



Depi Graduation Project

Land Type

Classification

A Deep Learning Project using EfficientNetB3

Background



Satellite imagery is now essential for agriculture, environmental monitoring, and urban planning. But analyzing satellite images manually is slow, inconsistent, and not scalable. This project builds an AI system that automatically classifies land types in Egypt using Sentinel-2 images and deep learning.

Problem Description



There is no simple, accurate tool for land-type classification specific to Egypt.

Main challenges include:

- Huge amount of satellite images
- Manual labeling is slow and error-prone

- Existing tools are expensive or not optimized for Egyptian land

- No ready deep-learning platform for automatic classification



Project Objectives

- Prepare and preprocess the EuroSAT dataset

- Apply augmentation to improve generalization

- Train EfficientNetB3 using transfer learning

- Build an analytical dashboard

- Evaluate with accuracy, confusion matrix, and performance metrics

- Deploy the model online for public use

Dataset



We used the EuroSAT Satellite Dataset containing 10 land classes:
AnnualCrop – Forest – HerbaceousVegetation – Highway – Industrial –
Pasture – PermanentCrop – Residential – River – SeaLake.
Dataset was split into: Training, Validation, Testing.



Preprocessing

To prepare images for training:

- Resizing to 224×224
- Normalization (0–1)
- Data augmentation: rotation, flip, zoom
- Shuffling and batching

Data Augmentation

```
train_datagen = ImageDataGenerator(  
    rescale=1/255.0,  
    rotation_range=20,  
    zoom_range=0.2,  
    width_shift_range=0.1,  
    height_shift_range=0.1,  
    horizontal_flip=True,  
)  
  
val_datagen = ImageDataGenerator(  
    rescale=1/255.0  
)
```



Model Architecture

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
efficientnetb3 (Functional)	(None, 7, 7, 1536)	10,783,535
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1536)	0
dense (Dense)	(None, 512)	786,944
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 10)	2,570

Total params: 11,704,377 (44.65 MB)

Trainable params: 11,591,892 (44.22 MB)

Non-trainable params: 112,485 (439.40 KB)

We used EfficientNetB3 because:

- High accuracy
- Lightweight and fast
- Fewer parameters
- Generalizes well on satellite images

Model Components:

- EfficientNetB3 backbone
- Global Average Pooling
- Dropout
- Dense Softmax layer



Training Setup

Training configuration:

- Optimizer: Adam
- Learning rate: 0.0001
- Epochs: 15–25
- Loss: Categorical Crossentropy
- Metrics: Accuracy



Evaluation Metrics

Model performance was evaluated using:

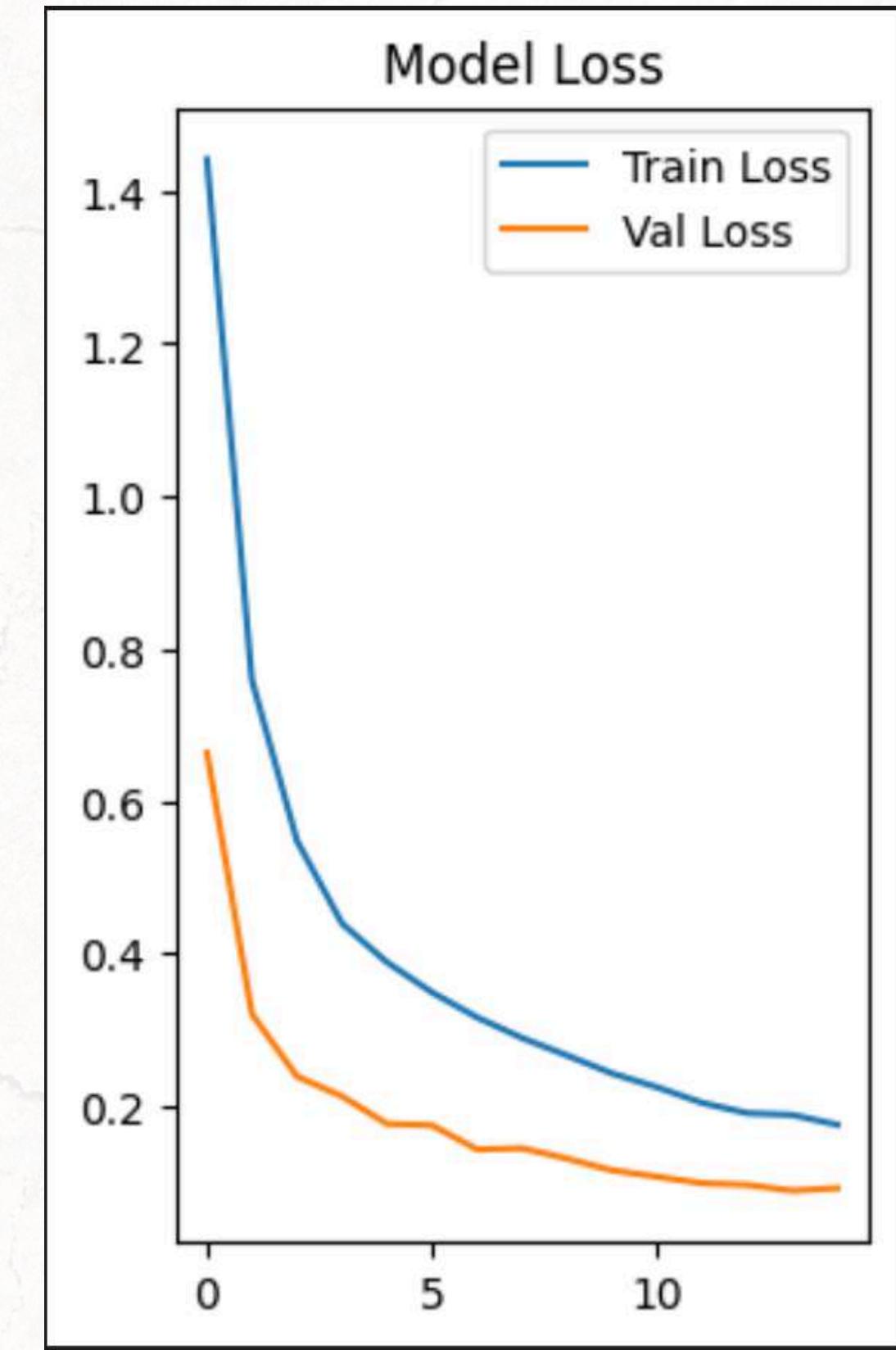
- Classification accuracy
- Precision & Recall
- F1-Score
- Confusion Matrix

These metrics reveal how well the model differentiates between the 10 land types.

Training Results

Training curves show:

- • Accuracy increased steadily
- • Loss decreased consistently
- • No major overfitting



Confusion Matrix

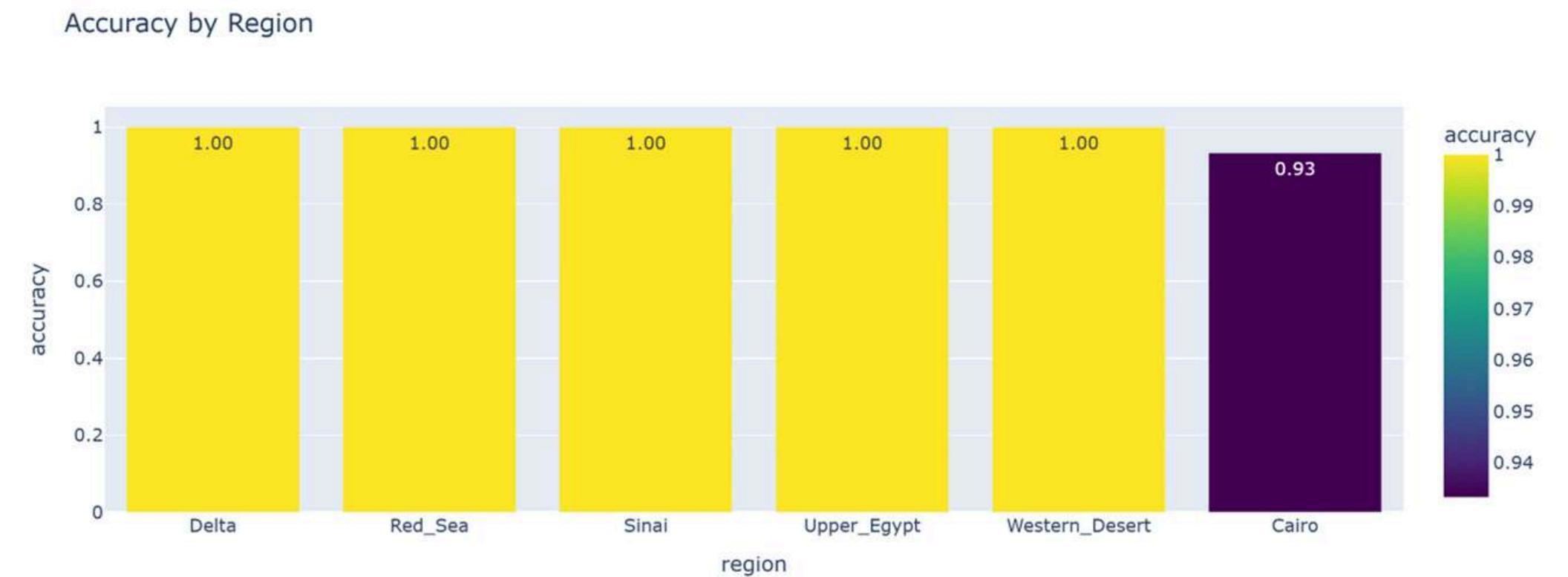
The confusion matrix shows the model's predictions for all land classes. It highlights which classes were classified correctly and which ones were confusing.

		Confusion Matrix										
		AnnualCrop	Forest	HerbaceousVegetation	Highway	Industrial	Pasture	PermanentCrop	Residential	River	SeaLake	
Actual	AnnualCrop	555	4	2	0	0	7	16	0	3	0	
	Forest	0	588	2	0	0	1	0	0	1	2	
HerbaceousVegetation	0	8	570	1	0	8	12	5	1	1		
Highway	1	0	1	484	1	0	1	1	10	0		
Industrial	0	0	2	1	487	0	1	21	2	0		
Pasture	2	4	3	0	0	395	1	0	1	1		
PermanentCrop	8	0	14	1	2	2	450	5	0	0		
Residential	0	0	0	0	0	0	0	614	0	0		
River	2	0	0	4	0	0	1	0	494	1		
SeaLake	0	7	0	1	0	2	0	0	0	585		

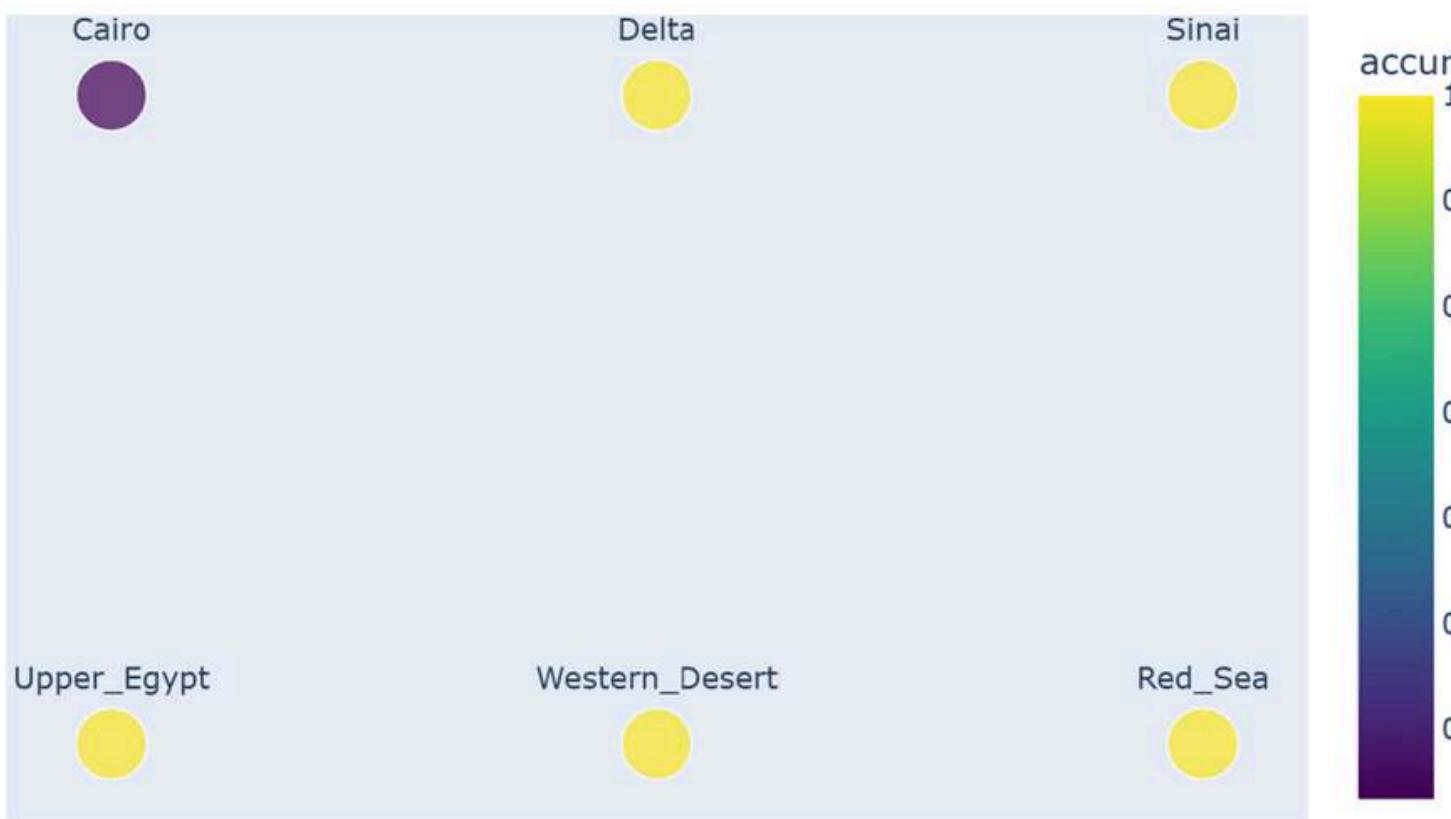
Dashboard Analysis

An interactive dashboard was created to analyze model performance:

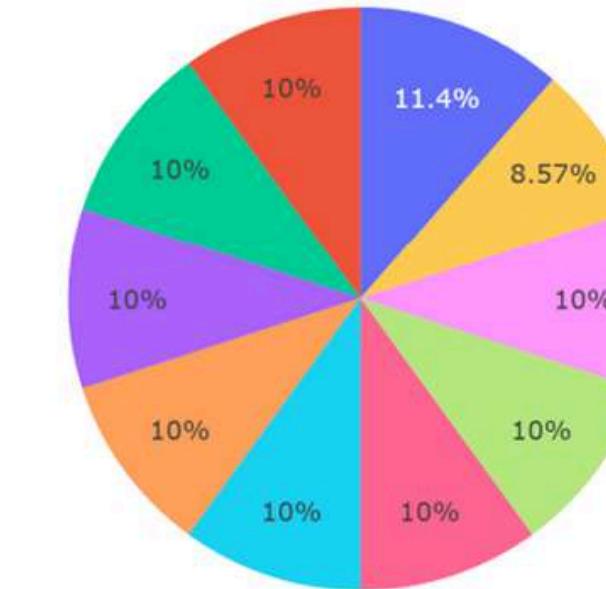
- Prediction per image
- Accuracy per region
- Distribution of predictions
- Class-wise accuracy by region



Egypt Regions – Land Classification Accuracy



Prediction Distribution



- AnnualCrop
- Forest
- HerbaceousVegetation
- Highway
- Industrial
- Pasture
- PermanentCrop
- Residential
- River
- SeaLake



Web Interface



A Flask-based web application was built to allow:

- Uploading satellite images
- Running EfficientNetB3 inference
- Displaying predicted class + confidence
- Showing Top-3 predictions
- Image overlay with label
- Land-type descriptions



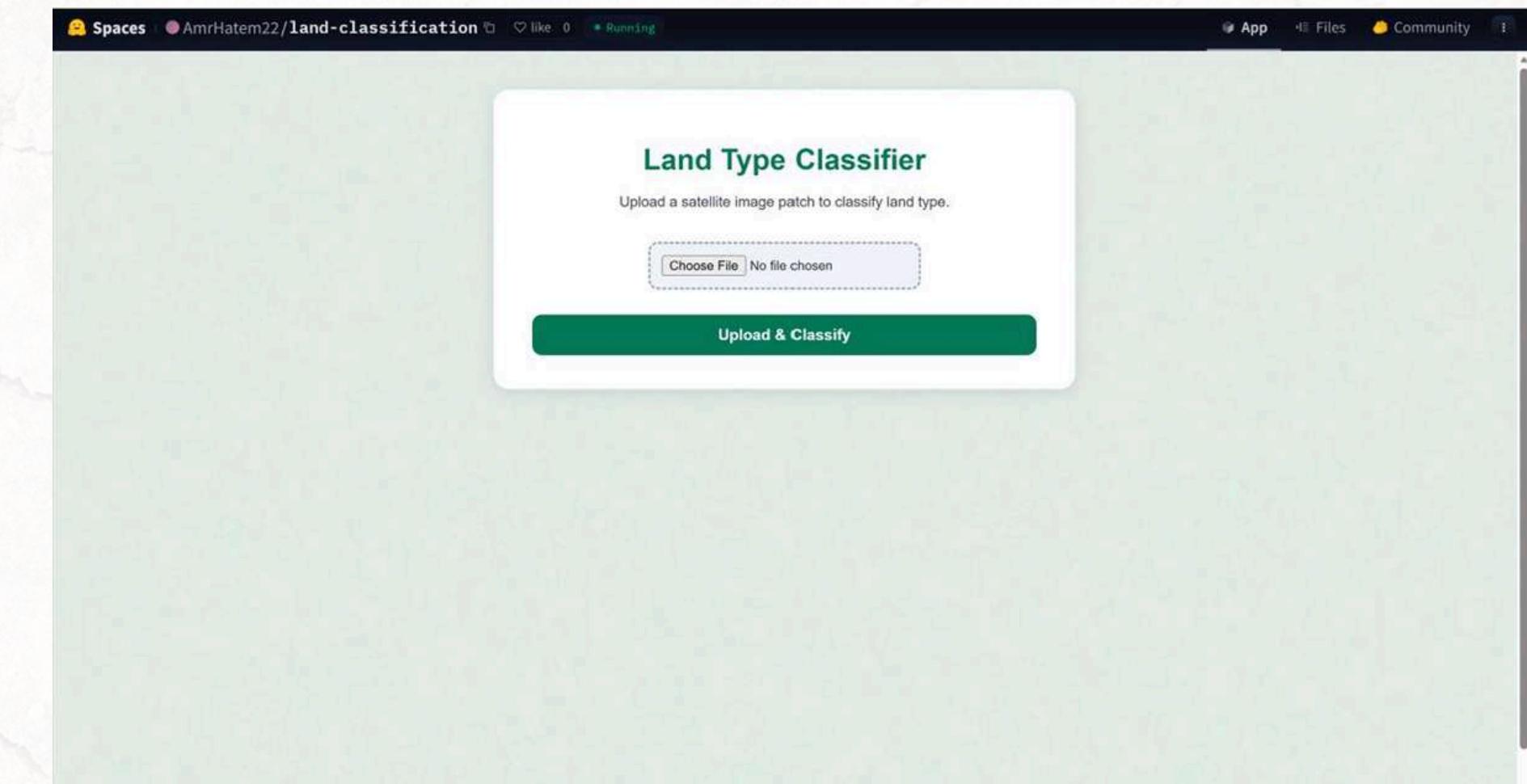


Deployment

The model was deployed on Hugging Face Spaces, allowing real-time online prediction without installation.

Features:

- Upload any satellite patch
- Automatic preprocessing
- Instant classification
- Fully web-based



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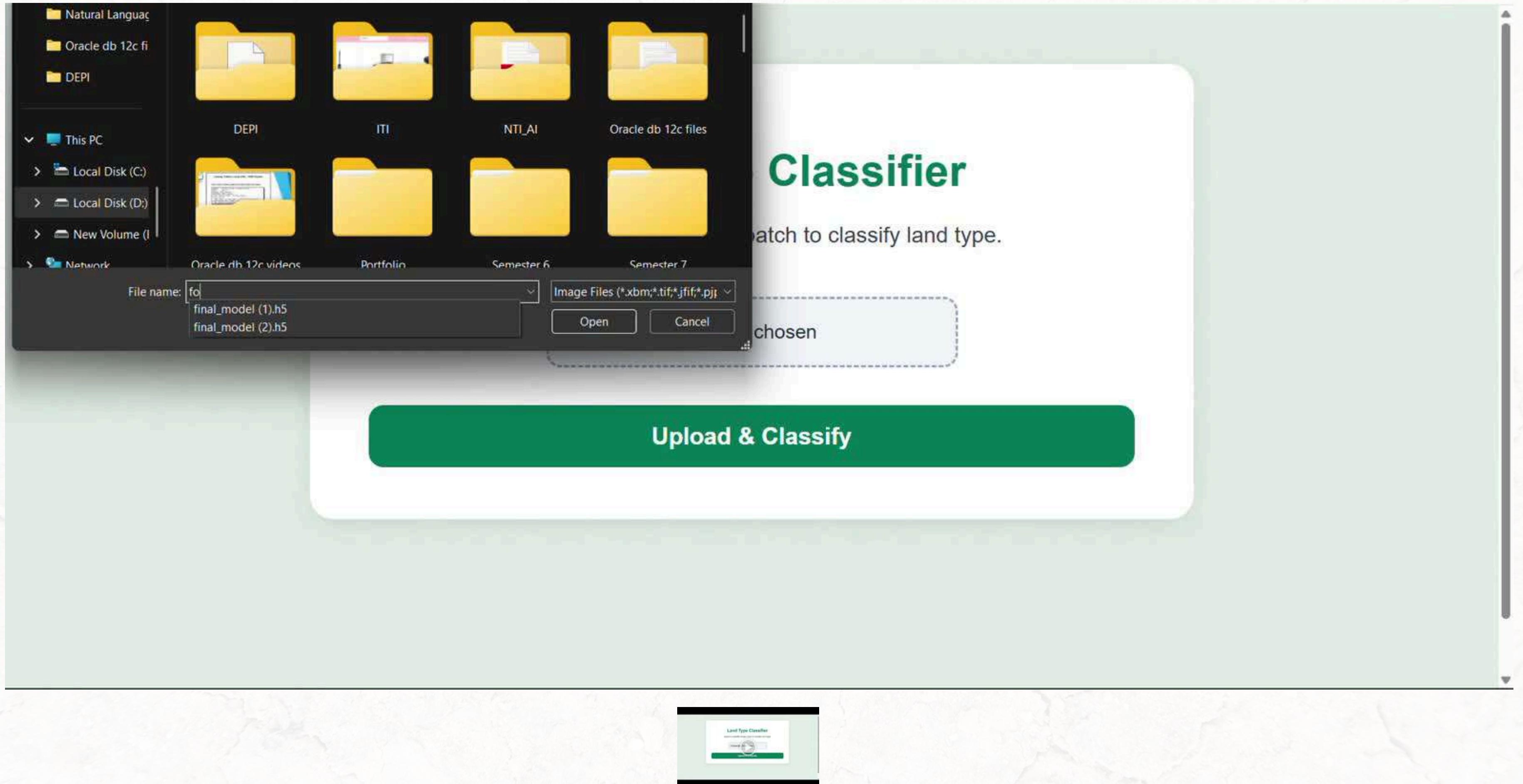
Conclusion & Future Work



The system achieved high accuracy in classifying 10 land types using satellite images. It can support agriculture, planning, and environmental applications.

Future Enhancements:

- Use larger and more diverse datasets
- Handle noisy/cloudy images better
- Deploy mobile/offline version (TFLite)
- Add segmentation capability (U-Net / DeepLab)
- Integrate results with real geographic maps



DEPI – Data Science & AI Track



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**Thank You
Any Question?**