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DEEP LEARNING-BASED AUTOMATIC BUILDING TYPES CLASSIFICATION FOR TRANSPORT PLANNING

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ABSTRACT - The present study proposes a building classification algorithm that uses deep learning techniques, namely object detection and image segmentation, to distinguish between residential and commercial structures. The algorithm is trained using images from the ISPRS Potsdam and Spacenet 3 (Vegas) datasets. According to the model's results, the model has obtained high precision, recall, and mean average precision (mAP) values for both classes. Despite the high-performance yield of the model, the robustness the model can be improved by expanding the training dataset to include more building images from diverse locations on Earth.

Keywords: Image Segmentation; Land use classification; Transportation Planning; YOLOv8.

1. INTRODUCTION

To incorporate land-use characteristics in transportation planning, we may need to have a land-use classified map to find out the potential areas for trip production and attraction. Over the years, researchers have proposed several building extraction techniques, including Fully convolutional networks over multi-source datasets [1], detection from low-contrast images [2, 3], building extraction at different scaled images [4, 5], and utilizing deep residual U-net over remote sensing images [6, 7, 8]. In satellite and aerial image analysis, significant work remains to be done beyond the straightforward extraction of features. More precise and in-depth information extraction and a broader classification of features within a geospatial context are required. object detection and segmentation, significant tasks of computer vision, have seen much development over the past two decades and developed several algorithms that have proven their potential significantly. some of the notable algorithms are, Fast-CNN [9], You only look once or Yolo [10], SSD: Single Shot Multibox Detector [11], and Spatial Pyramid Pooling [12]. This article proposes an approach useful for classifying different building types (Residential and Non-residential) through object detection.

2. MATERIALS AND METHODS

YOLOv8 [13] as model was utilized for the purpose and architecture is based on the YOLO architecture suggested by Redmon et al. (2016). Spacenet 3 [14] and the ISPRS Potsdam dataset were used. The images from all the datasets are resized to 960x960 resolution for faster training. The training and testing procedures are carried out using the Python platform (figure 2). The model was trained using a combined dataset made of ISPRS Potsdam dataset and Spacenet 3 (Vegas) dataset. Metrics like Mean Average Precision (mAP), Precision (P), and Recall (R)for performance evaluation were used.

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Table 1. Performance metrics details

SL No.	Metric	Formula	SL No.	Metric	Formula
1	Mean Average Precision (mAP)	$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i$	3	Recall (R)	$\frac{TP}{TP + FN}$
2	Precision (P)	$\frac{TP}{TP + FP}$	4	Accuracy	$\frac{TP + TN}{TP + FN + TN + FN}$

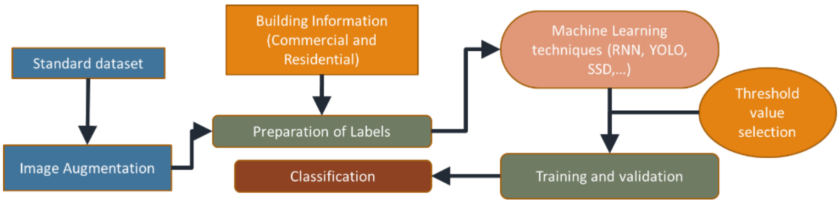


Figure 1. Workflow diagram

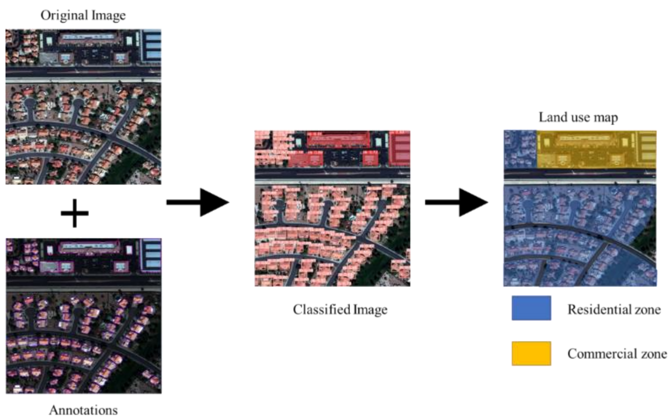
3. RESULTS AND DISCUSSION

A deep learning model is developed to classify buildings into residential and non-residential classes through object detection. The model is trained from scratch with 232 images for training and 9 images for validation. This model utilizes stochastic gradient descent (SGD) as an optimizer. For each dataset, the YOLOv8 algorithm is trained with 200 epochs combined with hyperparameter adjustment (learning rate initial = 0.007, learning rate final= 0.01, momentum = 0.937, weight decay = 0.0005, scale = 0.5, shear = 0) to create the building detection model. The performance metrics are depicted in Table 2. The model achieved an overall accuracy of 0.963.

Table 2. Performance Metrics

Class	Precision(B)	Recall(B)	mAP(50)_B	Precision(M)	Recall(M)	mAP(50)_M
Overall	0.944	0.892	0.945	0.944	0.892	0.944
CB	0.936	0.805	0.903	0.953	0.979	0.901
RB	0.953	0.979	0.986	0.953	0.979	0.986

CB = Commercial Building; RB = Residential Building; B = Bounding box; M = Mask
*Here all the non-residential buildings are considered commercial buildings.



(a) (b) (c)

Figure 2. Detection results of the model; (a) original image with annotations (Purple: RB and Pink: CB); (b) classified (predicted classifications) image; (c) land use map prepared using the classified image.

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4. CONCLUSION

The study demonstrates that the detection model correctly recognizes various buildings in an image. A more varied dataset that allows for the introduction of additional building architectures from various locations can improve model performance. This model may be used to identify the buildings and create a land-use map, which will help with an area's transportation planning quickly and accurately. This can be used as an alternate approach for preparing land-use classified maps for an area with improved speed and accuracy.

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