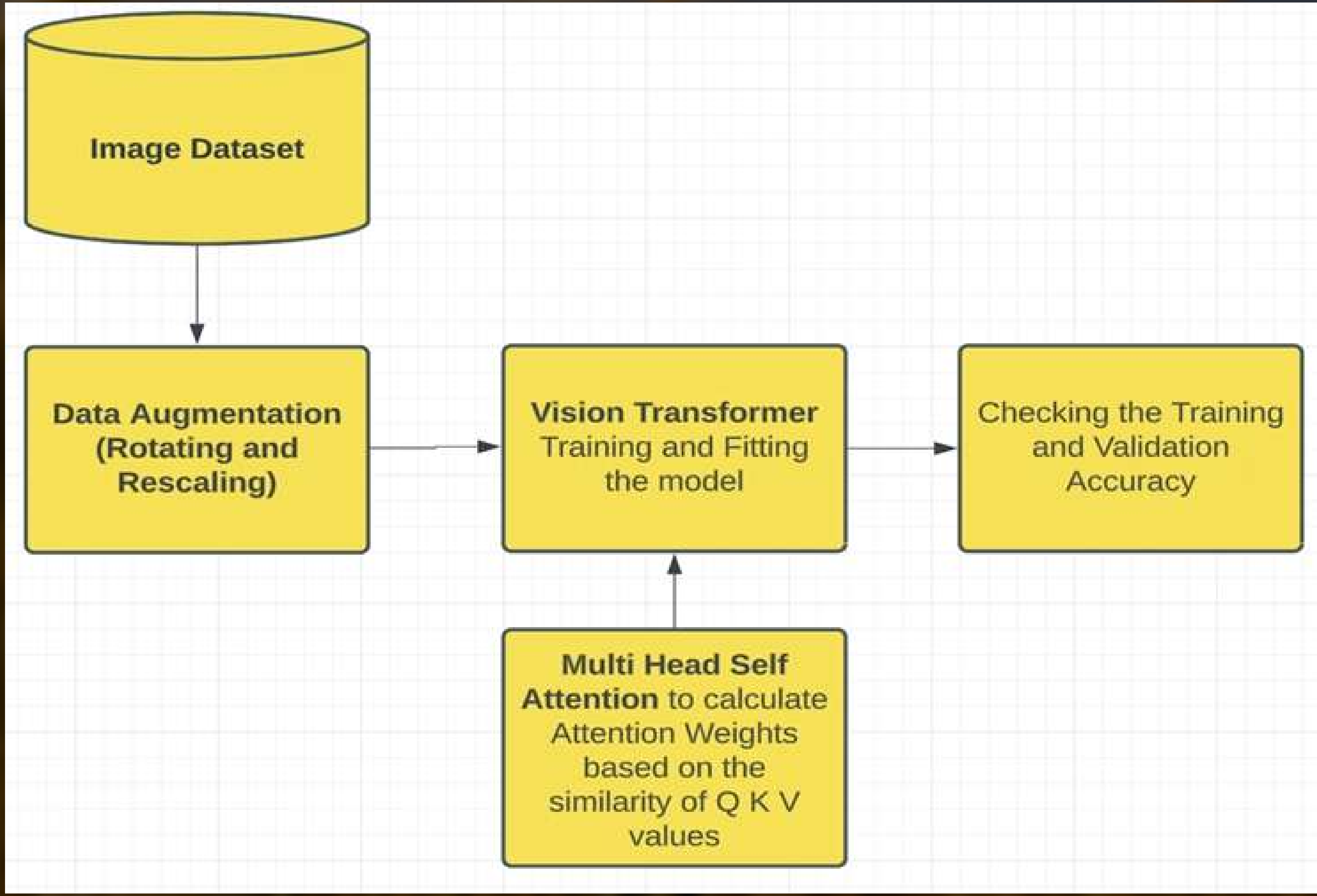
User Application

Future implementation

METHODOLOGY

FLOW CHART

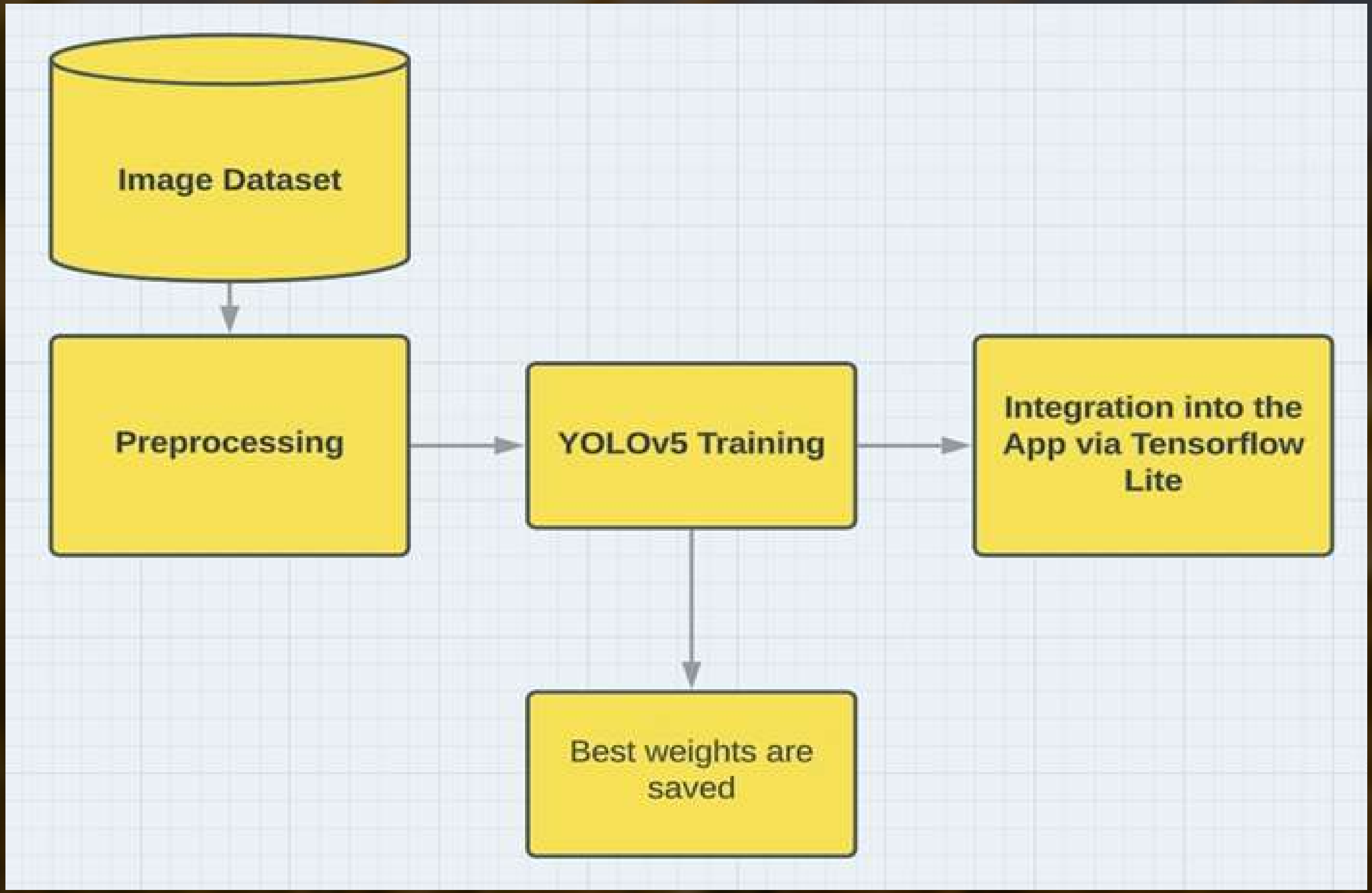
VIT MODEL ARCHITECTURE



METHODOLOGY

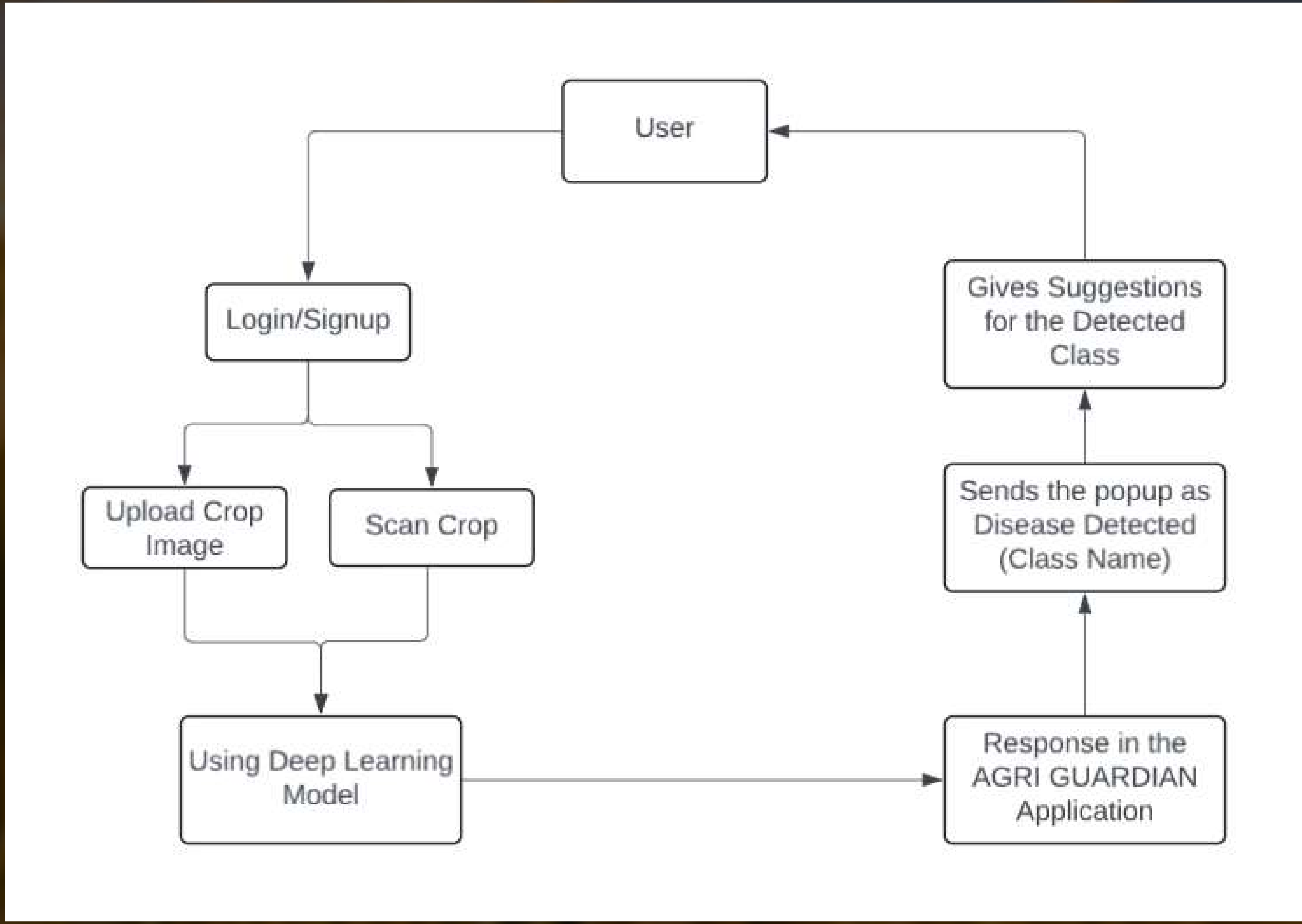
FLOW CHART

YOLOv5 MODEL ARCHITECTURE



METHODOLOGY

FLOW CHART



TECHNICAL STACK

Frontend:

- **Figma:** Designed the prototype of application for better planning and execution during the building process
- **Flutter:** It uses the Dart programming language, Here we used android studio to build the user interface (UI) of the mobile application, allowing users to interact with the system.
- **Flutter Packages:** We leverage various Flutter packages from the pub.dev repository to extend the functionality of our app, such as integrating with third-party services, implementing UI components, and enhancing app performance.

Flutter

TECHNICAL STACK

Backend:

- **Firebase:**
  Cloud platform for user authentication (login/signup) and data storage
  1.Firebase Authentication: Enables secure login and signup experiences (email/password, user details).
  2.Scalable User Management: Manages user accounts and credentials efficiently.

Ultralytics:

- Ultralytics is a library that develops deep learning models for computer vision tasks.

Tensorflow packages:

- **TensorFlow Lite:** For on-device working of implemented model tf-lite is used to integrate the trained model with application.

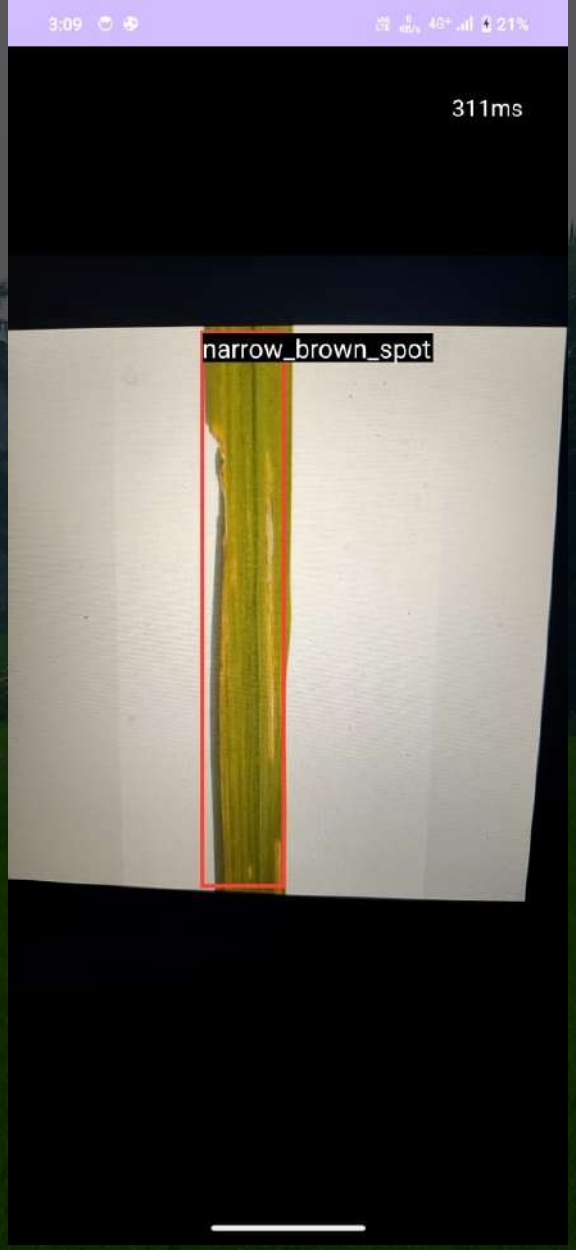
DEMO

Link to the Demo: Click Here

RESULTS

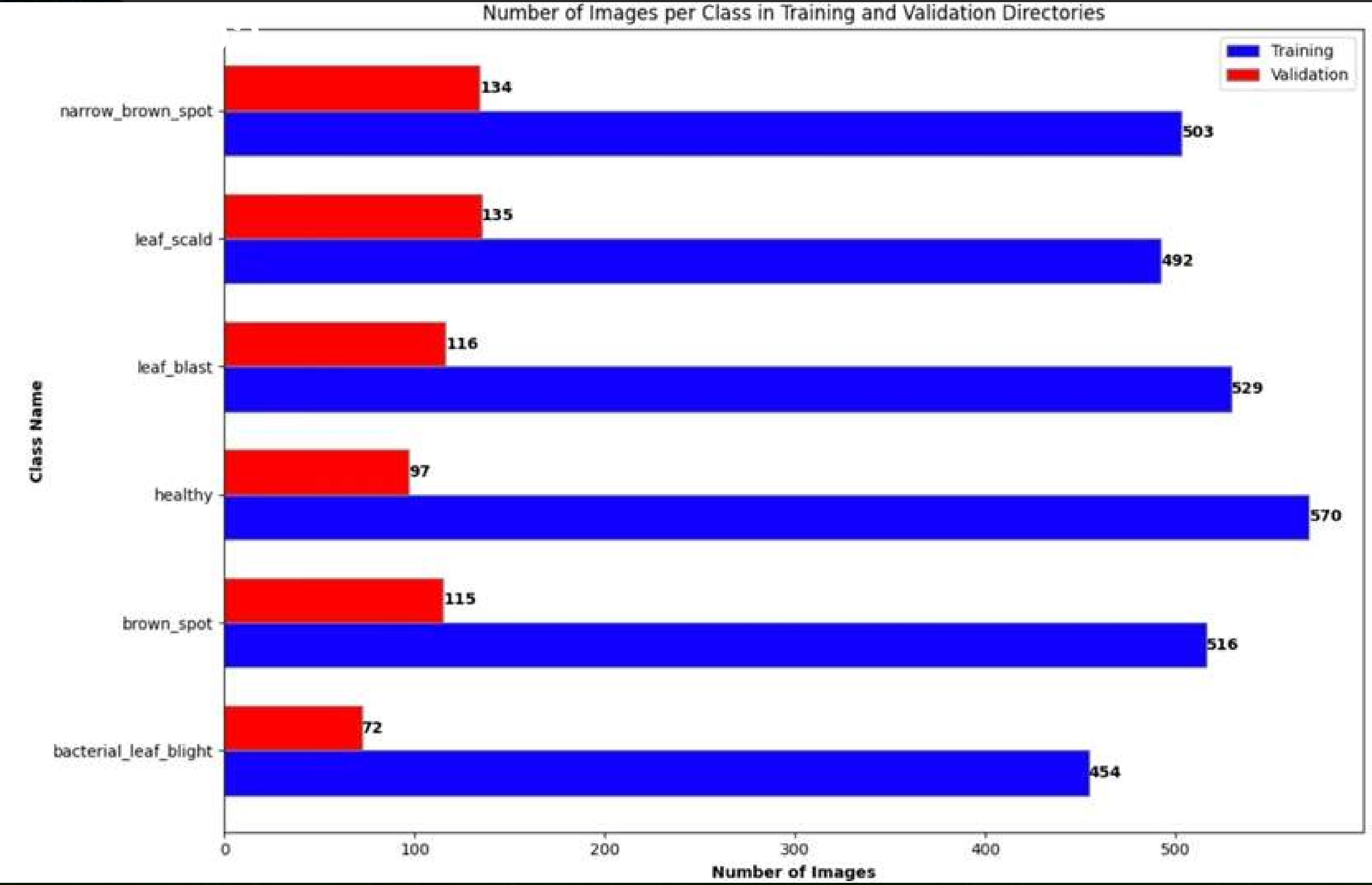
Testing on some random samples

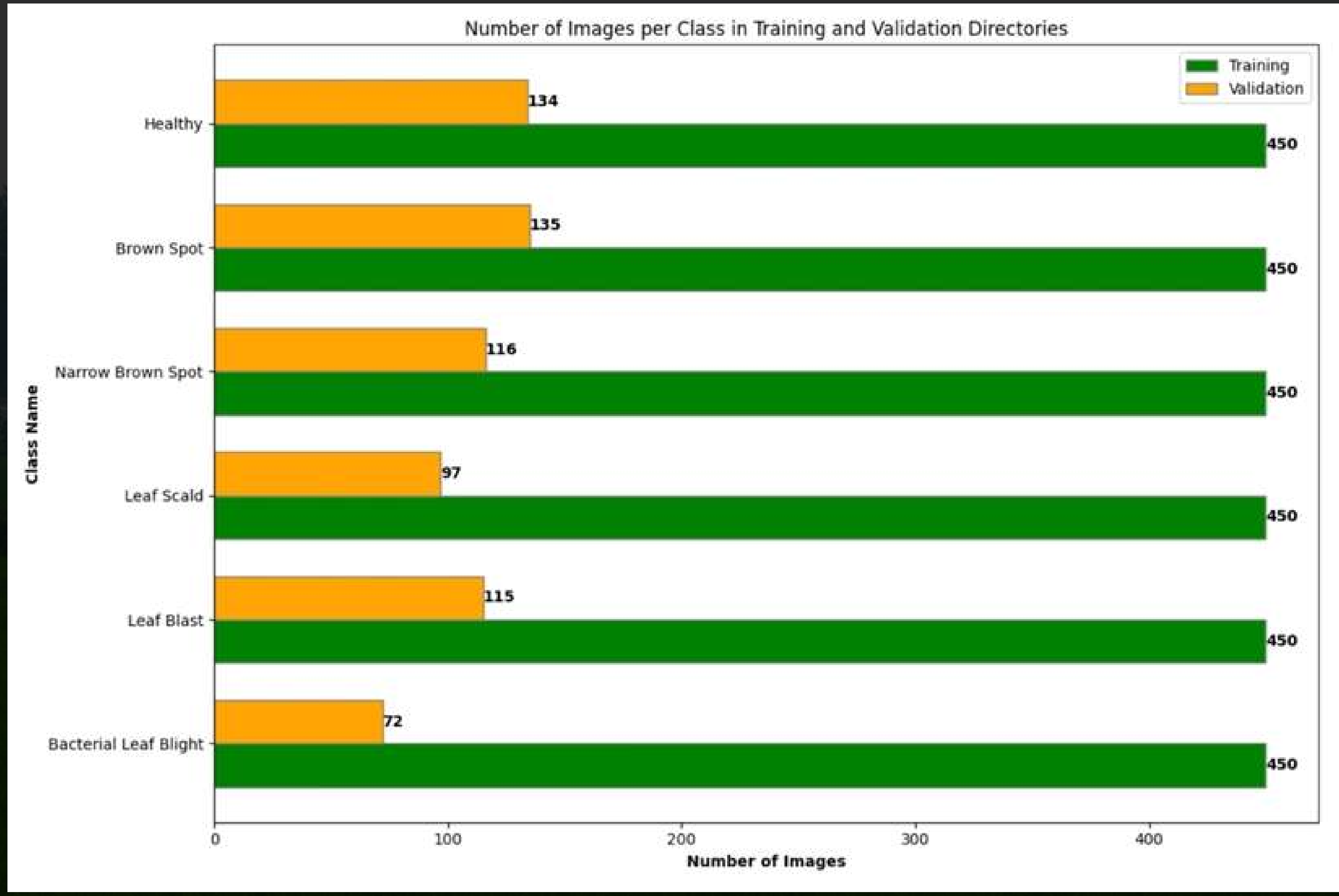
Narrow brown spot but predicted as bacterial leaf blight



Bacterial Leaf blight but predicted as narrow brown spot

DATASET PROBLEM IDENTIFICATION

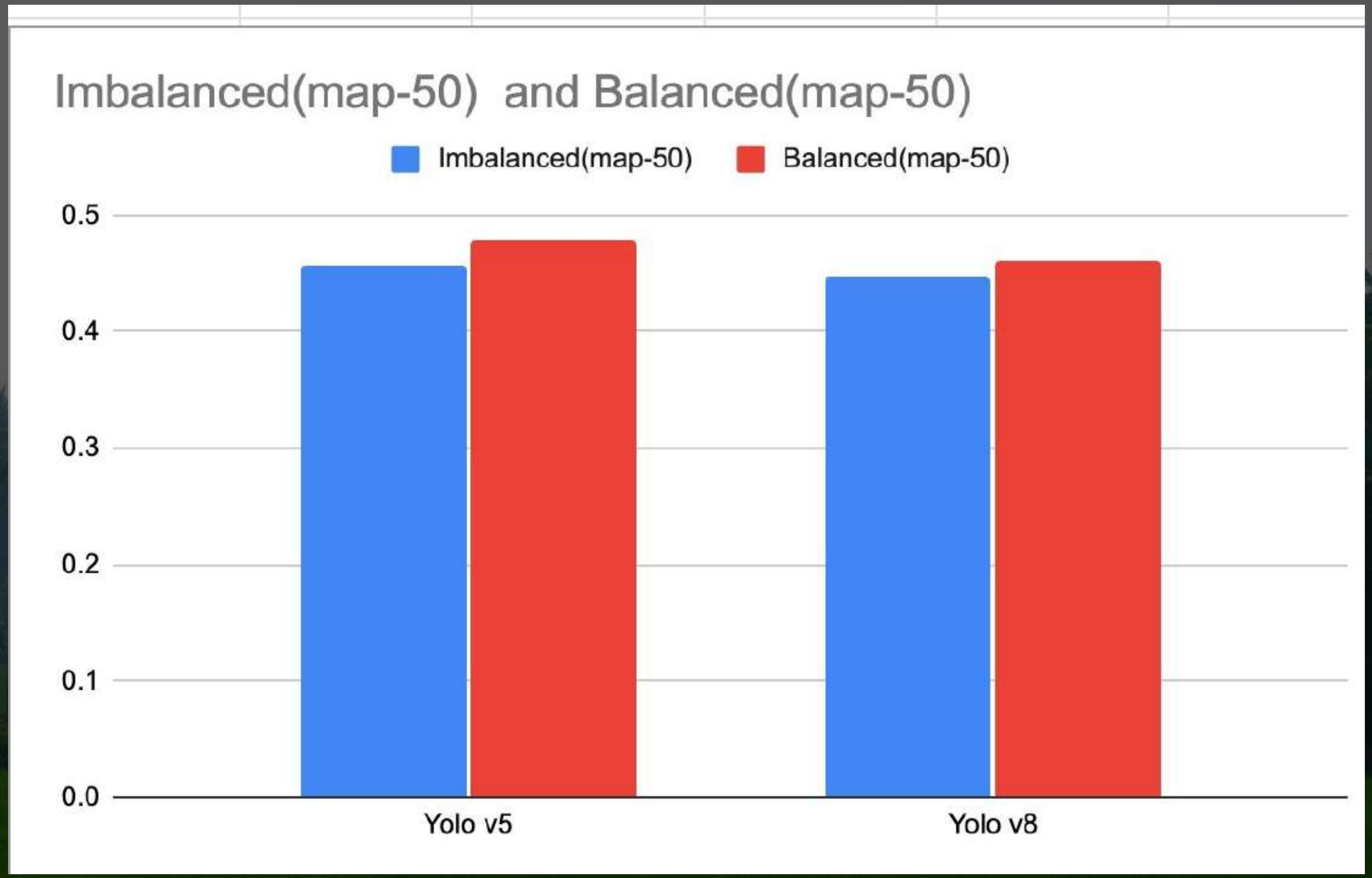




As shown in the plot the imbalanced dataset is tackled by down-sampling method which equalizes the number of images in the training process.

COMPARISON

Comparison	YOLOv5 (mAP50)	YOLOv8 (mAP50)
Imbalanced Dataset	45.7%	44.7%
Balanced Dataset	47.8%	46.2%



YOLOv5 Balanced dataset

```
Model summary: 157 layers, 7026307 parameters, 0 gradients, 15.8 GFLOPs
              Class     Images  Instances          P          R      mAP50
                all        669       1694      0.525       0.52      0.478
         Brown spot        669        533      0.345      0.304      0.239
        Leaf Blight        669        145      0.393      0.549      0.443
         Leaf Scald        669         85      0.836      0.729      0.735
         Leaf blast        669        257      0.277      0.265      0.188
  Narrow brown spot        669        528      0.442      0.356      0.343
            healthy        669        146       0.86      0.918      0.917
Results saved to runs/train/exp2
```

YOLOv5 Imbalanced dataset

```
Validating runs/train/exp2/weights/best.pt...
Fusing layers...
Model summary: 157 layers, 7026307 parameters, 0 gradients, 15.8 GFLOPs
              Class     Images  Instances          P          R      mAP50
                all        489       1317      0.486      0.514      0.457
         Brown spot        489        435      0.286       0.23      0.152
        Leaf Blight        489         89       0.27      0.393      0.301
         Leaf Scald        489         79      0.827      0.835      0.834
         Leaf blast        489        213      0.299      0.404      0.272
  Narrow brown spot        489        386      0.337      0.453      0.337
            healthy        489        115      0.897      0.765      0.844
Results saved to runs/train/exp2
```

COMPARISON

Comparison	YOLOv5 (mAP50)	Results
L.R= 0.01, Batch size = 32 Epochs = 10	33.9%	idating runs/train/exp/weights/best.pt... ing layers... el summary: 157 layers, 7026307 parameters, 0 gradients, 15.8 GFLOPs Class Images Instances P R mAP50 all 669 1694 0.364 0.39 0.339 Brown spot 669 533 0.134 0.386 0.122 Leaf Blight 669 145 0.304 0.434 0.292 Leaf Scald 669 85 0.525 0.624 0.603 Leaf blast 669 257 0.228 0.191 0.126 Narrow brown spot 669 528 0.265 0.371 0.248 healthy 669 146 0.731 0.336 0.641
L.R=0.01, Batch size = 16 Epochs = 10	35.4%	Validating runs/train/exp2/weights/best.pt... Fusing layers... Model summary: 157 layers, 7026307 parameters, 0 gradients, 15.8 GFLOPs Class Images Instances P R mAP50 all 669 1694 0.412 0.426 0.374 Brown spot 669 533 0.279 0.113 0.132 Leaf Blight 669 145 0.372 0.407 0.297 Leaf Scald 669 85 0.727 0.682 0.678 Leaf blast 669 257 0.275 0.117 0.116 Narrow brown spot 669 528 0.21 0.375 0.209 healthy 669 146 0.607 0.863 0.815 Results saved to **runs/train/exp2**
L.R=0.001, Batch size = 16 Epochs = 15	47.8%	Model summary: 157 layers, 7026307 parameters, 0 gradients, 15.8 GFLOPs Class Images Instances P R mAP50 all 669 1694 0.525 0.52 0.478 Brown spot 669 533 0.345 0.304 0.239 Leaf Blight 669 145 0.393 0.549 0.443 Leaf Scald 669 85 0.836 0.729 0.735 Leaf blast 669 257 0.277 0.265 0.188 Narrow brown spot 669 528 0.442 0.356 0.343 healthy 669 146 0.86 0.918 0.917 Results saved to **runs/train/exp2**

FUTURE SCOPE

- Integrate local languages into app interface and disease information, for better user accessibility.
- Build a pipeline of Segmentation, Object Detection and Classification.
- Enable in-app consultations with agricultural specialists.


THANK YO

Pitch

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