Area Classification: Iteration and Implementation of Area Classification AI for Enhancing Civil Development

Elle Bates
David Ajao
Naisha Bhandari
Jackson Choi

Abstract

The U.S. is an ethnically and economically diverse nation containing exceptional differences in socioeconomic and urbanization levels throughout the nation. In order to maximize the quality of life, the prediction of developmental and civil data is crucial for urban planners as it provides the basis for the problems within a community that should be addressed. Our goal was to create a tool that could utilize images taken by citizen scientists to supplement the existing geospatial data often used in civil development. Though pictures gathered using citizen science are able to provide extra context on their own, the tool created would involve automated classification, generating more information at a faster pace. Building and Infrastructure Recognition using AI at Large Scale (BRAILS) is a Python library that utilizes deep learning and computer vision. The BRAILS modules, Occupancy Classifier, and Year Built Classification, fine-tune a model that outputs a score (1-100) for urbanization level. The Convolutional Neural Network (CNN) model, supplemented by the BRAILS library, increased accuracy by accommodating additional urban features predicted by the BRAILS modules. Our CNN model was trained on a dataset of 50 high-quality representations of each urbanization level (urban, suburban, rural) from our Earth System Explorers, SEES2024, GLOBE Observer database using TensorFlow, reaching exceptional accuracy (90%) in determining urbanization level. Currently, the model only expands on the urbanization information given from geospatial imaging; however, in the future, the model could be expanded by incorporating national databases like the Socioeconomic Data and Application Center (SEDAC) and the US Census. This would provide a multitude of civil data that can provide additional context to the imaging, helping civil developers further determine the best course of action.

Keywords

Area Classification, Urbanization, CNN, BRAILS

Background

Urban development is the planning and executing of a city plan that strives to increase and benefit both social and economic growth (Gov.si). Disparities in social and economic sectors in an urban area have driven the need to examine and better plan for urban development. To properly plan for urban development, one must classify urban surroundings. Area classification is the act of examining an area and assigning descriptors. These can include how much water covers a photo of the area in question, how many trees are observed; or, in our case, whether the photo is of an urban, suburban, or rural area. This classification can be done on the GLOBE Observer app or website, or an individual can do it elsewhere. Building and Infrastructure Recognition using AI at Large-Scale (BRAILS) captures images and satellite data from other sources and outputs building features. This is especially useful for our project because we are predicting urban sprawl based on image features and descriptors.

There is little doubt that urbanization has increased in the past few years at an incredible, and at times untenable, rate. The rate of urbanization has also occurred at different speeds throughout the United States, as our nation is ethnically and economically diverse. Such factors can lead to stark differences and unequal growth in socioeconomic and urbanization levels. To maximize the quality of life, predicting developmental and civil data is thus very important for urban planners.

Methods

Our research objectives can be split into three parts: (1) collecting data; (2) training a model; and (3) applying functions to data to generate results. The first objective involved collecting training data from our cohort's GLOBE Observer photos, so that we could manually label the photos as rural, urban, and suburban. The next task involved training a Convolutional Neural Network (CNN) model based on our data so that it could classify an inputted photo as one of our three categories. Our final objective, which our team is still working on, involves applying certain BRAILS functions combined with corresponding census data to generate more information.

Regarding our methodology, the first step we accomplished was to find and label fifty high-quality representations of each of our urbanization levels. Once these were identified, we trained our model using the Python TensorFlow library. Then, we manually distinguished and labeled which photos BRAILS would easily be able to recognize, based on which photos contained a building and which ones did not. After labeling these photos, we supplemented our CNN with the fine-tuned BRAILS modules, Occupancy Classifier, and Year Built Classification. Through this, we are making a function that outputs a score from 1-100, representing the urbanization level. Based on this function, we will also supplement some time series images from Landsat and general socioeconomic data in order to plot current trends to predict future numbers, specifically median income level, and population.

Results

The effective accuracy of our CNN model in the classification of images into our defined categories Urban (97%), Suburban (81%), and Rural (92%) with a general model accuracy of approximately 90%.

Table 1. Data Table of Area Classification Model

Class Name	Precision	1-Precision	Recall	1-Recall	f1-score
Urban	0.9722	0.0278	0.8537	0.1463	0.9091
Suburban	0.8056	0.1944	0.9355	0.0645	0.8657
Rural	0.9167	0.0833	0.9167	0.0833	0.9167
Accuracy	0.8981				
Misclassification Rate	0.1019				
Macro-F1	0.8971				
Weighted-F1	0.8992				

Figure 1. Confusion Matrix of Area Classification Model

Area Classification Model				
TARGET / OUTPUT	Urban	Suburban	Rural	SUM
Urban	35 32.41%	1 0.93%	0 0.00%	36 97.22% 2.78%
Suburban	4 3.70%	29 26.85%	3 2.78%	36 80.56% 19.44%
Rural	2 1.85%	1 0.93%	33 30.56%	36 91.67% 8.33%
SUM	41 85.37% 14.63%	31 93.55% 6.45%	36 91.67% 8.33%	97 / 108 89.81% 10.19%

Discussion

We predict our model was able to best identify urban pictures due to the distinct architecture and features found in urban environments, such as the relatively muted tone of colors and buildings. Similarly, the abundance of greenery and trees found amongst rural areas allowed our model to also correctly classify rural areas with exceptional accuracy. Suburban areas, on the other hand, likely, due to their blending of features found both in urban and rural areas, likely confused the model in many test cases. We believe the accuracy of our model could greatly increase given the larger and more diverse sample sizes of each category. Another idea we thought about quickly improving our model is by possibly implementing a generally stronger classification model. Due to time constraints and unfortunate weather, our research was not able to fully produce all the features originally embarked on, such as implementing satellite and census data. Despite this, the portions of our project we completed within the time frame displayed exceptional accuracy and prowess. This gives us hope that, given more time our product could have a large impact on how the process of civil development and urban planning is handled in our ever-developing society. In the future, researchers David Ajao, Elle Bates, Naisha Bhandari, and Jackson Choi plan to continue work on this research goal with refined skills and plans in the future.

Conclusion

Overall, the AI model we created using TensorFlow and BRAILS was very accurate in classifying the photos into urban, suburban, and rural categories. We can observe that it was more accurate for the urban and rural at 97% accuracy and 92% accuracy for each of these categories, respectively, but proved to be less accurate for the suburban at only 81% accuracy. One proposed reason for this staggering difference in accuracy levels comes with the fact that suburban areas are literally "sub-urban", meaning that it is literally between rural and urban, blurring any differentiation between the three.

Our group's next steps are to add satellite data and photos from Landsat-8, as well as census data, to further train the AI model we created. We would also set stricter parameters for suburban images to increase the accuracy.

The product we have created can be utilized by urban planners and designers to create and implement both short and long-term projects based on the needs of the city that are identified based on the data this AI model provides. By providing urban planners with this data, they possess additional information and estimates for how certain urban development projects may impact growth and socioeconomics for an area. Every resident in an urban area deserves equal growth, urban projects, and socioeconomic development. Our goal is to provide such a model to assist with this drive.

Contributions

E.B.- Was responsible for writing a portion of the code, conducting research, assisting with creating our team patch, and working with the group to draft and edit the abstract. The research involved methods needed to define a clearer path for our project, including classifying the photos, learning and implementing BRAILS, researching the definitions necessary for our project, and reviewing numerous articles on what urban development encompasses and the necessity for sustainable urban planning. In preparation for our project turn-in, editing the full abstract to create a plain language abstract.Preparing the poster and thoroughly reviewing all aspects of our team project, such as the components, arguments, and work product, before submitting each component to their designated submission areas and uploading all code products to GitHub. Wrote the following sections: background, methods, conclusion, and acknowledgments, including references for this paper.

D.A. - Worked on training CNN model and writing portions of our code, Played a part in the coordination of project, classified all training and testing photos, worked on abstract and final paper, worked on literature review for our project

Acknowledgments
Thank you to our amazing mentors: Andrew Clark, Dr. Russanne Low, Peder Nelson, Cassie Soeffing, and Dr. Erika Podest.
We want to thank our peer mentors: Roayba Adhi, and Oseremen Ojiefoh.
We also want to thank the SEES program for the amazing experience and education.
The photos utilized in our project were found in the GLOBE Observer app.

References

Gov.si definition of urban development:
https://www.gov.si/en/policies/environment-and-spatial-planning/prostor-2/urban-development/
BRAILS user guide:
https://nheri-simcenter.github.io/BRAILS-Documentation/common/user_manual/userGuide.html
GLOBE API - GLOBE.gov. (n.d.). https://www.globe.gov/ru/globe-data/globe-api
Google Colab. (n.d.). https://research.google.com/colaboratory/faq.html
Paper about using Arcgis and R to predict urban development:
https://www.esri.com/arcgis-blog/products/arcgis-pro/analytics/a-deep-dive-into-predicting-urban-growth-using-arcgis-and-r/
NHERI SimCenter for BRAILS: https://simcenter.designsafe-ci.org/backend-components/brails/
An Image-Based Machine Learning Method for Urban Features Prediction With Three-Dimensional Building Information:
https://www.researchgate.net/publication/369791313_An_Image-Based_Machine_Learning_Method_for_Urban_Features_Prediction_with_Three-Dimensional_Building_Information
https://www.kaggle.com/datasets/dansbecker/urban-and-rural-photos
SEDAC: https://sedac.ciesin.columbia.edu/