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Enhanced building footprint extraction from satellite imagery using Mask R-CNN and PointRend

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ABSTRACT

The extraction of building footprints from aerial photos and satellite imagery plays a crucial role in change detection, urban development, and detecting encroachments on agricultural land. Deep neural networks offer the capability of extracting features and provide accurate methods for detecting and extracting building footprints from satellite imagery. Image segmentation, the process of dividing an image into coherent parts, can be accomplished using two types: semantic segmentation and instance segmentation. Convolutional neural networks (CNN) are commonly used for both instance and semantic segmentation tasks. In this paper, we propose a hybrid approach to extracting building footprints from low-resolution satellite imagery using instance segmentation techniques. Our analysis demonstrates that the mask region-based CNN (R-CNN) architecture with a ResNet-34 backbone and PointRend head to improve the bounding-boxes and mask prediction achieves the highest performance, as evidenced by various metrics, including an average precision (AP) score of 83.39% and an F-1 score of 85.71%. This approach holds promise for developing automated tools to process satellite imagery, benefiting fields such as agriculture, land use monitoring, and disaster response.

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1. INTRODUCTION

Building footprint extraction from satellite imagery is used in many geographic information systems (GIS) solutions such as disaster assessment, geospatial analysis, regional planning, population growth estimation, and change detection. Deep learning models have become the most technique used for computer vision problems in satellite imagery and the GIS field [1]–[3]. The deep learning models use a multi-layer neural network architecture to learn the features with different levels of abstraction [4].

Deep neural networks employ complex linear and nonlinear operations to create a layered architecture, extracting features from input data. Convolutional neural networks (CNNs) are frequently employed in computer vision, particularly for tasks like object detection. The region-based CNN (R-CNN) model was presented in [5]. which generates region proposals from the image using a search algorithm, then feeds these regions into a CNN for feature extraction, and utilizes a support vector machine (SVM) to classify the bounding boxes [6]. Fast R-CNN [7] use CNN to extract the features and cropping the region proposals with the feature map to generate the region of interest (RoI).

Fast R-CNN uses the fully connected layer and softmax for bounding boxes localization and classification [8]. You only live once (YOLO) [9] used another technique that splits the image into grids with a fixed size, and the CNN is applied on each to predict and classify the bounding boxes. Single shot multibox detector (SSD) [10] additionally uses decreased sizes of convolution layers for pyramid extraction of multiscale features and detect objects of different sizes. Recent works [11], [12] used CNN to detect main points of objects like points of the corner or points of the centre, and then predict the bounding boxes.

In some real-world problems such as car auto-drive, building footprint extraction, and we need to detect the exact object boundary (masks) so the segmentation technique will be better than object detection. Two types of image segmentation are semantic and instance segmentation. Semantic segmentation is to assign class labels to each image pixel used a fully convolutional network (FCN) [13]. Based on FCN architecture, SegNet [14] and U-Net [15] design an encoder and decoder architecture where the encoder is for down-sampling feature and the decoder is for up-sampling of the feature map. Instance segmentation can produce semantic pixel-wise labels and predict instance-aware labels that distinguish the individual objects in the same class. The Mask R-CNN first performs instantiation, followed by segmentation [16].

2. LITERATURE REVIEW

Recent works use complex CNN architecture. Maggiori *et al*. [17] designs a multi layer perceptron (MLP) architecture with a skipping layer connection same as the U-Net architecture to aggregate features. The SegNet is used by [18] to train an additional loss for the distance of the building boundary apart from the pixel-wise classification loss. Wu *et al*. [19] use the U-Net architecture with multiple constraints that restrict the output comparing with the ground-truth images chips.

Other works use the data-fusion technique to increase the performance of segmentation and use semantic segmentation. The researchers [20], [21] use the U-Net architecture with satellite imagery and GIS maps such as Google Map, OpenStreetMap, and others to utilize vectorized maps. Generative adversarial networks (GAN) have recently applied to semantic segmentation for building footprint extraction problems. Mattyus and Urtasun [22] designs a matching GAN architecture, which modifies the basic GAN model to semantic segmentation tasks. Pan *et al*. [23] uses the U-Net architecture improved by the GAN model to produce more accurate.

For instance segmentation models, the Mask R-CNN architecture is explored in [24] for extracting building footprint and achieves a satisfying performance of instance segmentation. Wen *et al*. [25] enhanced the Mask R-CNN architecture by presenting the rotational of predicted bounding boxes to enhance the quality of detected objects. In instance segmentation, the image labelling requires annotation for each object with its bounding box and pixel-wise segmentation mask for the sample training dataset. Thus, a limitation of the public availability datasets that is suitable for instance segmentation problems. Many publicly labelled datasets exist for other purposes such as LabelMe [26], ImageNet [27], PASCAL [28], Cityscapes [29], open images [30], and creating common object in context (COCO) [31].

The two most popular methods for annotating objects are COCO and PASCAL visual object classes (VOC). The semantic segmentation models are more used for building footprint extraction, mainly the U-Net architecture, recognizing small buildings. By contrast, instance segmentation models, although not fully explored, often provide better solutions because buildings in large-scale images are typically closely situated or connected. These models can effectively separate such buildings. This allows for the detection and segmentation of multiple objects within an image.

That can be performed using two pipeline stages. The first stage is generating region proposals for objects in the image using RoI. The second stage predicts the object class within the bounding boxes and the pixel level mask based. This technique uses two convolutional layers. The first is any convolutional base network architectures for extracting the features. The second is the final feature map used in classifying the pixels within the segments [16]. In this paper we propose a new hybrid approach for extracting building footprint from low-resolution satellite imagery using instance segmentation. We applied the instance segmentation technique by improving the Mask RCNN model base on ResNet-34 backbone [32], PointRend architecture [33] as a segmentation head.

2.1. Mask R-CNN model overview

Mask R-CNN stands as a state-of-the-art model in the realm of instance segmentation, leveraging the foundation of faster R-CNN—a region-based convolutional neural network [34]. Faster R-CNN excels in delineating bounding boxes for individual objects, providing not only their class label but also a confidence score. Before diving into Mask R-CNN, it's important to understand the architecture of faster R-CNN [34], which operates in two stages:

Stage 1: the initial stage involves two networks: the backbone network (such as ResNet, VGG, or Inception) and the region proposal network. These networks process the input image to generate a set of region proposals, identifying regions in the feature map that potentially contain objects.

Stage 2: in the second stage, the network predicts the object class and bounding box for each proposed region obtained in stage 1. However, proposed regions can vary in size, while the fully connected layers in the network require a fixed-size vector to make predictions. To address this, either the RoI Pooling (similar to MaxPooling) or RoIAlign method is used to standardize the size of the proposed regions. Faster R-CNN is designed to predict object classes and bounding boxes, while Mask R-CNN is an enhanced version of Faster R-CNN that includes an additional branch responsible for predicting segmentation masks for each RoI.

2.2. PointRend for model improvement

To overcome the challenge of smoothed-out boundaries generated by segmentation models, especially in cases with irregular object or scene boundaries, a novel neural network module called PointRend has been integrated into the existing model architecture. PointRend adopts a point-based rendering approach, drawing inspiration from classical computer graphics techniques to introduce a rendering perspective to segmentation challenges. Unlike traditional methods, PointRend employs an iterative subdivision algorithm to enhance predictions. By predicting labels for points at strategically selected locations using a compact neural network, it achieves high-resolution output efficiently, resulting in sharper and more accurate segmentation boundaries [33].

3. METHOD

This section aims to discuss the methodologies used for detecting and extracting building footprints from satellite imagery. According to Figure 1, the proposed algorithm consists of three main stages. In the first stage, data augmentation techniques is used to prevent overfitting and making the models more robust to noise. Next, the feature extraction is the core phase in data classification. As a final step, The feature map is a network head for bounding-box and masks prediction that applied to each RoI.

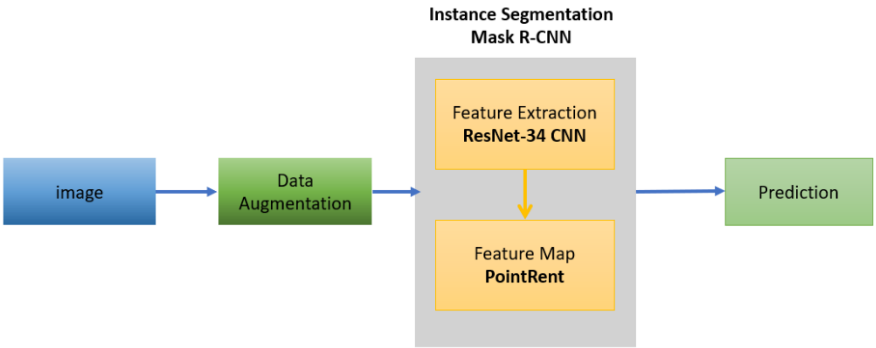

Figure 1. Proposed model for building footprint

3.1. Pre-processing stage

As a first stage, the used sample training tiles were 400×400 pixel image chips. A total of 242 image chips were generated with 3450 building footprint features. We split the dataset to 80 percent for training and 20 percent for validation, and for testing, we used different satellite imagery areas to ensure our model outcomes. Then we used the data augmentation technique. This can help to improve the performance of machine learning models by preventing overfitting and making the models more robust to noise. Some common data augmentation techniques include:

- Geometric transformations: these techniques involve randomly distorting the data, such as flipping, rotating, or cropping images.
- Color augmentation: these techniques involve changing the color of the data such as adjusting the brightness, contrast, or saturation.
- Noise augmentation: these techniques involve adding noise to the data, such as Gaussian noise or salt-and-pepper noise.

3.2. Feature extraction

The feature extraction phase is crucial in data classification. For this purpose, ResNet-34 will be used to extract features. This architecture is chosen for its higher accuracy compared to other ResNet variants [32]. Utilizing ResNet-34 ensures more precise and reliable feature extraction, enhancing the overall classification process.

3.3. Feature map

The feature map serves as a network head for predicting bounding boxes and masks, applied to each RoI. For our feature map architecture, we utilized PointRend [33], known for its high accuracy in detailed segmentation tasks. This choice ensures precise and efficient application of predictions to each RoI. PointRend's advanced capabilities significantly enhance the overall performance of our model.

3.4. Performance evaluation metrics

For evaluating our model we used standard COCO metric is average precision (AP) [16], [31], [32] and F1 Score. AP is the most used matrix in instance segmentation, that included in the original Mask RCNN research [16]. The AP value was calculated using the mean value from 10 IoU thresholds, starting from 0.5 up-to 0.95 with 0.05 steps size. The better model if AP closer to 1. Intersection over Union (IoU) measures the overlap between the target and predicted masks by dividing the number of intersecting pixels by the total number of pixels across both masks, as illustrated in Figure 2. Alternatively, IoU can be calculated using the values of false negatives (FN), true negatives (TN), false positives (FP), and true positives (TP) as shown in (1) to (5):

$$IoU(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

where A is actual bounding box, green box and B is predicted bounding box, red box.

$$IoU = \frac{TP}{TP+TF+TN} \tag{2}$$

$$\text{recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{precision} = \frac{TP}{TP+FP} \tag{4}$$

$$\text{F1} - \text{score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{5}$$

Figure 2. Intersection over Union bounding boxes

4. RESULTS AND DISCUSSION

4.1. Data

Since the lack of publicly available datasets for the building footprint problem using instance segmentation has forced researchers to manually annotate data [35], we consider manually annotating of the image tiles to generate a building footprint class. We used satellite imagery to generate our dataset 400×400 image chips, Figure 3. The dataset contains 242 image chips that were generated with 3,450 building footprint features [36].

4.2. Model training

The experiments machine was an Intel Core i7, 32 GB RAM CPU machine with an onboard NVIDIA GeForce GPU, 8 GB VRAM. The Python programming language is used for the implementation. The proposed hybrid approach was trained for 100 epochs. The cross-entropy loss function in (6) and stochastic gradient decent (SGD) in (6) were applied for optimization with a momentum of 0.9. The cross-entropy loss function is given by:

$$L(y, \hat{y}) = \sum_{i=1}^{n} y_i \log(\hat{y}) + (1 - y_i) \log(1 - \hat{y}) \tag{6}$$

where y is the true label, ŷ is the predicted label, and n is the number of classes.

Figure 3. Training datasets, sample image

The stochastic gradient descent (SGD) optimization algorithm can be represented as (7):

$$w_{i+1} = w_i - \eta \nabla Q_i(w_i) \tag{7}$$

where w_i and w_{i+1} represent the weights of the model at iteration i and $i + 1$, respectively. η is the learning rate that controls the step size of the update, and $\nabla Q_i(w_i)$ is the gradient of the loss function with respect to the weights at iteration i. The gradient is computed on a minibatch of samples randomly selected from the training data.

4.3. Evaluation

We tested our model on different geographical areas using satellite imagery, and it achieved high accuracy in detecting building footprints, Figure 4. Figures 4(a) and (b) are the ground truth samples, while Figures 4(c) and (d) are the predictions result from the model. We evaluate the proposed model using the primary challenge metric AP value, F1-score, and training time Table 1. Table 2 and Figure 5 show the AP scores of building footprint extraction using Mask R-CNN with different backbones CNNs.

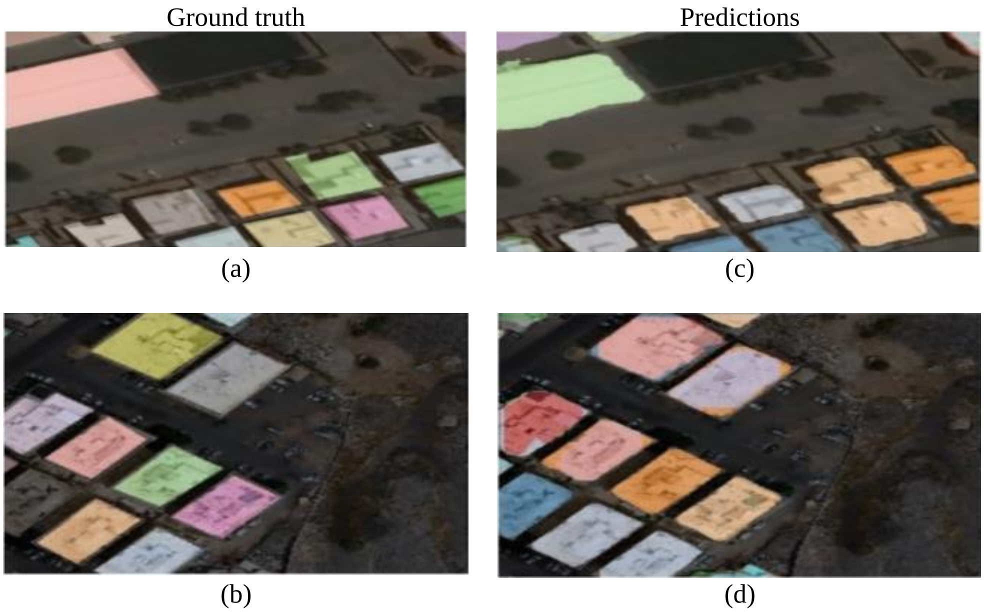

Figure 4. The deep learning model comparison outcome are the; (a), ground truth images (b) model prediction images, (c) ground truth images, and (d) model prediction images

Table 1. The performance of proposed model

AP (%)	F1 score (%)	Training time
83.39	85.71	43.3 mins

Table 2. Comparative AP score between Mask R-CNN with different backbones CNNs

Backbone	AP (%)
ResNet50-FPN	70.567
ResNet50-DC5	65.28
ResNet50-C4	67.835
ResNet101-FPN	75.213
ResNet101-DC5	74.408
ResNet-152	77.567

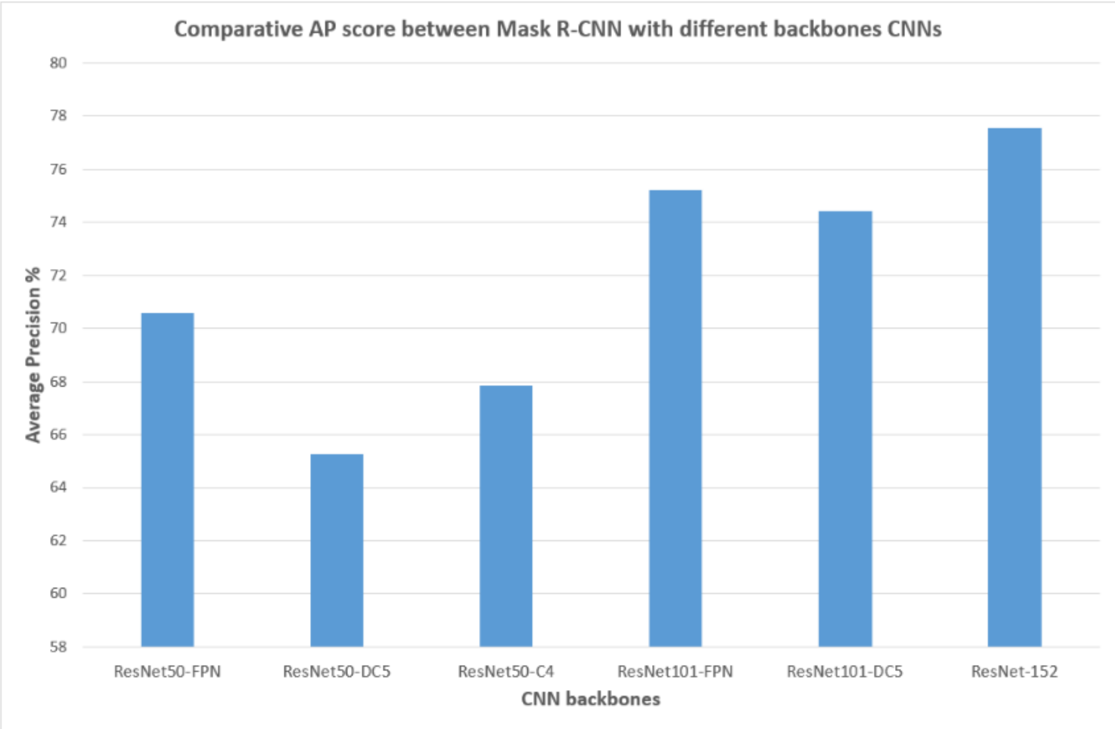

Figure 5. Comparative AP score between Mask R-CNN with different backbones CNNs

4.4. Comparison with similar works

In Table 3 the comparsion AP scores of our approach to the most recent approaches. Our approach outperformed the most recent approaches, achieving an AP of 83.39% with less training time. This is because our approach combines Mask R-CNN, ResNet-34, and PointRend, which allows it to extract more features and make more accurate predictions.

Table 3. Comparative AP score between our approach and the most recent approach

Model	Backbone	AP (%)	Training time (mins)
NourEldeen *et al*. [36]	ResNet-152	77.567	104.5
Our	ResNet-34	83.39	43.3

5. CONCLUSION

In conclusion, our study introduces a hybrid approach combining Mask R-CNN instance segmentation, ResNet-34 backbone architecture, and PointRend for building footprint extraction. The results showcase its high accuracy, achieving an impressive AP of 83.39%, with efficient training time. The proposed model holds promise for applications in urban planning, natural resource management, and hazard assessment. The combination of Mask R-CNN and ResNet-34 ensures precise instance segmentation, while PointRend addresses smoothed boundaries, enabling accurate footprint extraction even in complex environments. The approach's efficiency makes it practical for large-scale remote sensing tasks, extending its potential to various applications beyond building footprint extraction, such as object detection and classification. Overall, our hybrid approach stands as a promising tool for remote sensing researchers and practitioners due to its accuracy, efficiency, and versatile applications.

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