Crop Residue Prediction Using Semantic Segmentation

Project Story

- **Benefits of Crop Residue**
  - **Reduces erosion**
  - **Improves moisture retention**
  - **Increases organic matter → Enhances soil health**

- **Need for Automation**
  - **Measuring crop residue manually → Time-consuming & difficult**
  - **Technology solution:**
    - **Use mobile phones or drones to capture images**
    - **AI model analyzes images to estimate crop residue coverage**

Targeted Audience

This project is for the farmers and researchers interested in analysis of crop residue coverage of a given field

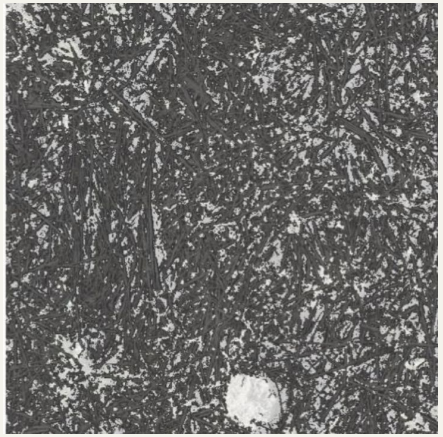
Roles and Responsibilities

- Saiman – Model development
- Akash – Data Augmentation, Model Searching
- Nipun – Application – Model integration
- Aayush – Preprocessing, Model Evaluation
- Puumaaya – Preprocessing, Data Cleaning

Pre-processing

- Combine Residue dataset with Sunlight dataset to create 4 classes

  - Residue | Sunlight -> Class 0
  - Residue | Shade -> Class 1
  - Background | Sunlight -> Class 2
  - Background | Shade -> Class 3



Data Augmentation

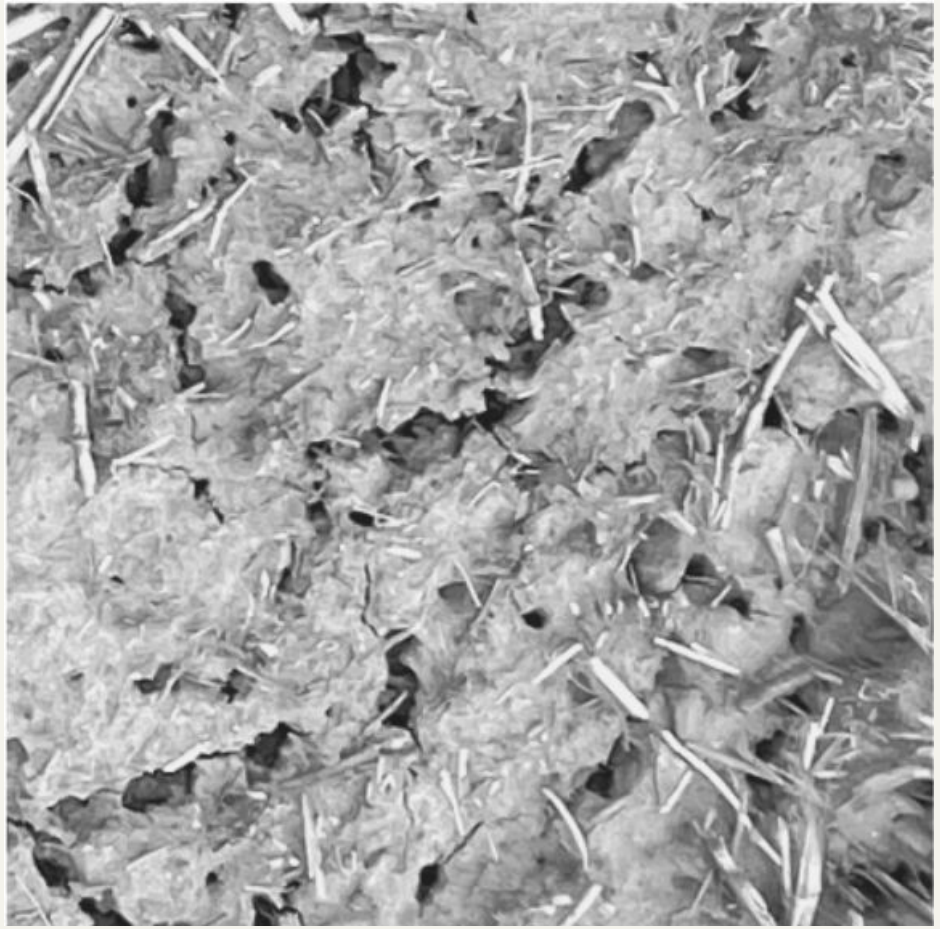
- Used the albumentations library in python
- Necessary due to the small size of training examples provided for this task.
- Following is the space of transforms, a transform was picked at random.

Data Augmentation

- The following transformations were applied with a .5 probability:
  - Horizontal Flip
  - Vertical Flip
  - Rotate by 90
- And these were applied with .2 probability
  - Randomly change the brightness and contrast
  - Adjust Hue, Saturation and Value by a maximum of 20,30,20 respectively
  - Add Gaussian noise between 10 and 50
  - Blur with a limit of 3

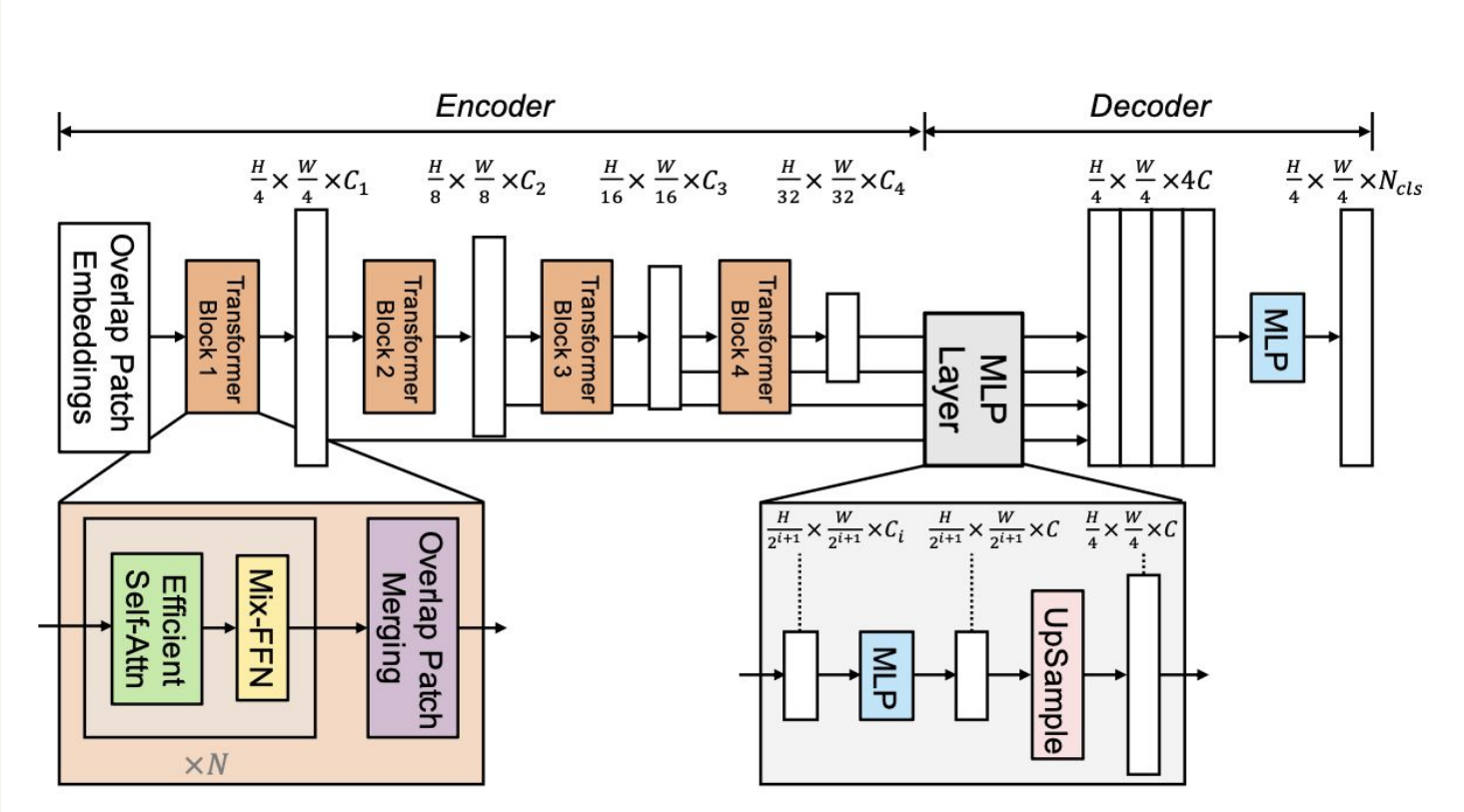
Original Image

Augmented Image



Model background

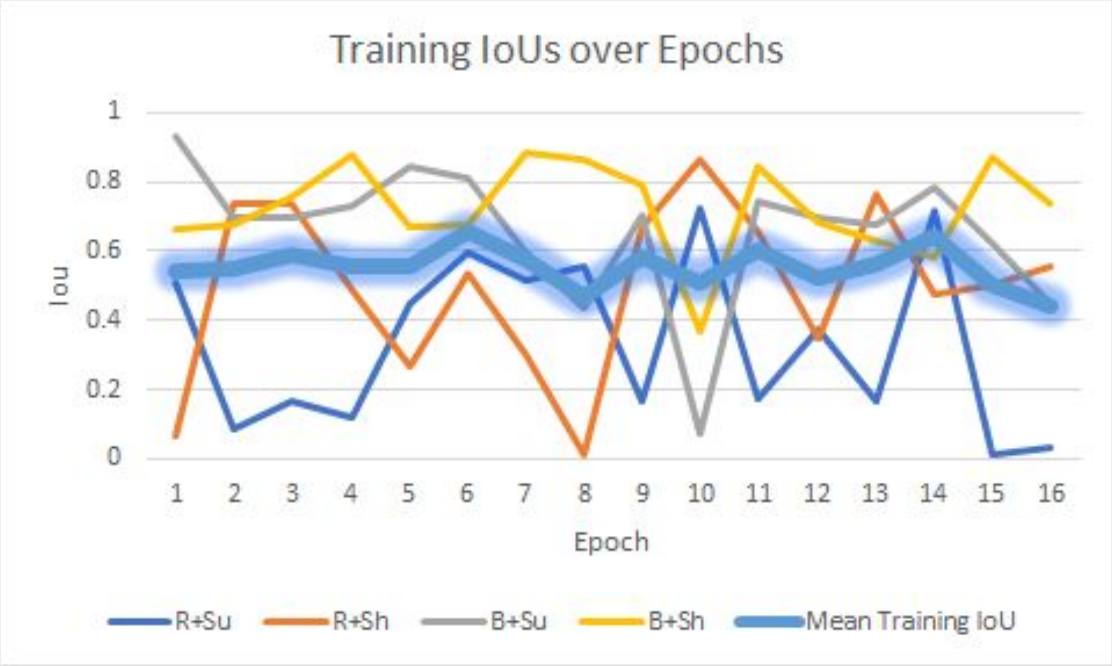
- Hierarchical Transformer Encoder and Lightweight MLP module
- Takes local and global features.
- Hierarchical features from encoders and MLP to fuse features and predict masks.

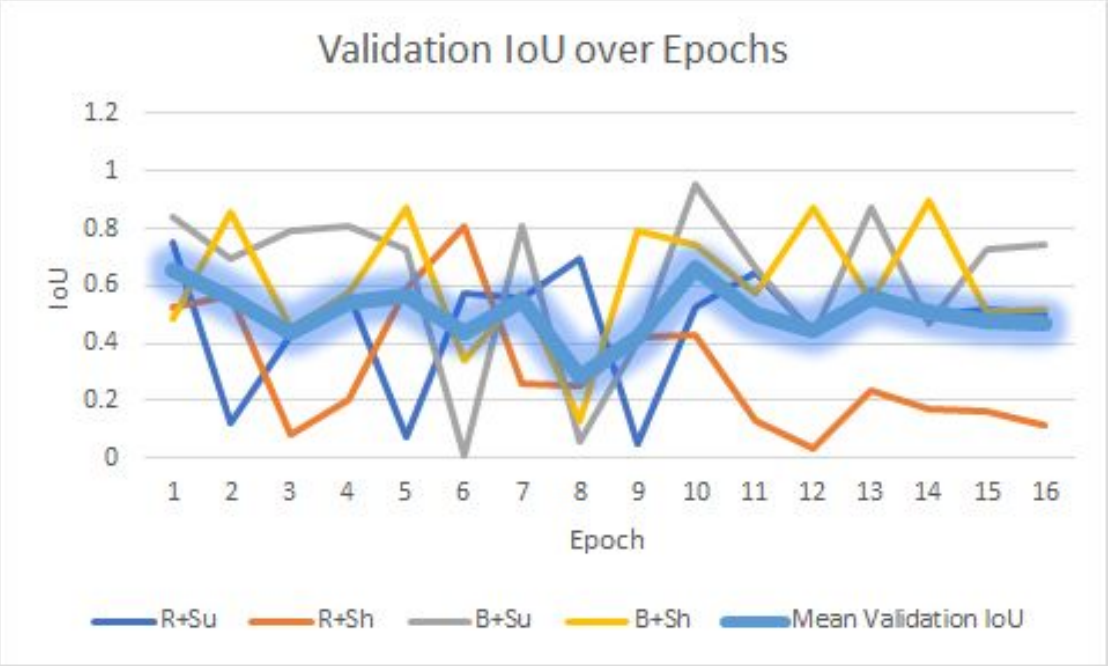


Model Creation

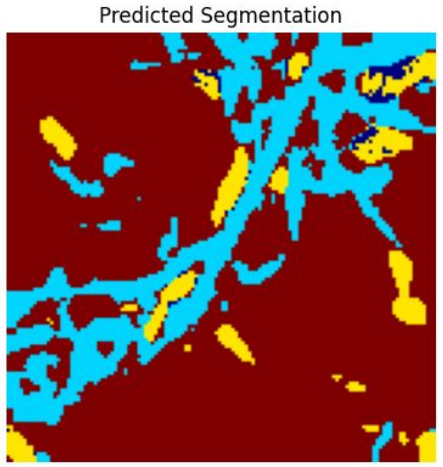
- Full-fine tuning the SegFormer model.
- Multi-scale feature recognition in SegFormer.
- No positional encoding instead the mixed feed forward network uses a CNN layer to give positional information.
- The final decoder layer aggregates information from different layers, and thus combining both local attention and global attention.

Testing


Training IoUs over Epochs
Iou
1
0.8
0.6
0.4
0.2
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Epoch
R+Su
R+Sh
B+Su
B+Sh
Mean Training IoU


Validation IoU over Epochs
IoU
1.2
1
0.8
0.6
0.4
0.2
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Epoch
R+Su
R+Sh
B+Su
B+Sh
Mean Validation IoU

Sample Prediction

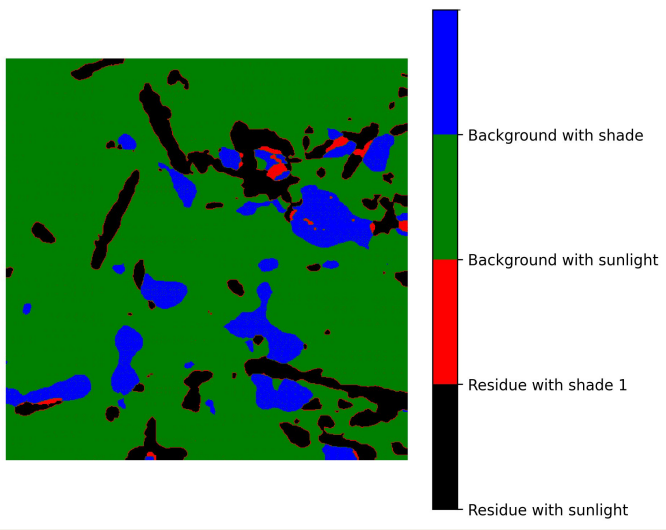


: Residue + Sunlight

: Residue + Shade

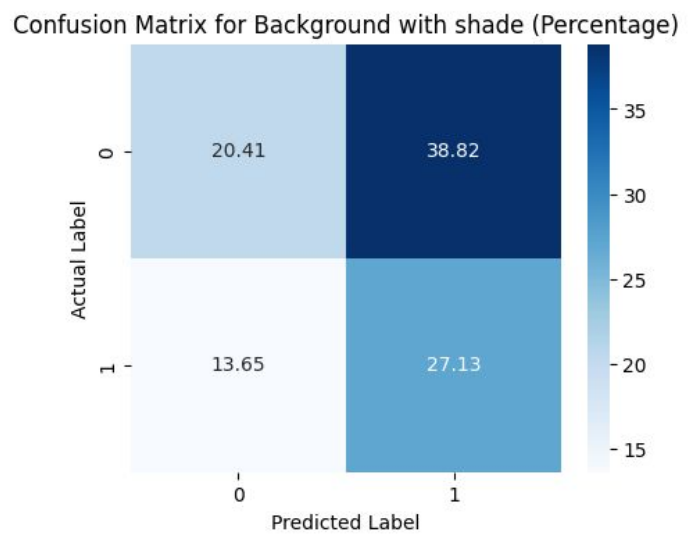
: Background + Sunlight

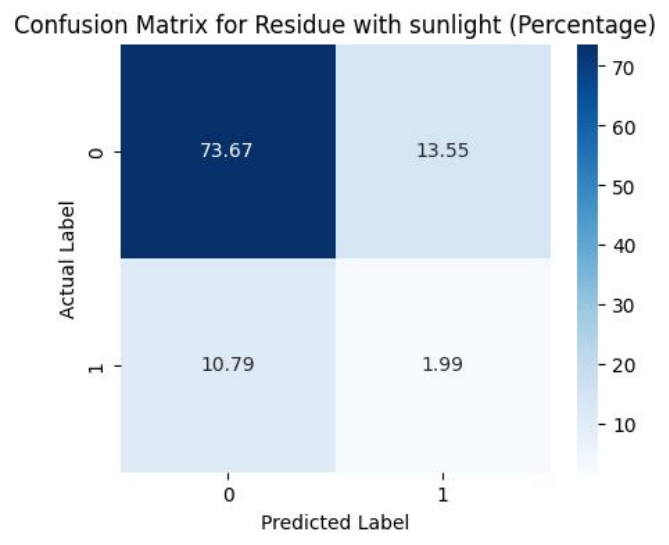
:Background + Shade

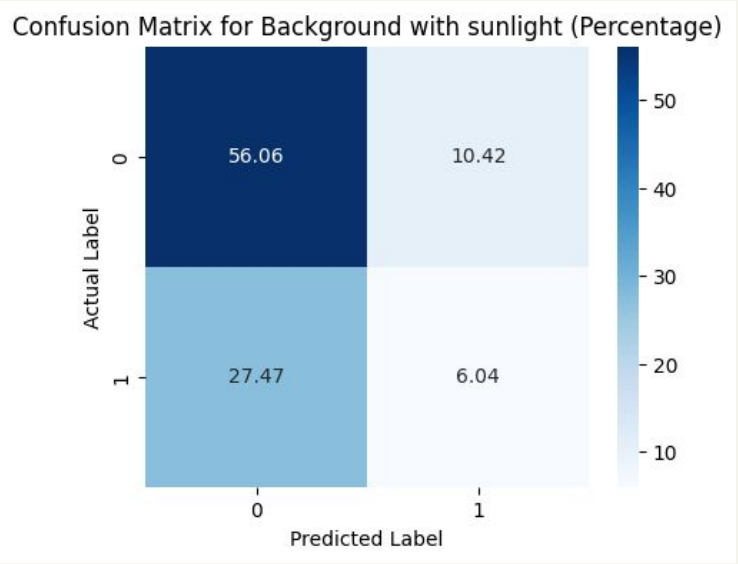


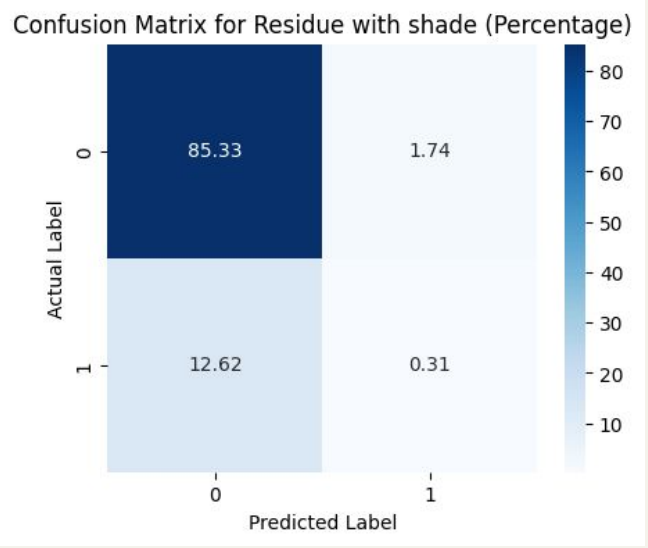
Residue with sunlight: 278.75 mm^2
Residue with shade 1: 17.91 mm^2
Background with sunlight: 2060.96 mm^2
Background with shade: 263.82 mm^2

Confusion Matrices









App Development

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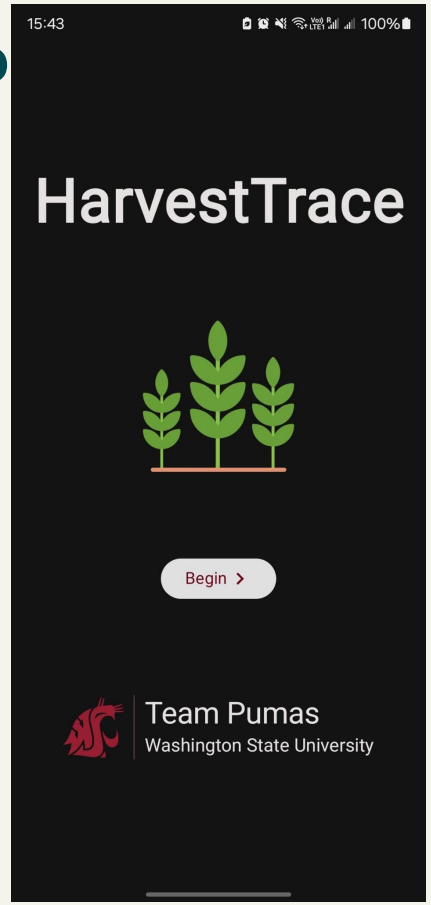

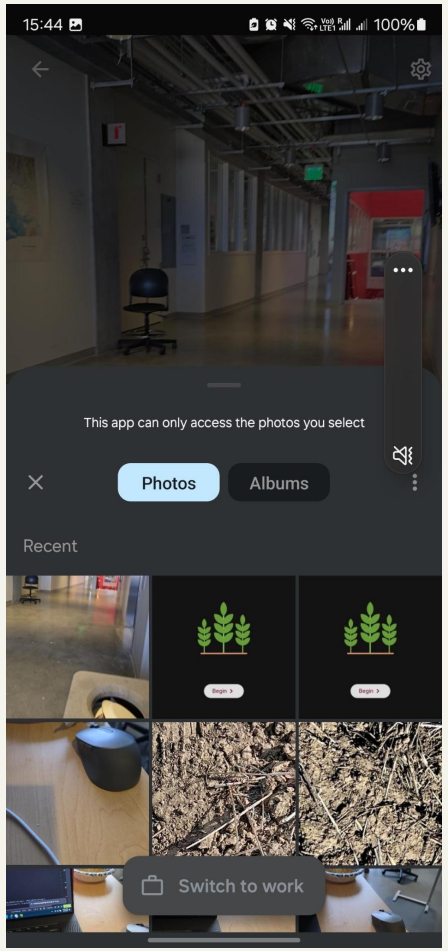

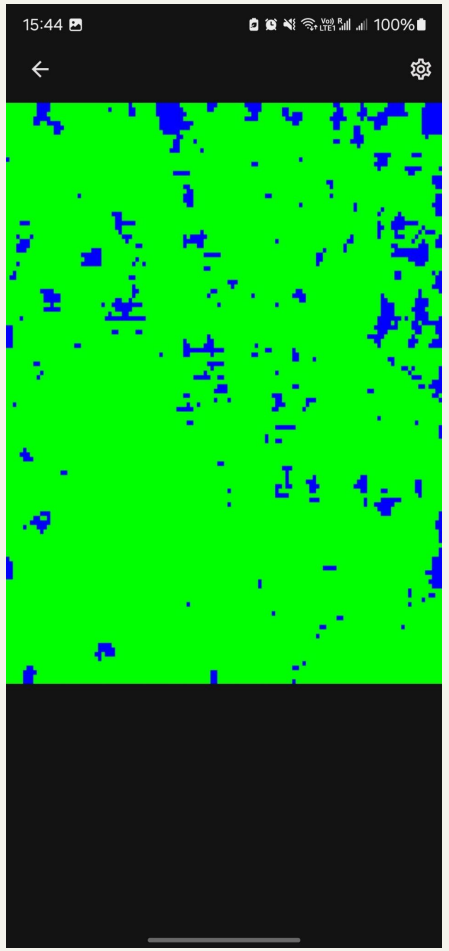

Key Findings

Optimized Crop Residue Management –>

By accurately identifying **residue vs. soil**, farmers can adjust tillage practices, leading to **better soil health**, **moisture retention**, and **reduced erosion**.

Enhanced Irrigation and Fertilization –>

Identifying **sunlit vs. shaded** areas helps in understanding microclimates within fields, allowing for **targeted irrigation** and **fertilizer application** to maximize yields

Promotes Sustainable Farming –>

Managing crop residue correctly reduces **soil erosion**, **runoff**, and **carbon emissions**, supporting **sustainable agricultural practices**.

Data-Driven Decisions –>

Companies can use this data to offer **advisory services** or integrate it into **farm management software** for **real-time decision-making**.

Code

The code developed and used in this hackathon can be found at https://github.com/raoakash1997/CropResiduePredictor

Model Info

- interest to introduce Transformers to vision tasks.
- Multi-scale feature recognition in SegFormer.
- Full fine-tuning.
- Hierarchical transformer encoder.
- Light-weight MLP modules, can be used in any test cases.
- No positional embedding.
- lightweight MLP decoder where the key idea is to take advantage of the Transformer-induced features where the attentions of lower layers tend to stay local, whereas the ones of the highest layers are highly non-local. By aggregating the information from different layers, the MLP decoder combines both local and global attention.