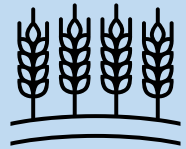
Project Idea

This project builds a Satellite based land use classification system that can identify different land types from satellite images.

Land Types (4 Classes)



Agriculture

Forest

Urban

Water

Beyond Classification

Here aim was not just Classification. The goal is to build a complete monitoring pipeline that can analyze, explain and visualize land use patterns clearly.

How the System Works

Model Training Pipeline

Collected Labelled Satellite Images

↓

A deep learning model is trained to learn visual patterns of different land types

↓

The model is tested on unseen data to measure accuracy

↓

Model is then applied to larger images by dividing it into tiles and predicting that tile

↓

These predictions are combined to create a land use overlay map

Generated Outputs

- Confusion Matrix
- Prediction Gallery
- Misclassification Gallery
- Grad-CAM explanation maps

Why This Project Is Different

Most project stop early

Most image classification projects stop at showing accuracy numbers

This project goes beyond that

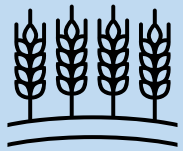
What this project adds

- Visual inspection of correct and incorrect predictions.
- Clear analysis of where the model makes mistakes.
- Explanation of model focus using Grad-CAM.
- Conversion of patch predictions into a full land use overlay map.
- A final dashboard that combines all outputs into one view.

Dataset and Class Design

The project works on satellite image dataset that contains multiple land cover categories such as forest, residential areas, rivers, and more

Final Categories



Agriculture

Forest

Urban

Water

Class Grouping Logic

Instead of directly using all raw classes, they are grouped into four final categories:

- **Agriculture**
- **Forest**
- **Urban**
- **Water**

For example:

- Residential, Industrial, and Highway were grouped into Urban.
- River and Lake were grouped into Water
- Crop related classes were grouped into Agriculture

This mapping was done to make the system practical and aligned with real land monitoring needs.

Model and Training Setup

Model Architecture

The system uses ResNet18 as the core model.

Transfer learning is applied, which means the model already has basic image understanding and is fine tuned for satellite images.

Training Configuration

Training setup includes:

- Image size resized to 224 by 224
- Cross entropy loss
- Adam optimizer
- 7 training epochs

The model achieved around 96% accuracy on the test set.

Evaluation Approach

Evaluation Views

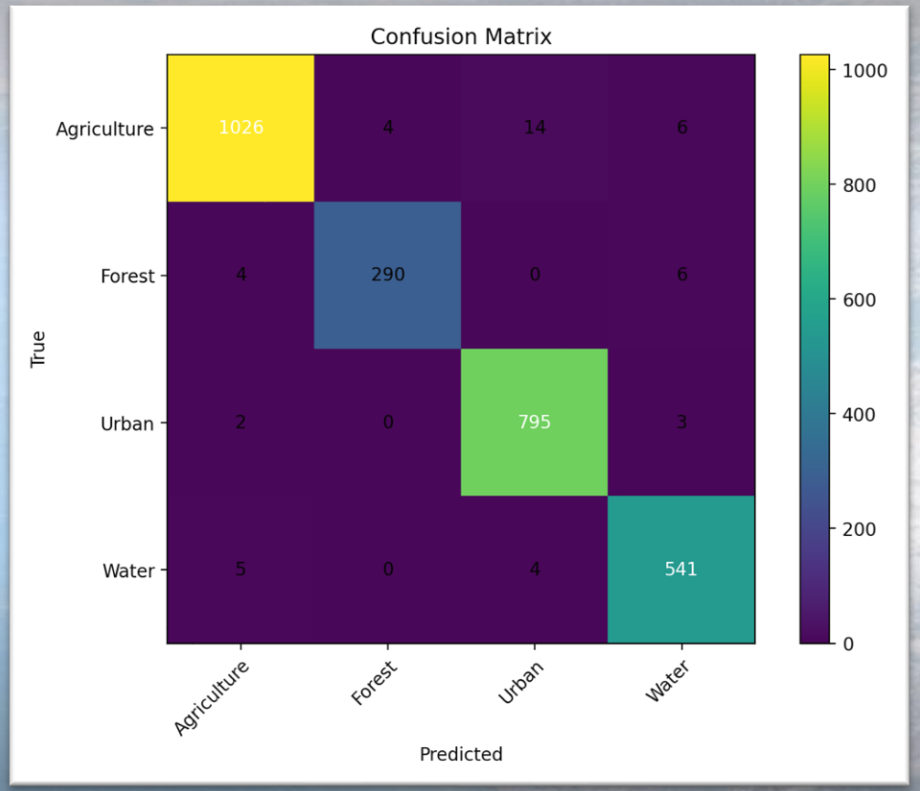
So, I evaluated the model using multiple views:

- Confusion matrix to see which classes are confused.
- Prediction gallery to visually check results.
- Misclassification gallery to study mistakes.
- Grad-CAM to understand where the model is focusing.

This gives a clear and honest understanding of how the model behaves, not just how good the numbers.

Confusion Matrix Analysis

Model Performance by Class



- **Agriculture**
  - 1026 images correctly classified
  - Very few confused with Forest, Urban or Water
  - Strong performance in this category
- **Forest**
  - 290 correctly classified
  - Small confusion with Agriculture and Water
  - No confusion with Urban
- **Urban**
  - 795 correctly classified
  - Very small confusion with Agriculture and Water
  - No confusion with Forest
- **Water**
  - 541 correctly classified
  - Very small confusion with Agriculture and Urban
  - No confusion with Forest

Prediction Gallery

Observations

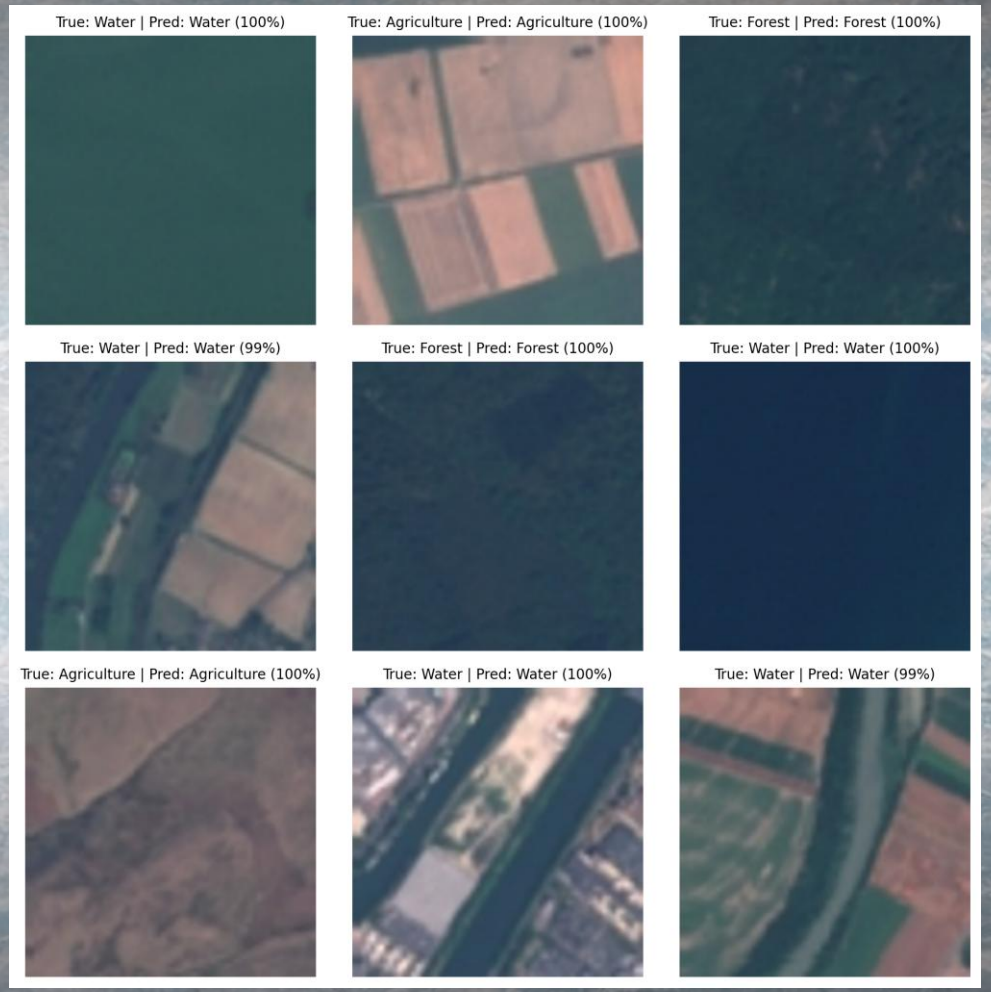
This image shows test images along with:

- True label
- Predicted label
- Confidence percentage

We can see clear visual patterns:

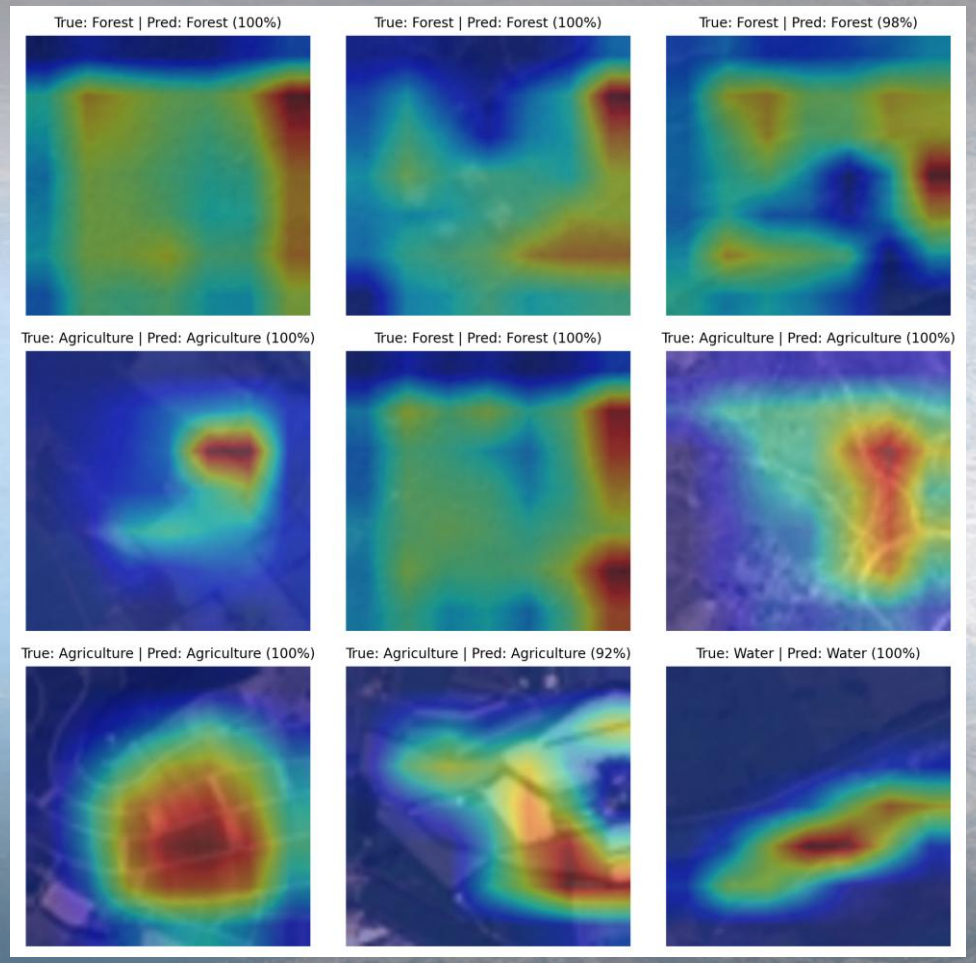
- Water images show large blue regions such as rivers and lakes
- Agriculture images show rectangular field patterns
- Forest images show dense green texture

All images shown here are correctly classified, which shows that the model can capture the visual patterns clearly, and the confidence values are high, mostly between 96 to 98%.



Grad-CAM Visualization

How Grad-CAM Works



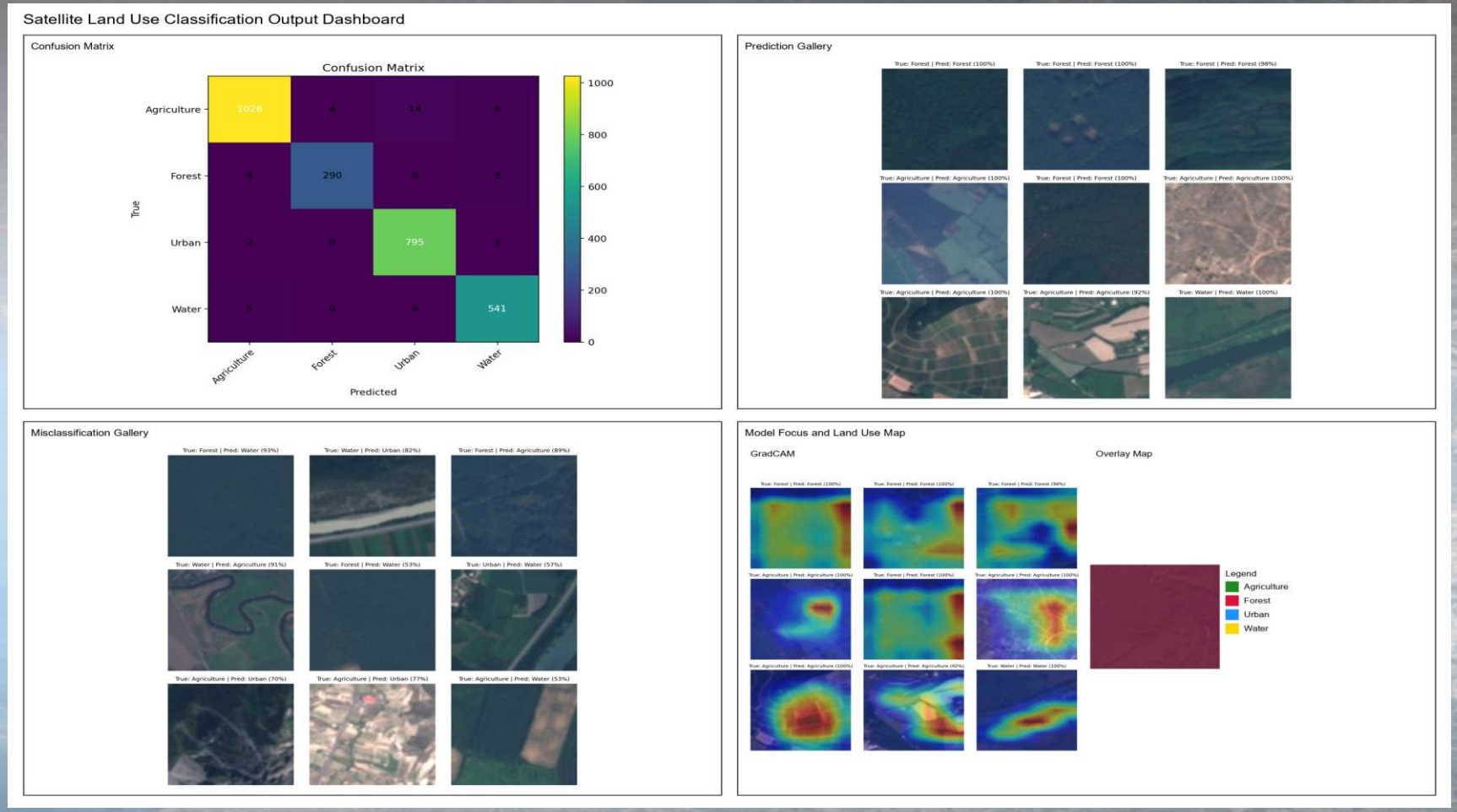
Grad-CAM highlights the regions of the image that the model focuses on while making a prediction, where red and yellow areas indicate high attention and blue areas indicate low attention.

From these examples we can observe:

- For Forest images, the model focuses on dense green texture areas.
- For Agriculture images, it highlights structured field patterns.
- For Water images, it concentrates on smooth blue regions.

This shows that the model is not making random predictions but is focusing on meaningful visual regions in the image, and Grad-CAM helps us verify whether the model is looking at the correct areas, which increases confidence in how the system makes its decisions.

Final Dashboard



This dashboard brings together the confusion matrix, prediction samples, misclassification analysis, Grad-CAM visualizations, and the land use overlay map into one structured view.