Final Project Report: EuroSAT Land Use Classification

1. Executive Summary

This report presents a comprehensive deep learning solution for classifying satellite images into various land use categories. The project leverages the EuroSAT dataset and a custom Convolutional Neural Network (CNN) to build, evaluate, and deploy a web-based classification system using Streamlit. It also explores the practical implications of land type classification in urban planning, agriculture, and environmental monitoring.

2. Methodology

2.1 Data Collection & Preprocessing

The EuroSAT dataset was used, containing over 27,000 RGB satellite images at 64x64 resolution, categorized into 10 land use types. Preprocessing included image resizing, normalization, and data augmentation techniques such as flipping, rotation, and zooming. The dataset was split into training (80%), validation (10%), and testing (10%) sets.

2.2 Model Development

A CNN architecture was developed using TensorFlow/Keras with two convolutional layers followed by max pooling, dropout for regularization, and fully connected layers. The model was trained using Adam optimizer and categorical crossentropy loss for 10 epochs. Data augmentation helped improve generalization, and early stopping was monitored using validation accuracy.

2.3 Model Evaluation

The final model achieved approximately 81% validation accuracy. Evaluation metrics included accuracy, loss curves, and a confusion matrix to assess class-level performance. The model showed strong performance on major categories like Forest, River, and Residential areas.

3. Deployment

The trained model was deployed using Streamlit, a Python web framework. Users can upload a satellite image via a clean user interface and receive the predicted land type with confidence levels in real-time. The app was deployed on Streamlit Cloud, making it publicly accessible with minimal setup.

4. Business & Research Applications

- Urban Planning: Classifying land helps planners understand current land usage and develop sustainable urban layouts.
- Agriculture: Identifying agricultural lands supports crop monitoring, resource allocation, and yield prediction.
- Environmental Monitoring: Detecting changes in land use supports conservation efforts, deforestation tracking, and climate impact analysis.
- Disaster Response: Rapid classification aids emergency teams in assessing terrain after natural disasters.

5. Performance Monitoring

The model's accuracy and confidence levels are continuously tracked during inference. Future plans may include integrating logging, alerts, or cloud monitoring tools to track input quality, inference latency, and prediction drift.

6. Conclusion

This project successfully demonstrated an end-to-end pipeline for land use classification using deep learning. It combines robust data preprocessing, CNN model development, and a user-friendly web interface. The solution holds significant potential in real-world applications for smart cities, sustainable agriculture, and environmental intelligence systems.