# Semantic Segmentation of Spectrogram Signals with LightSegNet: An Efficient and Lightweight Approach

Nguyen Thi Thuy
Department of Electrical and Electronics Engineering
Ho Chi Minh City University of Technology and Education
Ho Chi Minh City, Vietnam
Email: 22139069@hcmute.edu.vn

***Abstract*—Semantic segmentation is a crucial task in image processing, particularly in the analysis of spectrogram signals. In this paper, we propose an efficient method for semantic segmentation using LightSegNet, a lightweight neural network architecture designed to balance segmentation accuracy and computational efficiency. We applied the model to a spectrogram dataset from Kaggle and achieved a peak validation Intersection over Union (IoU) of 0.9584 after just 10 training epochs. The results show that LightSegNet delivers strong segmentation performance while maintaining a low computational footprint, making it suitable for real-world applications on resource-constrained devices.**

***Index Terms*—Semantic segmentation, spectrogram, LightSegNet, deep learning, SE block, IoU**

## I. Introduction

Semantic segmentation aims to assign a class label to each pixel in an image, offering a fine-grained understanding of visual data. In the context of spectrogram analysis, semantic segmentation enables the identification of distinct signal regions, supporting applications such as audio classification, speech processing, and biomedical signal interpretation.

However, state-of-the-art segmentation models like DeepLab and U-Net often have large parameter sizes, posing challenges for deployment on embedded systems. To address this, we introduce **LightSegNet**, a compact encoder-decoder architecture that incorporates Squeeze-and-Excitation (SE) blocks to enhance feature representation without significantly increasing the model size.

We trained and evaluated LightSegNet on a spectrogram dataset using a combined loss function of Cross-Entropy and Dice Loss. Our experiments demonstrate that LightSegNet achieves high segmentation accuracy with minimal computational cost, paving the way for practical deployment.

## II. Methodology

### A. Dataset and Preprocessing

We used the spectrogram signal dataset from Kaggle (via KaggleHub), consisting of RGB input images and corresponding label masks. The label masks encode 3 classes using distinct RGB values:

- Class 0: (2, 0, 0)
- Class 1: (127, 0, 0)
- Class 2: (248, 163, 191)

The dataset was split into 80% for training and 20% for validation. For data augmentation, we applied:

- Horizontal flip (p=0.5) and vertical flip (p=0.2)
- Random brightness/contrast adjustment (p=0.3)
- Affine transformations: translation, scaling, and rotation (p=0.5)
- Normalization and tensor conversion

The validation set was only normalized to ensure unbiased evaluation.

### B. Model Architecture: LightSegNet

**LightSegNet** follows an encoder-decoder structure designed to be efficient and compact:

- **Encoder**: Two convolutional blocks with $3 \times 3$ convolutions, Batch Normalization, ReLU activation, and MaxPooling. The first encoder uses 26 channels, the second uses 52 channels.
- **Bottleneck**: A 96-channel convolutional block incorporating an SE module to recalibrate channel-wise features for improved representation.
- **Decoder**: Two upsampling layers with skip connections from the encoder. Each upsampling block includes convolutional layers to refine spatial information.
- **Classifier**: A $1 \times 1$ convolutional layer that maps the output to the desired number of classes (3).

The total parameter count is approximately **300.000**, significantly lower than models like DeepLabv3+ (¿40 million). The inclusion of the SE block enhances attention to important features without adding excessive complexity.

### C. Loss Function and Optimization

We used a combined loss function:

$$\mathcal{L} = \mathcal{L}_{CE} + \mathcal{L}_{Dice}$$

where:

- $\mathcal{L}_{CE}$: Cross-Entropy Loss – for pixel-wise classification

- $\mathcal{L}_{Dice}$: Dice Loss – for overlap accuracy between predicted and ground truth masks

The model was trained using the Adam optimizer with a learning rate of 0.0005 and weight decay of $1 \times 10^{-4}$, for 10 epochs and a batch size of 16.

### D. Evaluation Metrics

We evaluated performance using:

- **Pixel Accuracy**: Measures the ratio of correctly classified pixels
- **IoU (Intersection over Union)**: Measures the overlap between predicted and ground truth regions, and serves as the primary segmentation metric

## III. Experiments and Results

### A. Training Setup

Training was performed on a GPU (if available) or CPU using PyTorch. Training and validation metrics were logged in `training_log.csv`, including:

- Training and validation loss
- Training and validation IoU

### B. Performance Results

Table I summarizes the performance over 10 epochs.

TABLE I: Training and Validation Results

| Epoch | Train Loss | Val Loss | Train IoU | Val IoU |
|---|---|---|---|---|
| 1 | 0.6119 | 0.3076 | 0.6910 | 0.8433 |
| 2 | 0.2477 | 0.1579 | 0.8742 | 0.9226 |
| 3 | 0.1794 | 0.1532 | 0.9088 | 0.9195 |
| 4 | 0.1466 | 0.1133 | 0.9258 | 0.9408 |
| 5 | 0.1294 | 0.1023 | 0.9339 | 0.9491 |
| 6 | 0.1164 | 0.0928 | 0.9403 | 0.9520 |
| 7 | 0.1062 | 0.0904 | 0.9452 | 0.9540 |
| 8 | 0.0970 | 0.0902 | 0.9499 | 0.9530 |
| 9 | 0.0984 | 0.0899 | 0.9487 | 0.9516 |
| 10 | 0.0952 | 0.0801 | 0.9510 | **0.9584** |

### C. Validation IoU Curve

Figure 1 illustrates the steady increase in validation IoU across epochs, plateauing after epoch 5 and peaking at epoch 10.

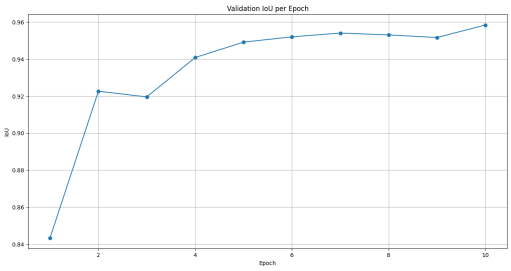


Fig. 1: Validation IoU per Epoch

### D. Computational Efficiency

Despite having only 1.2M parameters, LightSegNet achieves competitive or superior performance compared to heavier models. This proves its practicality for spectrogram segmentation and potential use in embedded systems or real-time applications.

## IV. Conclusion

This paper presents **LightSegNet**, an efficient and lightweight neural network architecture for semantic segmentation of spectrogram signals. The model achieved a peak validation IoU of 0.9584 after 10 epochs on a Kaggle dataset. The inclusion of SE blocks and a dual-loss function significantly improved accuracy while maintaining low model complexity. Future work will explore scaling LightSegNet to larger datasets and further optimization for deployment on edge devices.

## References

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