



Advancing Urban Environment Studies in Murcia, Spain through an Automated Facade Image Classification Model



María Isabel De La Cruz Luis, Sandra Martínez Cuevas, César García Aranda, María del Carmen Morillo Balsera, and Enrique-Maria Poveda Lorente ETSI Topografía, Geodesia y Cartografía, Universidad Politécnica de Madrid, Madrid, Spain

Contact author: m.delacruz@alumnos.upm.es

1. Overview

Background & Motivation

Urban sustainability is strongly influenced by land use and city structure. Traditional remote sensing methods often miss street-level details essential for understanding urban transformation.

Why Façade Images?

Façades offer rich visual indicators of:

- Construction quality Maintenance levels
- Socio-economic context
- They reveal micro-scale urban dynamics often hidden in satellite imagery.

Method Overview

We propose a novel GeoAI-based methodology combining:

- Convolutional Neural Networks (CNNs) for automatic
- image classification •Cadastral data for urban context
- •GIS tools for spatial integration and visualization

Case Study: Murcia, Spain

A Mediterranean city experiencing fast-paced urban growth, offering a diverse urban fabric for analysis.

Objective

To create a scalable and replicable framework for: ✓ Classifying façade images
✓ Identifying urban patterns

Supporting territorial planning with high-resolution

Impact

This integrated approach enhances urban analysis by bridging the gap between visual data, spatial intelligence, and AI-driven insights.

2. Introduction

- Urban sustainability is shaped by land use and urban form; rapid growth often affects vulnerable areas (Gómez, 1994).
- •GeoAl, which combines GIS and Al, enhances urban analysis by applying machine learning to spatial data (Li et al., 2022).
- •Deep learning models like CNNs are increasingly used to analyze façade imagery, offering insights into construction quality and socio-economic context (Belinga & El Haziti,

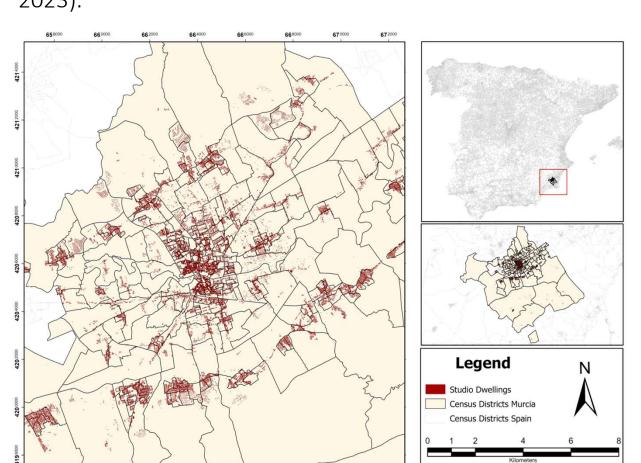
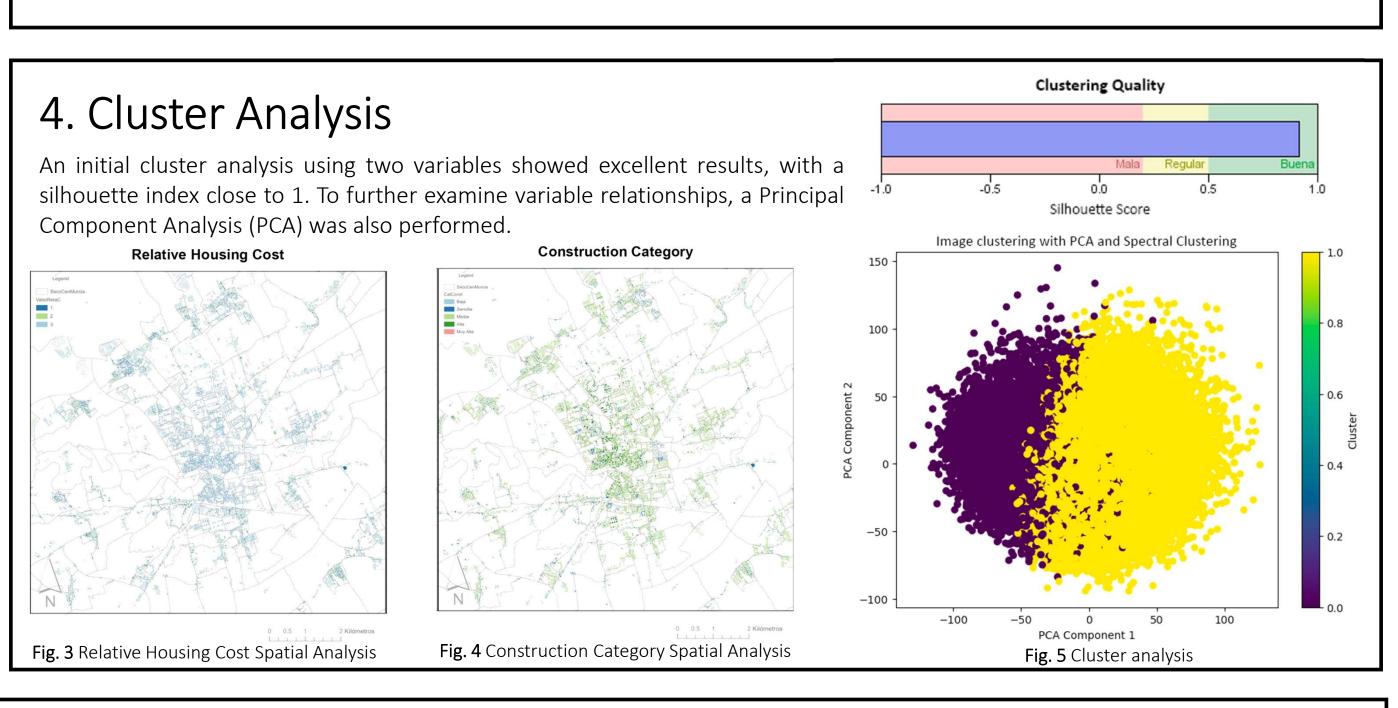


Fig. 1.- Study area: Region of Murcia, Spain

- •Murcia, located in an agricultural valley along Spain's Mediterranean coast, has experienced rapid urban expansion, leading to the loss of farmland and smaller settlements.
- •Initially focused on the historic city center, Murcia's growth has expanded northward through new developments (Martí & Moreno, 2014).
- •Since 1980, Murcia has become one of Spain's fastestgrowing cities, with a 55% population increase and a 110% rise in real estate development (Statistical Atlas of Urban Areas in Spain, 2024).

3. Methods Geospatial Machine Learning Fig. 2.- Research Workflow



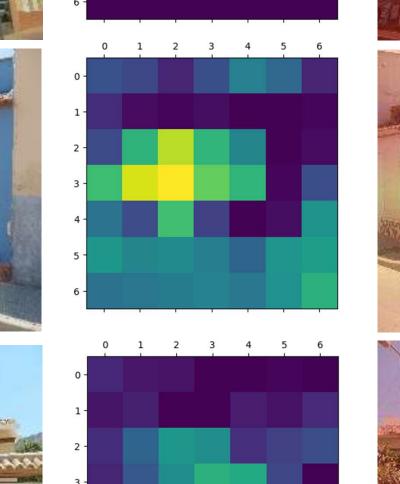
closer ties to Rural Murcia.

the central part of the city.

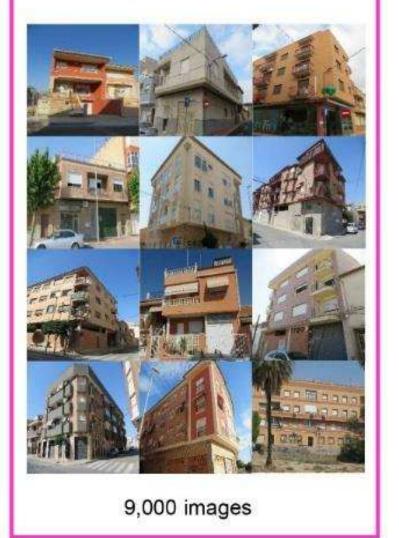
5. Classification Model The EfficientNetB0 model was trained in Python using 19,000 façade images, split into two clusters. • A 5-fold cross-validation and an 80/20 train-validation split ensured balanced performance. TensorFlow, Keras, and SCIKIT-learn handled the model workflow, with ImageDataGenerator for preprocessing and the Adam optimizer for efficient training.. Fig. 6 Performance metric plots per fold Key metrics results for each fold Fold Accuracy (%) Precision Recall 92.42 0.93 0.92 0.1849 91.00 0.2084 0.93 0.9 0.94 0.93 92.84 0.1822 0.1855 0.94 0.92 91.16 0.94 0.88 0.2000 Average 92 0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 Fig. 7 Model evaluation plots

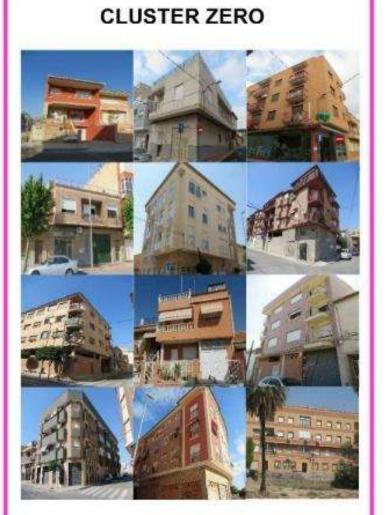












• They predominantly appear in central Heights of two or more levels The central district is the most expensive (average relative value of 2.9)

relative value of 1.89) • 36% have a life condition of 1

CLUSTER ONE

10,000 images

CLUSTER ZERO

- Collective dwellings type predominates
- Average relative value between 2 and 3
- The cheapest area is Rural Murcia (Average
- 27% remain in their original state
- 36% have a life condition of 2

CLUSTER ONE • Predominantly located in peripheral district

- Maximum height of two levels
- Single-Family dwellings predominate
- Average relative value below 2 The northern district is the most expensive
- (average relative value of 1.89) The cheapest area is Rural Murcia (Average relative value of 1.46)
- 20% remain in their original state.
- 30% have a life condition of 1 • 50% have a life condition of 2

Fig, 9 Architectural and Physical Features of Classified Façades

• The map displays the geographic layout of the identified clusters, enabling a clear visualization of territorial segmentation based on construction and urban attributes across districts.

Fig, 10 Spatial Analysis of Clusters derived from the Classification Model

Western District South-Central District

Rural Murcia

• Cluster One is primarily located in suburban areas, marked by dispersed

• Cluster Zero represents a compact, dense urban fabric that characterizes

urban settlements situated farther from the central core and exhibiting

 This cartographic analysis supports the interpretation of urban development trends and enhances the understanding of spatial differentiation across the territory.

7. Conclusion

- Despite limited variability in façade images, the model achieved successful autonomous classification using cluster
- II. The classification model accurately grouped façades into two categories, which correspond to spatial patterns in Construction Category and Relative Housing Cost.
- III. Urban differences were clearly identified: taller, collective buildings dominate central areas, while shorter, singlefamily dwellings are more common in the periphery.
- IV. The model offers a fast and scalable alternative to manual building surveys, significantly reducing time and resource
- V. It enables a preliminary assessment of the urban housing stock, supporting municipal planning and simplifying
- VI. The approach lays the foundation for identifying priority areas for climate adaptation, with potential long-term benefits exceeding initial investments.
- VII. Overall, the model serves as a valuable tool for urban analysis and planning, with potential applications across Spanish
- VIII. This GeoAI-based model offers a fast, scalable approach to urban façade classification, supporting data-driven planning in rapidly evolving cities.

8. References

- BELINGA, A.-G., & EL HAZITI, M. (2023). Overviewing the emerging methods for predicting urban Sprawl features. E3S Web of Conferences, 418, 03008. https://doi.org/10.1051/e3sconf/202341803008
- FAWCETT, T. (2006). An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010
- JOLLIFFE, I. T., & CADIMA, J. (2016). Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2065),
- 20150202. https://doi.org/10.1098/rsta.2015.0202 MARTÍ CIRIQUIÁN, P., & MORENO VICENTE, E. (2014). La transformación urbana y territorial de la ciudad de Murcia y su entorno (1977-2010). Estudios Geográficos, 75(276), 261–309.
 - https://doi.org/10.3989/estgeogr.201407 SIMONYAN, K., & ZISSERMAN, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition.
- SOKOLOVA, M., & LAPALME, G. (2009). A systematic analysis of performance measures for classification tasks. Information Processing & Management, 45(4), 427–437. https://doi.org/10.1016/j.ipm.2009.03.002

Acknowledgments



The authors would like to express their gratitude to

Andrei Saavedra for his valuable technical collaboration

and support during the development of this research.

Funding was provided by the Twin-ER: Earthquake Risk

Pilot Digital Twin. Grant PID2023-149468NB-I00, funded

by MCIU/AEI/10.13039/501100011033 and FEDER/EU

