Improving building detection accuracy: analysis of building location characteristics in open-access satellite data

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Abstract:

Geospatial information, comprising the locations and attributes of buildings, roads, and other infrastructures, forms the foundation for urban planning and disaster management. This information is indispensable for policymaking based on scientific evidence. However, certain countries and regions face challenges due to poorly maintained or outdated geospatial data. The adoption of deep learning in remote sensing has recently advanced land-use classification, building detection, and road detection, significantly improving the efficiency of geospatial information management (Ma et al. 2019).

Detecting buildings from remote sensing data typically requires high-resolution satellite images, which are costly and limited with respect to accessibility. Although open-access satellite data offer global coverage with frequent revisits, low resolution poses a significant challenge for accurate building detection (Jozdani et al. 2022).

As illustrated in Figure 1, we propose a building detection framework that enhances detection accuracy by constructing multiple detection models tailored to specific building location characteristics, such as building density and size. First, we fine-tuned a super-resolution model to increase the resolution of Sentinel-2 images from 10 m to 2.5 m, thereby improving the visibility of relatively small buildings.

We then classified the study area using a logistic regression model based on population, Normalized Difference Vegetation Index, nighttime light intensity, and distance to the coastline. The classification accuracy of the test data was 0.893, indicating high accuracy. For label 0, few buildings areas and label 2, numerous buildings areas, the F1-scores exceeded 0.9, demonstrating that these variables used in this study could classify the data with high accuracy. However, the F1-score for label 1, large buildings areas was 0.333, indicating low accuracy, with numerous instances misclassified as label 2. This classification facilitates the grouping of areas into distinct categories based on the building location characteristics. Subsequently, we developed separate building detection models for each classified area using U-Net (Ronneberger et al. 2015) and evaluated their performance against a general detection model trained on all data.

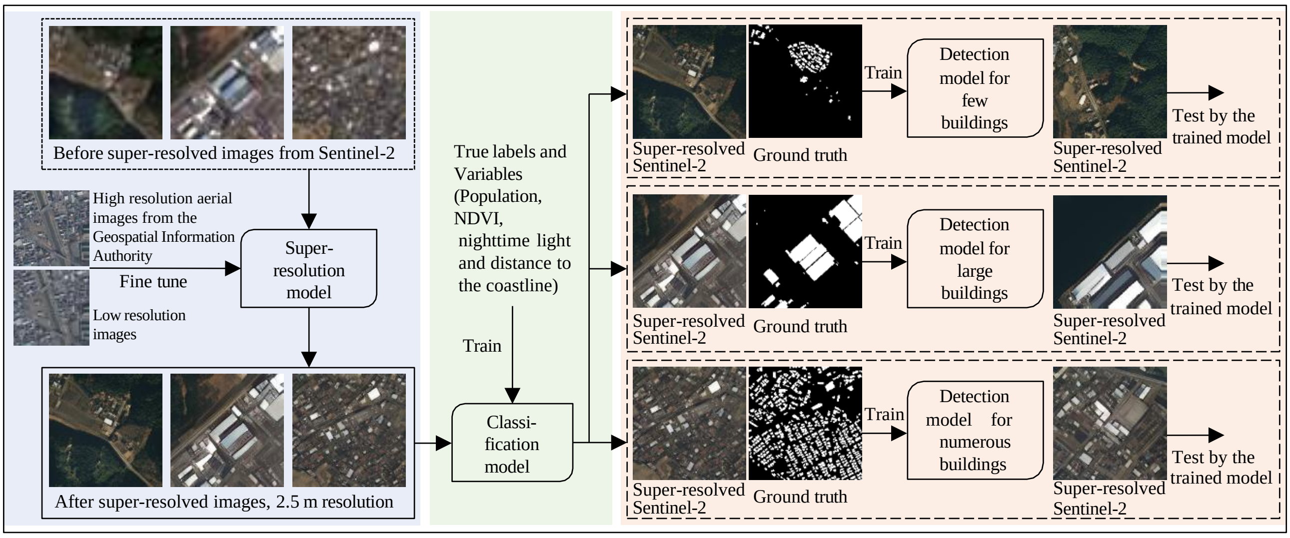

Figure 1. Building detection framework based on super-resolution and building location characteristics classification

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Figure 2 shows the building detection results for each label using the models for each label and the model trained without classification (single model). In Figure 6 (1), the model for label 1 ((c), (d) and (e)) detected buildings with excellent accuracy. In contrast, the single models ((f), (g) and (h)) detected the number of buildings correctly but failed to accurately detect the size of each building.

Figure 2 (2) shows that densely packed small buildings were often detected as a single cluster by both models, and this tendency was more pronounced in the single models ((f), (g) and (h)). The consideration of Binary Cross Entropy (BCE) as a loss function resulted in buildings being more distinct than those with Jaccard Loss (JL), indicating that using the BCE was preferable for detecting small buildings.

Our results demonstrate that models optimized for specific building location characteristics significantly outperform the general model, particularly for areas with large buildings. This study highlights the importance of considering building location characteristics when constructing detection models and provides a framework for improving the accuracy of building detection using low-resolution, open-access satellite data.

However, the practical application of the proposed method has several limitations. First, the accurate detection of small buildings remains difficult, primarily because of the low resolution of Sentinel-2. Reconsidering the sizes of the buildings targeted for detection may be necessary. Second, improving the detection accuracy in few-building areas and numerous-building areas is necessary. Although the areas were classified into three categories in this study, further improvements in the classification methods and an increase in the number of classifications could enhance detection accuracy. Addressing these challenges will enhance building detection models for real-time monitoring of building conditions anywhere, anytime.

Moreover, the building detection models developed in this study have the potential to play a critical role in disaster management and urban planning. In particular, monitoring the latest building location conditions in high-risk areas can enable effective risk management. For example, by comparing building location conditions before and after a natural disaster, it becomes possible to assess the extent of damage at no cost. This is particularly valuable in developing countries, where resources for large-scale surveys may be limited.

Additionally, the proposed models can reduce the costs and labour associated with updating building location data by pre-identifying regions with a high likelihood of changes. This capability may also allow for more frequent updates, minimizing the time intervals between revisions.

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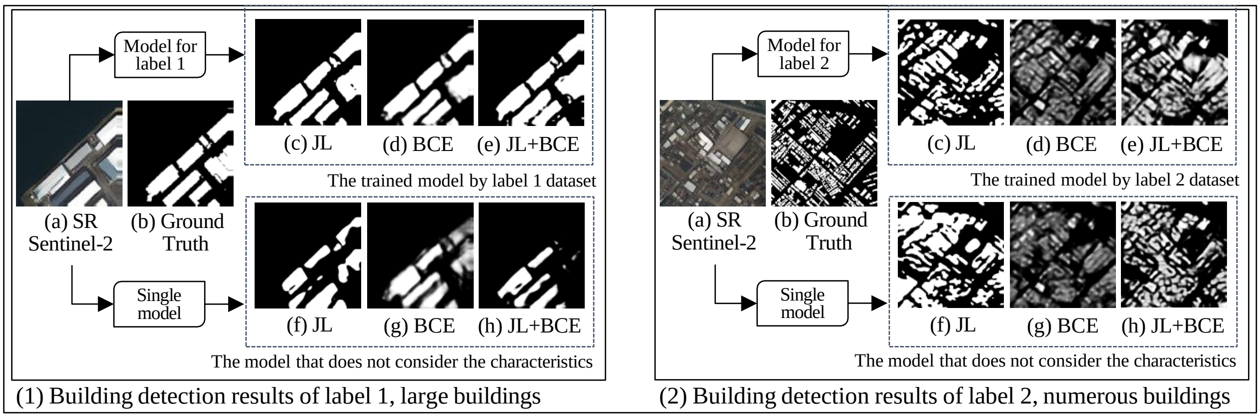

Figure 2. Building location estimation by the detection model

