

Lesion Stroke Segmentation: A Deep Learning Approach

Ansari Shahid Ahmed

B.Voc in Artificial Intelligence and Data Science Anjuman- I-Islam Abdul Razzak Kalsekar Polytechnic

Abstract

Stroke remains one of the leading causes of death and long-term disability worldwide. Accurate and rapid detection of stroke lesions in brain MRI scans is essential for timely intervention and effective treatment planning. Manual segmentation is tedious and prone to variability. This research proposes an automated method for lesion stroke segmentation using a 2D U-Net deep learning architecture enhanced by the Focal Tversky loss function to address class imbalance. Training on the ATLAS v2.0 dataset ensures robustness, while rigorous evaluation using Dice Similarity Coefficient, Intersection over Union (IoU), and Sensitivity demonstrate the model's ability to segment small, irregular lesions. This automated approach aims to support radiologists, minimize manual workload, and contribute to improved patient outcomes.

1. Introduction

Stroke is a major global health concern, ranking as a leading cause of mortality and disability. Timely diagnosis and accurate assessment of lesion size and location are critical for treatment planning and patient prognosis. However, traditional manual segmentation of brain lesions is time-consuming, requires expertise, and can be inconsistent due to inter-observer variability. Advances in deep learning, particularly convolutional neural networks (CNNs), have revolutionized medical image segmentation. The U-Net architecture, with its encoder-decoder design and skip connections, has shown remarkable success in biomedical imaging tasks. This study employs a 2D U-Net with the Focal Tversky loss to overcome class imbalance, which is a common challenge in medical datasets where lesion regions are much smaller than the healthy tissue. By automating the segmentation process, this work contributes towards more efficient and reproducible stroke diagnosis.

2. Methodology

Dataset: The ATLAS v2.0 dataset includes 955 T1-weighted MRI scans with expert-annotated lesion masks. It is divided into training, testing, and generalization subsets to ensure robust model evaluation.

Preprocessing: Images were normalized and augmented using techniques such as rotation, flipping, brightness adjustments, and elastic deformations to increase dataset diversity and improve generalization.

Model Architecture: The 2D U-Net used consists of an encoder path for feature extraction, a bottleneck layer, and a decoder path for upsampling and precise localization. Skip connections retain spatial context. Regularization techniques, including batch normalization and dropout, prevent overfitting.

Loss Function: The Focal Tversky loss balances precision and recall, penalizing false negatives more heavily. This is crucial for detecting small, complex lesions.

Training: Implemented in Python using TensorFlow and trained in Google Colab with GPU acceleration. Evaluation metrics included Dice coefficient, IoU, Sensitivity, and Precision.

Software Tools: OpenCV, Albumentations, PyBIDS, NiBabel, GitHub, and DVC were used for data handling, augmentation, version control, and reproducibility.

3. Results

The trained U-Net model achieved high Dice and IoU scores on the test set, demonstrating reliable segmentation of stroke lesions. Visualization of predicted masks confirmed that the model effectively captured small, irregular lesions with high boundary precision. Accuracy plots showed stable training and minimal overfitting due to the use of data augmentation and regularization. These results indicate that the model can generalize well across diverse subjects and scanning sites.

In comparative analysis with standard loss functions, the Focal Tversky loss outperformed traditional Dice loss and Binary Cross-Entropy, proving its effectiveness in handling severe class imbalance.

4. Conclusion

This research demonstrates the feasibility and effectiveness of an automated approach for lesion stroke segmentation using a 2D U-Net combined with the Focal Tversky loss function. The model showed promising results on the ATLAS v2.0 dataset, achieving accurate delineation of small, complex lesions. By automating this process, the workload on radiologists can be significantly reduced, diagnosis can be accelerated, and patient outcomes can be improved.

Future work will focus on incorporating multi-modal MRI data (such as FLAIR and DWI), exploring advanced architectures like Attention U-Net and Transformer-based models, and evaluating the method on larger, more diverse datasets to further enhance generalizability and clinical applicability.

ACKNOWLEDGEMENT

I sincerely thank the faculty of Anjuman-I-Islam Abdul Razzak Kalsekar

Polytechnic, especially the Department of Artificial Intelligence and Data Science, for their valuable guidance, continuous support, and encouragement throughout this project. My heartfelt appreciation goes to the Hugging Face open-source community for providing powerful and accessible NLP tools, which were instrumental in implementing Visual Image Caption Generator Using Deep Learning. I am also grateful to my peers, mentors, and everyone who directly or indirectly contributed to the successful completion of this work.

References

1. Olaf Ronneberger, Philipp Fischer, Thomas Brox. 'U-Net: Convolutional Networks for Biomedical Image Segmentation'.
2. Yutong Xie, Bing Yang, Qingbiao Guan et al. 'Attention Mechanisms in Medical Image Segmentation: A Survey'.
3. Risheng Wang, Tao Lei, Ruixia Cui et al. 'Deep Neural Networks for Medical Image Segmentation'.
4. Reza Azad, Ehsan Khodapanah Aghdam, Amelie Rauland et al. 'Medical Image Segmentation Review: The Success of U-Net'.
5. Geert Litjens et al. 'Deep Learning for Medical Image Analysis'.
6. Liew SL et al. 'ATLAS v2.0: An Open Dataset for Stroke Lesion Segmentation Research'. Available at: <https://atlas.grand-challenge.org/Data/>
7. Özgün Çiçek et al. '3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation'.
8. Aitik Gupta, Joydip Dhar. 'A Hybrid Approach for Improving U-Net Variants in Medical Image Segmentation'.
9. Kaiming He et al. 'Deep Residual Learning for Image Recognition'. 10. Vaswani A et al. 'Attention is All You Need'.