Machine Learning

Final Project Report: Land Cover Classification Project

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1 Problem Description

Classifying different types of land cover in satellite images, such as forests, rivers, and city zones, is a key part of this task. It's done using machine learning, which can be challenging because of the varied and intricate nature of the Earth's geography.
The project employs a Convolutional Neural Network (CNN) model, known for its effectiveness in image recognition tasks. The CNN's ability to extract and learn spatial hierarchies in image data makes it well-suited for classifying intricate patterns observed in satellite imagery.

2 Model Selection

The CNN model was chosen due to its proven track record in image classification tasks. Its architecture, capable of capturing spatial relationships in data, is ideal for interpreting the complex features of satellite images.
The approach to utilizing a pre-trained model , CNN models often come pre-trained on extensive datasets, equipping them with a robust foundation for recognizing a wide array of general image attributes. Utilizing such a pre-trained CNN for our task enables us to leverage transfer learning. This means we can fine-tune the model to our specific dataset, allowing it to adjust more effectively to the distinct aspects of our images and the various land cover types we aim to classify.

3 Data Preparation

The dataset is comprised of satellite images, each labeled with specific land cover types. These images represent a variety of geographical features.
Prior to feeding the data into our model, essential preprocessing steps were undertaken. This includes normalization and resizing of images to maintain uniformity across the dataset.
A significant enhancement to our data preparation phase was the data augmentation which is a powerful strategy to increase the diversity of our training data. The augmentation process involved several transformations, specifically:
Random Horizontal and Vertical Flips
Random Rotation
Color Jitter
The augmentation techniques were applied only to the training dataset to create a more comprehensive and varied set of training examples .This aims to reduce overfitting .

4 Training and Parameters

The training process involved splitting the dataset into training and validation sets, defining an appropriate batch size, and setting the number of epochs for the training loop.
Key hyperparameters such as learning rate, momentum, and weight decay were carefully chosen, potentially utilizing a grid search method to find the optimal combination.
The optimal combination found : learning rate: [0.01],'momentum': [0.95],'weight decay': [1e-4]

5 Model Evaluation and Results Analysis

The model's performance was evaluated using accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's strengths and weaknesses in classifying various land cover types.

By breaking down the accuracy metric into specific categories, we gain a clearer understanding of how well the model performs for each type of land cover.

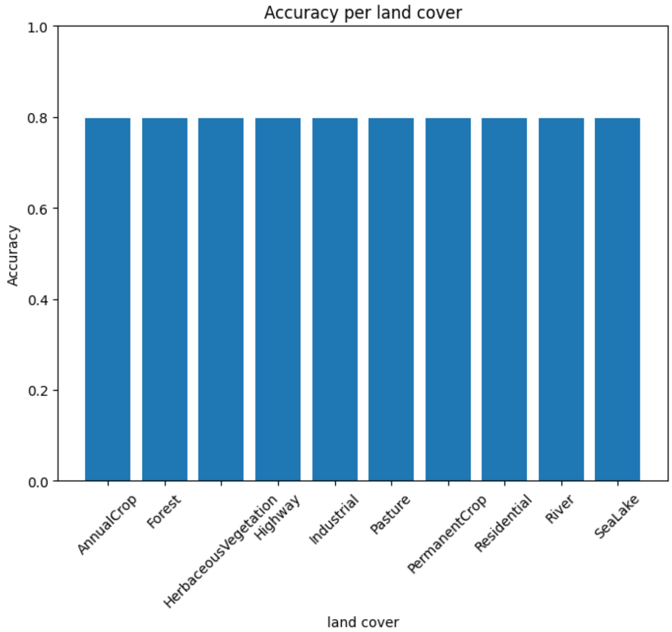

Figure 1: Accuracy per class

The confusion matrix helps identify not just the overall errors but also specific types of errors, such as which classes are most often confused with each other. This helps gaining deeper insights into the model's performance across different classes, highlighting the challenges in classification.

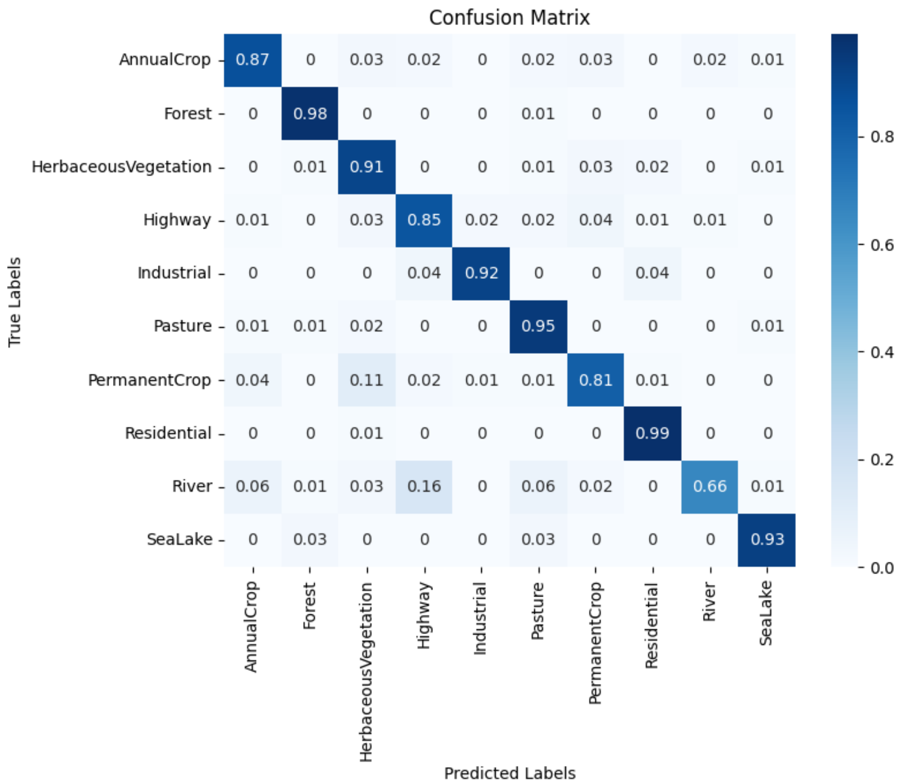

Figure 2: The confusion matrix

A high accuracy in certain categories indicates the model's strength in classifying those land covers, while lower accuracy in others might highlight areas where the model struggles or the data is insufficient or more complex.

6 Results Visualisation

A critical part of the training phase was monitoring the model's performance. This was achieved by plotting The evolution of loss and accuracy over the course of training.
To provide a clear visual representation of the model's learning trajectory, we plotted the training and validation loss, as well as the training and validation accuracy, after each epoch

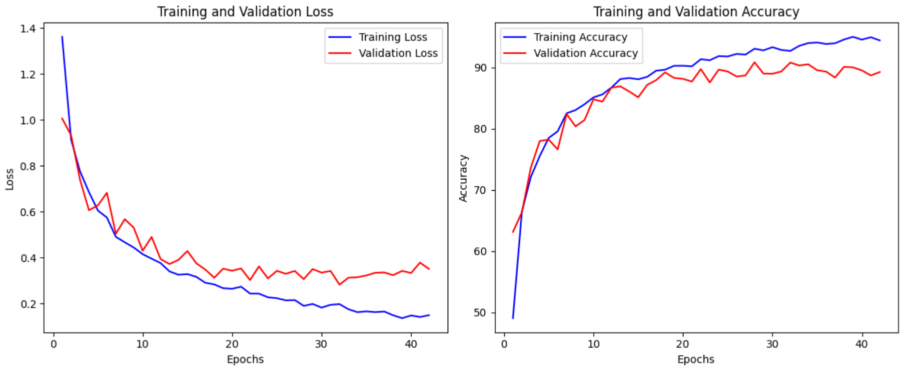

Figure 3: Traing and Validation : Loss and Acuuracy

The loss plot shows the model's error rate decreasing as it learns from the training data. A convergence of training and validation loss indicates good model generalization.
The accuracy plot reveals the percentage of correctly classified instances in both the training and validation sets. An upward trend in these plots signifies improving model performance.

7 Individual Contributions

Ouahi Noussayma : Preprocessing data, including normalization, resizing, and augmentation.Reporting the results
Djaider Soufyane : Focusing on the development and optimization of the machine learning model.
Charifi Yasmine: Implementing model evaluation metrics like accuracy, precision, recall, F1-score and the confusion matrix.
Sraidi Youssef : focusing on developing the explainability aspect of the project but was unable to complete it in time due to certain challenges.

8 Conclusion

This project successfully demonstrated the application of a Convolutional Neural Network (CNN) in classifying land cover types from satellite images. Despite facing challenges, particularly in the area of model explainability, the project achieved its primary objective of developing an effective classification model.