
URBAN TYPOLOGY AND AMENITY CLASSIFICATION OF SATELLITE IMAGERY USING DEEP CONVOLUTIONAL NEURAL NETWORKS

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Abstract

Understanding the spatial structure and amenity composition of urban neighborhoods is essential for supporting data-driven urban planning, land use analysis, and livability assessment. This project investigates the application of convolutional neural networks (CNNs) to classify neighborhood typology and detect the presence of public amenities using high-resolution satellite imagery. Using Google Earth Engine to extract Sentinel-2 image tiles and OpenStreetMap data to annotate typology and amenity labels, we construct a geospatial dataset covering diverse urban environments. The classification task includes both multiclass typology prediction (e.g. residential, industrial, mixed-use) and multi-label detection of features such as parks, green spaces, and water bodies. This interim report focuses on data acquisition, preprocessing, and automated labeling, establishing the foundation for supervised image classification using CNNs. By combining remote sensing data with open geospatial annotations, this work aims to enable scalable urban structure analysis from overhead imagery alone.

Keywords: Remote sensing, convolutional neural networks, urban typology, satellite imagery, Google Earth Engine, OpenStreetMap, land use classification, geospatial data, image labeling, amenity detection

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Introduction and Problem Statement

Urban environments can be shaped by population growth, infrastructure development, land use policy, and socio-economic factors. Understanding the structural composition of cities is a fundamental challenge to urban planning, infrastructure design, and sustainability assessment. Traditional approaches to analyzing urban environments often rely on manually collected zoning maps, land use records, and survey data, which can be costly and inconsistent across regions.

Recent advances in satellite imaging and machine learning offer an alternative, scalable approach for understanding urban spaces. High-resolution satellite imagery provides a consistent, global view of our environment, while convolutional neural networks (CNNs) extract semantic features from image data. Combined, these developments create new opportunities for urban typology classifications such as residential, industrial, or mixed-use areas and detecting the presence of critical amenities like parks, cultural landmarks, and green spaces directly from visual data.

This project investigates the use of CNNs to perform typology classification and amenity detection from overhead imagery. The core objective is to build a supervised image classification pipeline that operates on tiles extracted from Sentinel-2 imagery and labeled using open geographic data from OpenStreetMap. Each tile is annotated with both a single urban typology class and multiple amenity presence flags, enabling a multi-task learning setup. The pipeline is designed to be modular and scalable, with potential applications in regional planning, land use monitoring, and livability assessment.

The current progress of the project focuses on building a geospatial dataset by extracting tiles from Google Earth Engine and automatically assigning labels through spatial intersection with vector data from OpenStreetMap. Future progress will involve training CNN-based classifiers, evaluating model performance across various urban contexts, and exploring the use of unsupervised pretraining to improve feature extraction from unlabeled imagery.

Literature Review

The application of convolutional neural networks (CNNs) to remote sensing data has gained significant traction in the recent years, driven by advances in both computer vision and the increasing availability of satellite imagery. Foundational work in deep learning by Goodfellow, Bengio and Courville (2016) established that CNNs are a powerful architecture for image classification and segmentation tasks, with later refinements focused on transfer learning and residual networks.

In the context of land use and urban structure classification, well-established datasets such as EuroSAT have demonstrated the viability of CNNs for distinguishing urban typologies from Sentinel-2 imagery. Helber et al. (2019) introduced EuroSAT, a labeled dataset of Sentinel-2 tiles for land cover classification across ten classes, including industrial and residential categories. Their results highlight the potential of multispectral imagery and standard CNNs such as ResNet-50 to perform high-accuracy classification on geospatial tasks.

More recently, researchers have explored self-supervised learning approaches to address the challenge of limited labeled data in remote sensing. Ayush et al. (2021) introduced GEOGRAPHY-AWARE contrastive learning (GeoCLR), demonstrating improved performance in land cover classification using unlabeled satellite image patches. This method suggests that self-supervised pretraining could substantially benefit tasks like urban amenity detection where labeled data is sparse or noisy.

In practical terms, this thesis builds on the publicly available Sentinel-2 dataset, which offers a 10-meter resolution of multispectral imagery with global coverage and regular updates. The Google Earth Engine platform facilitates scalable access to these images, and detailed documentation from the European Space Agency (2023) and Earth Engine community resources make it feasible to incorporate this dataset into machine learning workflows for urban analysis. We believe that this work extends the prior work by introducing multi-label amenity detection and automated spatial labeling across cities.

Data

This project will use two primary sources of data: high-resolution satellite imagery from the Sentinel-2 satellite and geospatial features data from the OpenStreetMap (OSM). Together, these datasets will provide both the visual and the semantic information necessary to support supervised learning for neighborhood classification and amenity detection.

Sentinel-2 is a European Space Agency (ESA) operated satellite that can provide global coverage at 10-20 meter spatial resolution across 13 spectral bands. This project will be using the red, green and blue bands of the level-2A surface reflectance product, accessing it through Google Earth Engine (GEE), which provides preprocessed images with atmospheric correction such as cloud filter. The dataset will be accessed through GEE Python API and geemap interface to generate tiles in the ROI.

We will retrieve the typology and amenity labels by accessing the vector data from OpenStreetMap's OSMnx library. The dominant typology for each tile will be retrieved from

landuse related tags, whereas various other categories will be used for amenity labels. Labeling will be performed by intersecting each tile with the relevant landuse and amenity tags.

For purposes of this project, we will be focusing on the Chicago metropolitan area, though this can be scaled up based on the success and performance of our model. Although currently we focus only on geospatial data, future studies could include time-series components to research temporal aspects such as change detection or urban growth analysis over time.

Methods

This project will follow a multi-stage pipeline that combines geospatial data extraction, automated labeling, and deep learning for image classification using a CNN architecture. The current focus is on dataset preparation including preprocessing of geospatial data, land use and amenity label dataset extraction from OSM and tile geospatial data intersection with land use and amenity labels.

Image Tile Generation

At this stage of the project, we are able to generate around over 4000 tiles within the Chicago metropolitan area using the Google Earth Engine Python API. These tiles are extracted from cloud-filtered Sentinel-2 images and are measured at 512 x 512 meters. The tiles are spaced out at fixed intervals and seemingly overlap slightly on the horizontal axis, and initial efforts were not able to get rid of this overlap. To avoid exporting partial or edge-case tiles, the tile centers are constrained to fall within a safety margin of the ROI. This is ensured by checking each tile geometry to confirm it's fully within the bounding box that is initially defined. This process is currently time-consuming, and we aim to improve efficiency in the later stage. Finally, tiles are downloaded as RGB GeoTIFFs at a 10-meter resolution, which is about 51 x 51 pixels per tile.

Automated Labeling via Spatial Intersection

We are currently in the process of assigning a typology label and a set of amenity labels to each tile by intersecting them with vector data retrieved from OpenStreetMap using the OSMns library. The goal of this process is to automate annotation of image tiles and create a supervised dataset that can be used to train our CNN algorithm.

The planned approach for our CNN model will be aimed to classify each tile based on the Sentinel-2 RGB images. The model will consist of two output heads, one for single-label typology classification and one for multi-label amenity detection. The model will differ from that presented in EuroSAT in that it will be constructed from scratch instead of using transfer learning.

Results

Discussion

Conclusions

Directions for Future Work

Acknowledgements

Data & Code Availability

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Appendix