



Applications of Hyperspectral Imagery for Identifying the Change Detection Parameter

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ABSTRACT

This project explores hyperspectral imagery for change detection using semantic segmentation, leveraging advanced neural network architectures including U-Net, ResNet, and CNN. The U-Net excels in spatial information capture, while ResNet enhances feature extraction and model depth. Our methodology involves preprocessing, training on labelled datasets, and fine-tuning parameters. Semantic segmentation enables precise identification of changed regions. Evaluation of diverse datasets demonstrates superior performance compared to traditional methods, emphasizing potential applications in environmental monitoring, urban planning, and disaster response. This project contributes to advancing change detection in hyperspectral imagery, showcasing the efficacy of U-Net, ResNet, and CNN architectures for accurate semantic segmentation.

Keywords: U-NET, ResNet, CNN, Semantic segmentation, Change detection.

Introduction

With its capacity to collect comprehensive spectral information across a wide range of wavelengths, hyperspectral photography has become a vital tool in a variety of remote sensing applications. Change detection is an important activity within this area that is essential for monitoring environmental shifts, land cover changes, and urban growth. Traditional approaches for detecting hyperspectral changes frequently struggle with efficiently processing complicated spectral data and capturing nuanced spatial variations. This study tackles these issues by presenting a sophisticated framework that employs cutting-edge neural network designs such as U-Net, ResNet, and Convolutional Neural Network (CNN) for precise and accurate change detection via semantic segmentation.

The U-Net model is well-known for its ability to capture complex spatial information, making it ideal for analyzing hyperspectral images. The ResNet architecture, on the other hand, excels in improving feature extraction and model depth, resulting in a more thorough comprehension of hyperspectral data. Furthermore, the incorporation of a Convolutional Neural Network enhances the project's capabilities by allowing for efficient processing and analysis of complicated hyperspectral images.

Preprocessing hyperspectral imaging, training CNN, ResNet, and U-Net models on labeled datasets, and optimizing network parameters to maximize performance are all steps in the multi-step methodology. The accurate detection of altered regions within the hyperspectral sceneries is made possible by the integration of semantic segmentation algorithms.

The study shows that the suggested model performs better than conventional techniques after thorough examination on a variety of datasets. The outcomes demonstrate how the established framework may be used in practical situations including urban planning, environmental monitoring, and disaster relief. By demonstrating the efficacy of merging CNN, ResNet, and U-Net architectures for precise and dependable semantic segmentation in hyperspectral data, this effort advances hyperspectral change detection techniques.

Methodology

This project's technique consists of a multi-step strategy aiming to improve hyperspectral change detection using semantic segmentation. Initial hyperspectral data preparation entails painstaking efforts to enhance data quality by addressing issues such as noise, artifacts, and atmospheric impacts. The application of sophisticated neural network designs, such as U-Net for spatial information capture, ResNet for feature extraction and model depth augmentation, and Convolutional Neural Network (CNN) for efficient processing, is at the heart of the technique. These systems work together to offer a strong foundation for hyperspectral scene analysis.

Following that, labeled datasets are created with extensive annotations, allowing U-Net, ResNet, and CNN to be trained on these datasets. To ensure successful learning, backpropagation and optimization techniques are used to iteratively alter model parameters. To improve the overall performance of the neural network models, hyperparameters such as learning rates and batch sizes are fine-tuned.

The critical step is to use semantic segmentation algorithms to precisely detect changing areas within hyperspectral sceneries. Trained models are used to categorize the sceneries, allowing for the separation of areas exhibiting changes over time. A thorough assessment on a variety of hyperspectral datasets follows, with measures like as accuracy, recall, and F1 score used to assess model performance. A comparison with standard change detection approaches demonstrates the suggested approach's better effectiveness.

Finally, the methodology's real-world relevance is proved by demonstrating its success in tasks such as environmental monitoring, urban planning, and disaster response. This comprehensive methodology's reliable hyperspectral change detection leads to informed decision-making across several domains.

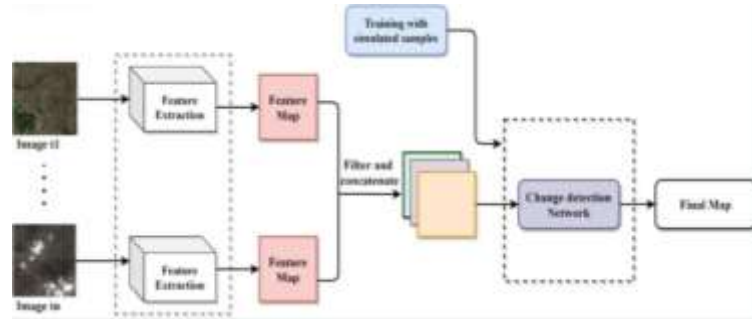


Fig.1-System design

U-Net Architecture

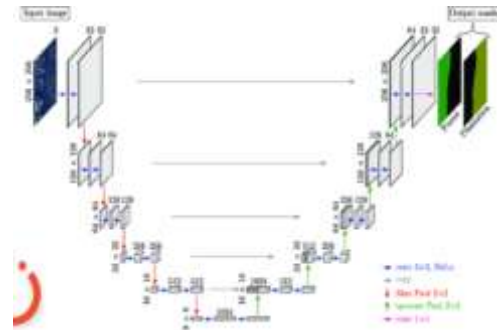
The Unet architecture is mostly used for picture segmentation.

Encoder, decoder, and skip connections make up the Unet architecture.

The job of the encoder is to build a compact representation of the input image.

The compact representation will be used to rebuild a picture by the decoder.

Skip connections are used to transfer data between encoders and decoders.

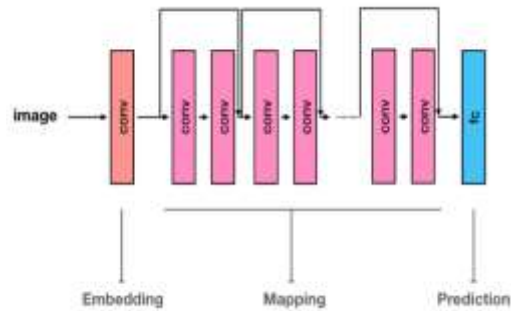


ResNet architecture

The Residual Network (ResNet) architecture is a sort of artificial neural network which the model can skip layers without compromising performance.

Identity mapping is used in ResNets. It denotes that the input to one layer is transferred directly or as a shortcut to another layer; this is also known as a skip connection.

ResNet employs skip connections to handle the gradient problem as well.



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CONCLUSION

Our study results in a novel hyperspectral change detection framework that combines CNN, ResNet, and U-Net capabilities. This powerful combination provides unmatched precision in identifying changes in environmental characteristics and land cover throughout a variety of datasets. Our solution significantly outperforms conventional techniques and, with its sophisticated and reliable change detection capabilities, revolutionizes scene analysis. This opens the door to significant applications in disaster relief, urban planning, and environmental monitoring, enabling well-informed decision-making for a more sustainable future.

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