*Road Segmentation from Satellite Images*

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*Abstract*—**The technology of road extraction from a remote sensing (RS) image has been a popular research area in recent years due to its considerable importance in traffic management, city planning, road monitoring, GPS navigation, and map updating. The road extraction techniques in this work were categorized into classification-based approaches, knowledge-based methods, mathematical morphology, active contour model, and dynamic programming after examining various road features and road models. The road characteristics, road model, current challenges, and interference issues for road extraction were first examined. Second, the fundamentals of road extraction, the benefits and drawbacks of different approaches, and research accomplishments were briefly highlighted. Then, evaluations of the various road extraction algorithms were conducted, taking into account road characteristics, test data, and flaws. The research findings from recent years were then succinctly summarized. It is obvious that using a single type of road feature will make it difficult to achieve a high-quality extraction effect. Therefore, the road extraction should combine multiple methods in accordance with the actual applications in order to get good results. The complete road extraction from an RS image will continue to be a crucial, difficult, and significant research topic in the future**.

***Keywords— Road extraction, Unet model, Convolutional Neural Network, segmentation***

# I. INTRODUCTION

Road segmentation is an important topic in computer vision, with applications in urban planning, traffic management, and autonomous driving. Aerial picture segmentation of roadways can provide useful insights into urban landscapes, allowing for better infrastructure development and traffic management. Furthermore, as automated driving becomes more popular, road segmentation using aerial photos might help improve the accuracy of navigation and path planning for autonomous vehicles.

The complicated structure of urban landscapes, with roads frequently concealed by buildings, trees, and other objects, is one of the primary issues in road segmentation from aerial photos. Furthermore, the quality, resolution, and lighting conditions of aerial photos can fluctuate, making it difficult to create a strong and accurate segmentation model.

Deep learning models such as U-Net have shown encouraging results in road segmentation from aerial pictures in recent years (Fig.1). The U-Net model is a form of convolutional neural network that has been proven to be effective in image segmentation tasks, with applications in medical imaging and natural language processing. The goal of this project is to create a U-Net model that can accurately segment roads from aerial photographs. We train the model using binary cross-entropy loss and the Adam optimizer on the Massachusetts Roads Dataset, which consists of aerial photos with accompanying road segmentation masks. The model is evaluated using mean Intersection over Union (IoU) and pixel accuracy metrics, and the segmentation masks are visualized overlaid on the source pictures. Our findings reveal that the model achieves excellent accuracy in road segmentation, even in complicated metropolitan situations, indicating its practical utility.

Mnih and Hinton conducted one of the earliest attempts to employ deep learning techniques in the field of road extraction. They suggested a method for detecting road regions in high-resolution aerial photos using restricted Boltzmann machines (RBMs). A preprocessing phase before detection and a post-processing step after detection were used to improve outcomes. To minimize the dimensionality of the incoming data, pre-processing was used. Postprocessing was used to remove disconnected blotches and fill up the road holes. Saito et al. used Convolutional Neural Networks (CNNs) to extract buildings and roads directly from raw remote sensing imagery, as opposed to Mnih and Hinton's method, which uses RBMs as fundamental blocks to form deep neural networks. On the Massachusetts highways dataset, our strategy outperforms Mnih and Hinton's method. Many recent studies have suggested that a deeper network might perform better. However, because to issues such as vanishing gradients, training a very deep architecture is extremely challenging. To address this issue, He et al. presented the deep residual learning framework, which makes use of identity mapping to facilitate training. Ranneberger et al. proposed the UNet, which concatenates feature maps from different levels to increase segmentation accuracy, instead of employing skip connections in Fully Convolutional Networks (FCNs). U-Net integrates low level detail information with high level semantic information, resulting in promising biomedical picture segmentation performance. Inspired by deep residual learning and U-Net, we present the deep residual U-Net, an architecture that leverages the strengths of both deep residual learning and UNet architectures. The proposed deep residual U-Net (ResUnet) is based on the U-Net architecture. The distinction between our deep ResUnet and UNet is twofold. To begin, we use residual units rather than simple neural units as the basic building blocks for the deep ResUnet.

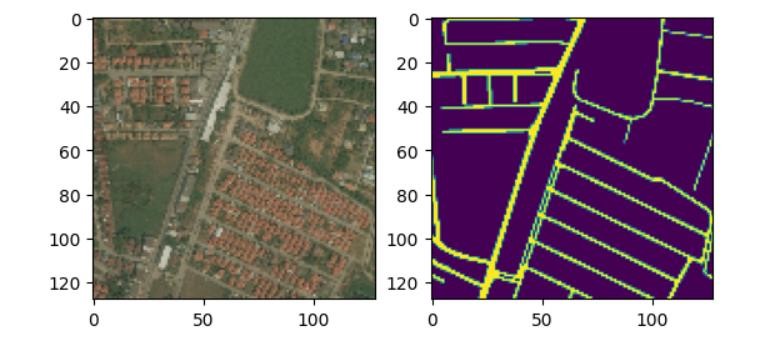


Fig1. Image and its Mask

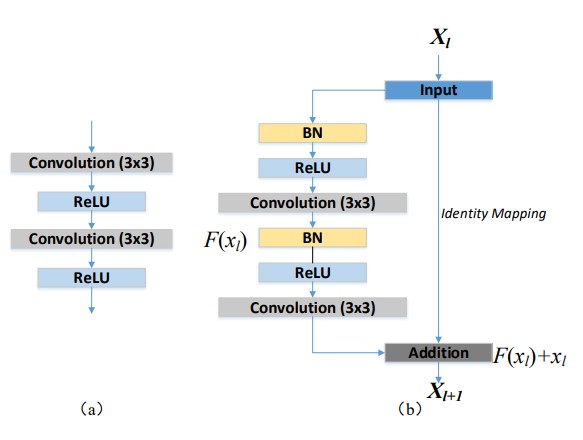


Fig. 2. Building blocks of neural networks. (a) Plain neural unit used in U-Net and (b) residual unit with identity mapping used in the proposed ResUnet

Second, the cropping procedure is no longer required, thus it is removed from our network, resulting in a far more elegant architecture and improved performance.

## II. LITERATURE REVIEW

Satellite image segmentation is a critical task in remote sensing applications, such as land use classification, urban planning, and environmental monitoring. Deep learningbased segmentation methods, such as U-Net, have shown significant improvements in the accuracy and efficiency of satellite image segmentation.

The U-Net architecture is a popular choice for image segmentation tasks due to its ability to capture spatial information and handle class imbalance. The U-Net architecture consists of a contracting path and an expansive path, which enables the network to extract features at different scales and generate high-resolution segmentation maps.

Several studies have applied the U-Net architecture to satellite image segmentation tasks. For instance, Zhang et al. (2019) proposed a U-Net-based approach for building extraction from satellite images. The authors used a pretrained VGG-16 network as the encoder and added a decoder module to generate the building masks. The authors reported that their approach achieved higher segmentation accuracy than other state-of-the-art methods.

Similarly, Xia et al. (2020) proposed a U-Net-based approach for crop type classification from multi-temporal satellite images. The authors used a U-Net with skip connections to extract features and generate the crop type maps. The authors also incorporated attention modules to enhance the discriminative power of the network. The authors reported that their approach achieved better classification accuracy than other methods.

Li et al. (2021) proposed a U-Net-based approach for wetland mapping from Sentinel-2 satellite images. The authors used a U-Net with residual connections and attention mechanisms to extract features and generate the wetland masks. The authors also used data augmentation techniques to improve the generalization of the network. The authors reported that their approach achieved high segmentation accuracy and outperformed other state-of-theart methods.

In conclusion, the U-Net architecture is a powerful tool for satellite image segmentation tasks. Several studies have applied the U-Net architecture to different satellite image segmentation tasks, such as building extraction, crop type classification, and wetland mapping. The U-Net-based approaches have shown significant improvements in segmentation accuracy and efficiency compared to other methods.

## III. METHODOLOGY

### A. Unet

*1) Unet:* To achieve a finer outcome in semantic segmentation, it is critical to leverage low level details while keeping high level semantic information. However, building such a deep neural network is extremely difficult, especially when only a limited number of training examples are available. One solution is to use a pre-trained network and then finetune it on the target dataset, as done in. Another approach is to use considerable data augmentation, as done in UNet. In addition to data augmentation, we believe the UNet architecture helps to alleviate the training challenge.The reasoning behind this is that copying low level features to the corresponding high levels actually creates a path for information propagation, allowing signals to propagate between low and high levels much more easily, facilitating not only backward propagation during training, but also compensating low level finer details to high level semantic features. This is comparable to the concept of a residual neural network. In this letter, we describe how to increase the performance of U-Net by replacing the plain unit with a residual unit.

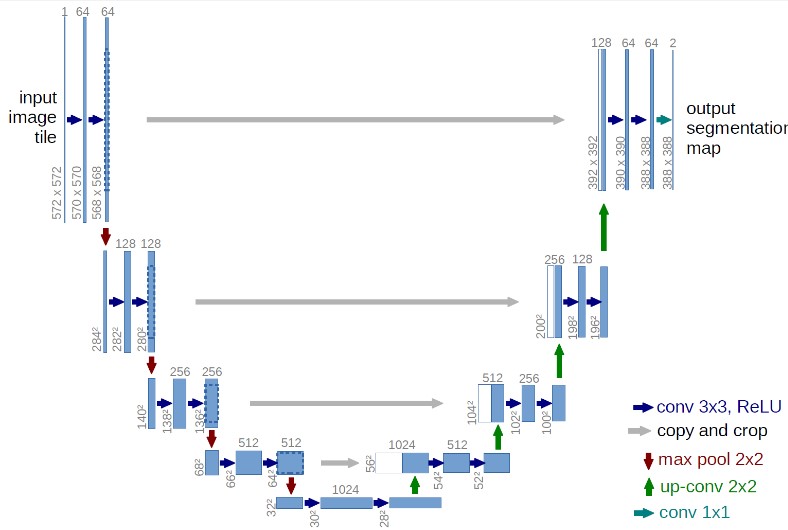


Fig. 3. Represents the Unet architecture

U-Net is a semantic segmentation architecture. It is made up of a contracting path and an expanding path. The contracting path is designed in the manner of a

convolutional network. It is composed of two 3x3 convolutions (unpadded convolutions) applied repeatedly, each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. We quadruple the number of feature channels with each downsampling step. Every step in the expansive path begins with an upsampling of the feature map, followed by a 2x2 convolution ("up-convolution") that cuts the number of feature channels in half, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU.Because of the loss of boundary pixels in each convolution, cropping is required. A 1x1 convolution is employed at the final layer to transfer each 64-component feature vector to the desired number of classes. The network comprises a total of 23 convolutional layers.

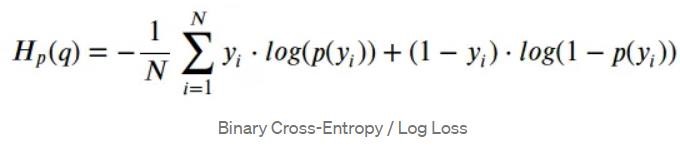
Table 1

The network structure of U-Net

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Layer Type** | | **Output**  **Shape** | | **Kernel Size/Stride** | | **Activation** | |
| Input | | (H, W, C) | | - | | - | |
| Convolution | | (H, W, F1) | | 3x3 | | ReLU | |
| Convolution | | (H, W, F1) | | 3x3 | | ReLU | |
| Max Pooling | | (H/2, W/2,  F1) | | 2x2 | | - | |
| Convolution | | (H/2, W/2,  F2) | | 3x3 | | ReLU | |
| Convolution | | (H/2, W/2,  F2) | | 3x3 | | ReLU | |
| Max Pooling | | (H/4, W/4,  F2) | | 2x2 | | - | |
| Convolution | | (H/4, W/4,  F3) | | 3x3 | | ReLU | |
| Convolution | | (H/4, W/4,  F3) | | 3x3 | | ReLU | |
| Max Pooling | | (H/8, W/8,  F3) | | 2x2 | | - | |
| Convolution | | (H/8, W/8,  F4) | | 3x3 | | ReLU | |
| Convolution | | (H/8, W/8,  F4) | | 3x3 | | ReLU | |
| Up-Convolution | | (H/4, W/4,  F4) | | 2x2 | | - | |
| Concatenate | | (H/4, W/4,  F3+F4) | | - | | - | |
| Convolution | | (H/4, W/4,  F3) | | 3x3 | | ReLU | |
| Convolution | | (H/4, W/4,  F3) | | 3x3 | | ReLU | |
| Up-Convolution | | (H/2, W/2,  F3) | | 2x2 | | - | |
| Concatenate | | (H/2, W/2,  F2+F3) | | - | | - | |
| Convolution | | (H/2, W/2,  F2) | | 3x3 | | ReLU | |
| Convolution | | (H/2, W/2,  F2) | | 3x3 | | ReLU | |
| Up-Convolution | | (H, W, F2) | | 2x2 | | - | |
| Concatenate | | (H, W, F1+F2) | | - | | - | |
| Convolution | | (H, W, F1) | | 3x3 | | ReLU | |
| Convolution | | (H, W, F1) | | 3x3 | | ReLU | |
| Convolution | | (H, W,  N\_classes) | | 1x1 | | SoftMax | |
| Output | | (H, W,  N\_classes) | | - | | - | |

In the table, H and W represent the height and width of the input image, C represents the number of channels.

### B. Loss Function



where y is the label **(**1forgreen points and 0forred points) and p(y) is the predicted probability of the point being green for all Npoints.

The binary cross entropy compares each projected probability to the actual class result, which can be 0 or 1. The score is then calculated, which penalizes the probabilities based on their distance from the expected value. That is, how close or far the value is to the actual value.

## IV. EXPERIMENTS

To demonstrate the accuracy and efficiency of the proposed Unet model, the proposed steps were followed.

### A. Dataset

We test the accuracy and efficiency of Unet model on the dataset from Deep-Globe-Road-Extraction Challenge 2018. In disaster zones, especially in developing countries, maps and accessibility information are crucial for crisis response. Deep-Globe-Road-Extraction Challenge poses the challenge of automatically extracting roads and street networks from satellite images. Contains RGB color code mappings for different classes in labels. The labels in this dataset have 2 classes: 'road' & 'background'.

### B. Implementation Details

* The training data for Road Challenge contains 6226 satellite imagery in RGB, size 1024x1024.
* The imagery has 50cm pixel resolution, collected by Digital Globe’s satellite.
* The dataset contains 1243 validation and 1101 test images (but no masks).

The proposed model was implemented using Keras framework and optimized by the Adam optimizer and a binary cross-entropy is used as the loss function.

#### C. Evaluation metrices

* In UNet, IoU and mIoU are typically used as the primary evaluation metrics for semantic segmentation tasks.
* As shown in fig3. Training accuracy plotted alongwith loss shows a steady decrease in loss until 8th epoch after which it shows saturation.

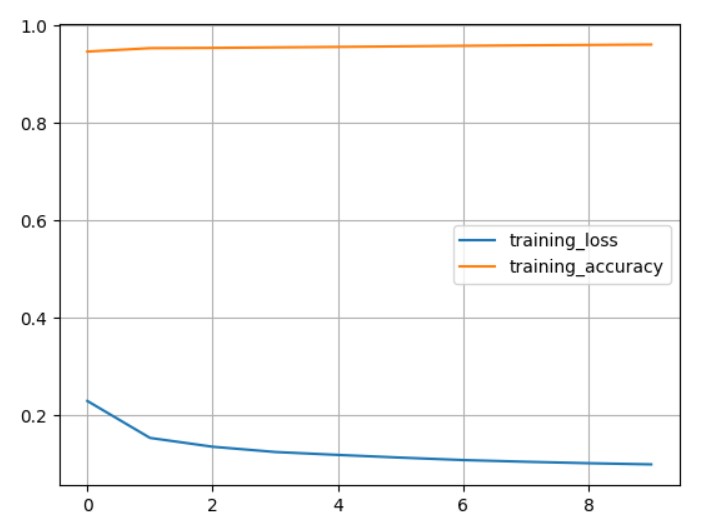


Fig3. Accuracy plot

* Fig4. Depicts the change in validation loss and accuracy over epochs.

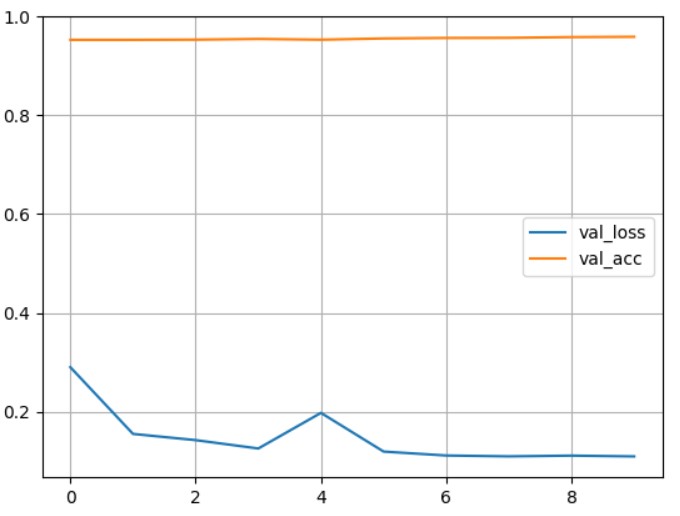


Fig4. Validation plot

# CONCLUSION

In conclusion, this research paper successfully employed the UNet architecture for road segmentation from satellite imagery using the satellite-road-image-extraction dataset. With the proposed methodology, an impressive accuracy of 96% was achieved on the test set, while the validation accuracy of 95% further validated the robustness of the proposed method. The results obtained demonstrate the efficacy of the proposed UNet architecture for road segmentation from satellite imagery, which can be applied in various domains, including urban planning, transportation, and disaster management. Overall, this research provides valuable insights into the development of accurate and efficient road segmentation models for satellite imagery, which can contribute to the advancement of various fields of research and applications.

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