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Semantic Image with Convolutional Neural Networks and Deep Learning

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Abstract: *Semantic image segmentation is a vast area of interest for computer vision and machine learning researchers. Many vision applications need accurate and efficient image segmentation and segment classification mechanisms for assessing the visual contents and perform the real-time decision making. The application area includes remote sensing, autonomous driving, indoor navigation, video surveillance and virtual or augmented reality systems etc. The segmentation and classification of objects generate the specific performance parameters for various applications which require detailed domain analysis. There are broad range of applications where remote sensing image scene classification play an important role and has been receiving remarkable attention. This demand coincides with the rise of deep learning approaches in almost every field or application target related to computer vision, including semantic segmentation or scene understanding. This survey paper provides a review of different traditional methods of image segmentation and classification. By comparing these methods with semantic image segmentation using deep learning it is assumed to show the far better result.*

Keywords: Image segmentation, Region-based, CNN, U-Net

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