Automatic Hemorrhage Segmentation in Brain CT Scans Using Curriculum-Based Semi-Supervised Learning

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INTRODUCTION

One of the major neuropathological consequences of Traumatic brain injury (TBI) is intracranial hemorrhage (ICH), which requires swift diagnosis to avert perilous outcomes. Hence, this study introduces an automatic hemorrhage segmentation technique via curriculum-based semi-supervised learning. It employs a pretrained lightweight encoder-decoder framework (MobileNetV2) [1] on labeled and unlabeled data. The model integrates consistency regularization for improved generalization, offering steady predictions from original and augmented versions of unlabeled data.

MOTIVATION

Traumatic brain injury (TBI) is a serious neurological emergency with high morbidity and mortality rates worldwide. In the United States, around 1.7 million people suffer annually from this silent endemic with expected total medical expenses of approximately $76.5 billion [2]. Primary brain injuries may result in temporary or permanent neuropathological deficits such as intracranial hemorrhage (ICH). Timely diagnosis of brain hemorrhage is extremely critical to mitigate possible complications due to delayed diagnosis. Manual segmentation of brain hemorrhages is a time-consuming and labor-intensive task for radiologists and medical professionals. Automating this process with predictive modeling can save valuable time and resources, allowing for timely intervention and treatment particularly in geographic areas with limited access to professional medical facilities. The training procedure employs curriculum learning [3] to progressively train the model at diverse complexity levels.

OBJECTIVES

- **Develop an automatic brain hemorrhage segmentation approach by utilizing curriculum-based semi-supervised learning.**
- **Evaluate the model with pixel-level segmentation accuracy as well as slice-level classification accuracy.**

COMPUTATIONAL TOOLS

jupyter OpenCV NumPy PyTorch

METHODS

The overall methodology is based on the semi-supervised learning paradigm, where both labeled (80%) and unlabeled (20%) data are utilized to improve the model performance. The framework is trained by a combined loss function utilizing both supervised and unsupervised mechanism.

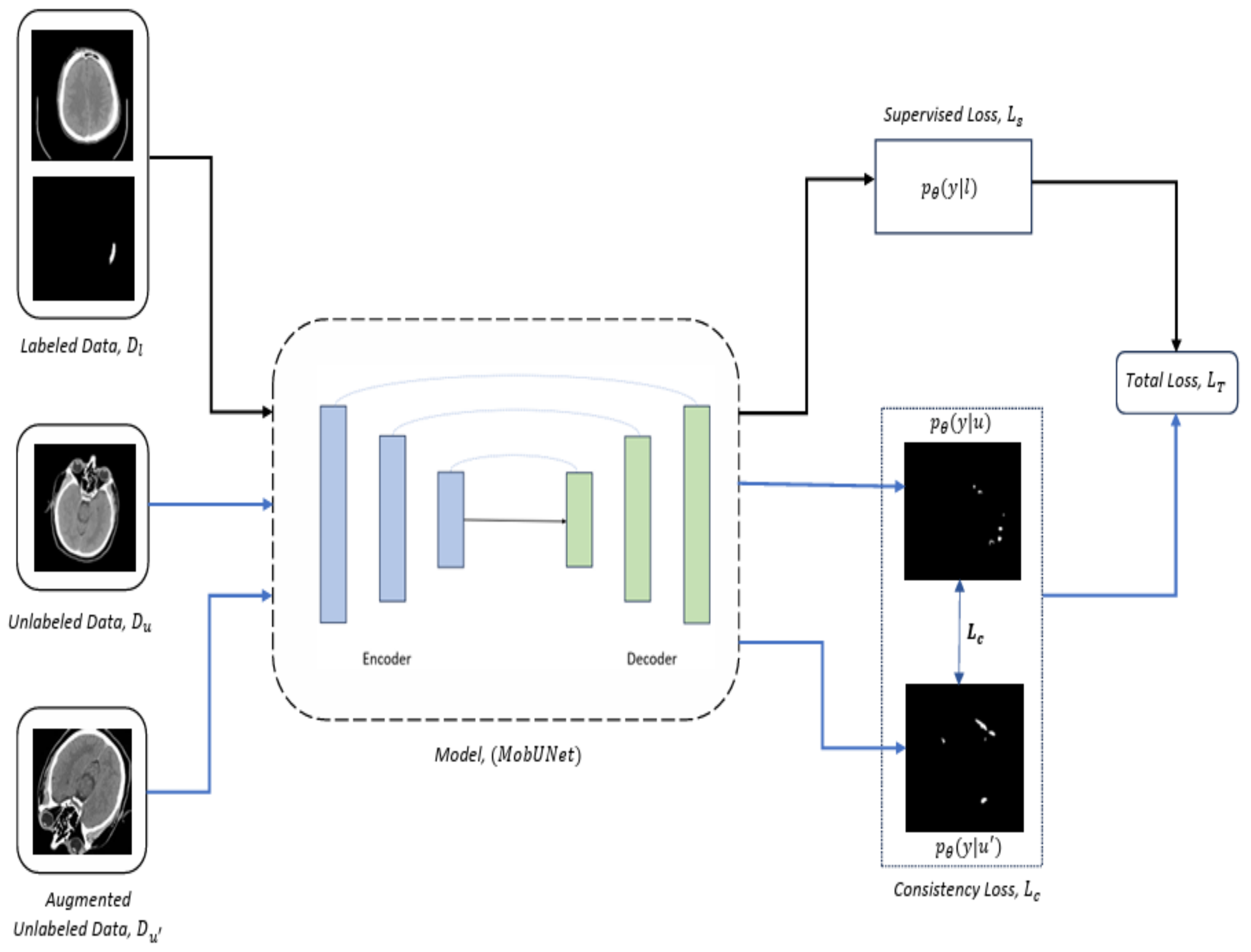

Fig. 1 Schematic illustration of the proposed method

- **Consistency Regularization**

$$\mathcal{L}_C = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{p}_{u_i} - \hat{p}_{u_i'}\right)^2$$

- **Curriculum Learning**

$$\tau = \frac{1}{M \times N}\sum I(i,j)$$

EVALUATION STRATEGY

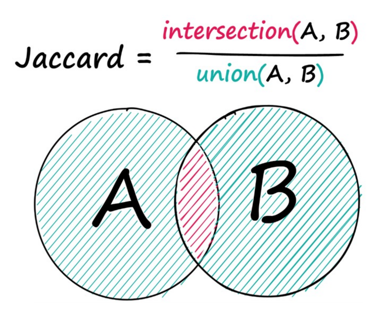

Fig. 2 Similarity between the sets A & B

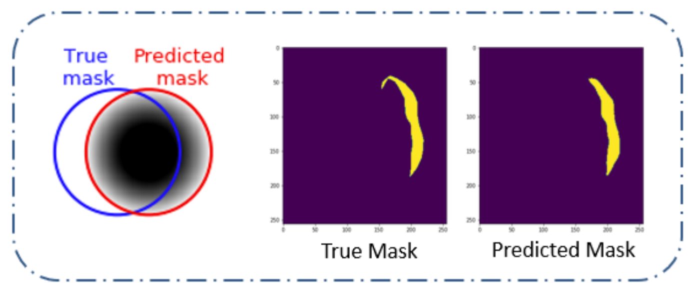

Fig. 3 Segmentation evaluation

RESULTS

The proposed method produced average Dice coefficient and Jaccard index values of 57.3% and 42.8%, respectively, for hemorrhage segmentation. In addition, the method is able to classify the brain hemorrhage with an overall accuracy of 87.86%.

RESULTS (CONT.)

Table 1. Comparison of Dice coefficients (%) and Jaccard indices (%) on the PhysioNet dataset with different ratios of labeled examples

Method		Data Proportion		Metrics	
Baseline	Architecture	Labeled Data [%]	Unlabeled Data [%]	Jaccard Index	Dice Coefficient
Supervised	UNet	100%	-	0.275 ± 0.02	0.398 ± 0.04
Supervised	MobUNet	100%	-	0.292 ± 0.01	0.410 ± 0.03
Semi-Supervised	UNet	80%	20%	0.368 ± 0.02	0.496 ± 0.05
Semi-Supervised	MobUNet	80%	20%	0.410 ± 0.04	0.542 ± 0.02
Semi-Supervised [Proposed]	MobUNet + Curriculum	80%	20%	0.428 ± 0.02	0.573 ± 0.01

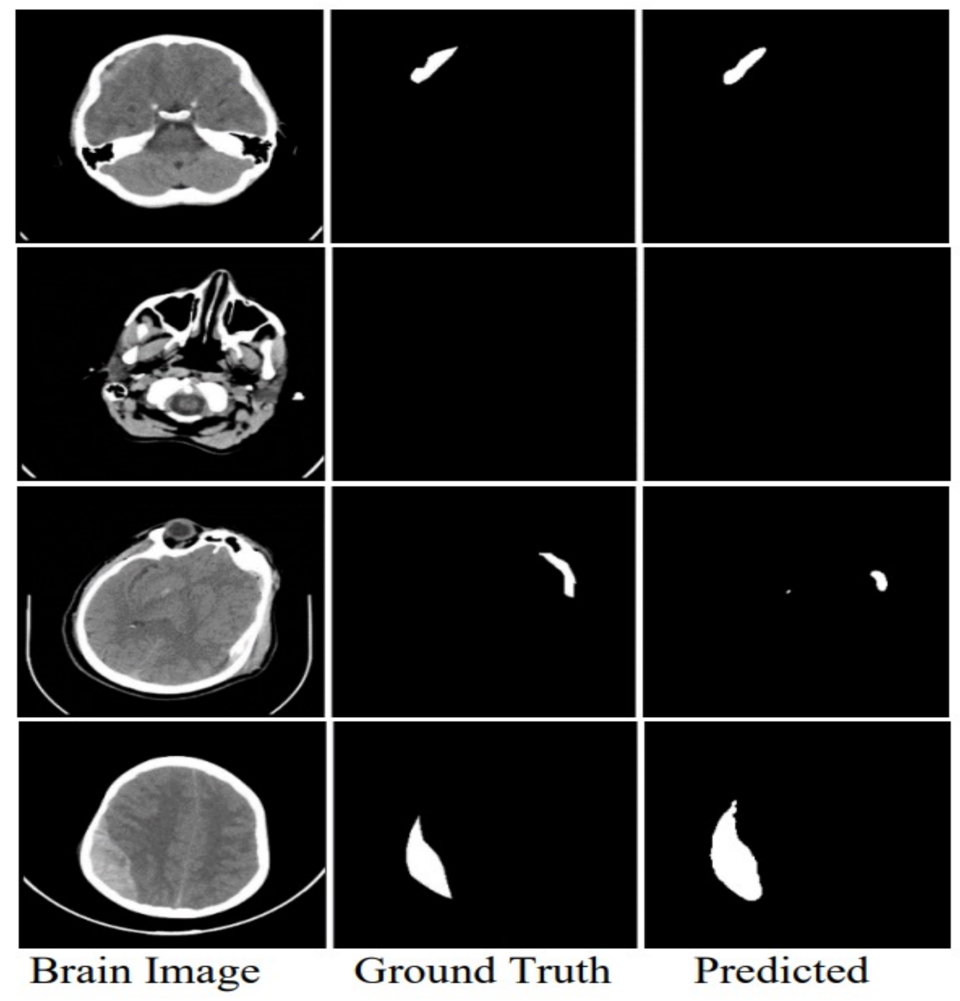

Fig. 4 Comparison between the proposed model's output and corresponding ground truth

CONCLUSIONS

Incorporating both labeled and unlabeled data improves the performance model significantly, as seen in the increased indices values compared to their fully supervised counterparts. Our future efforts will include more sophisticated deep learning architectures and comprehensive datasets to improve the segmentation accuracy and robustness for clinical applications. Other factors such as intracranial pressure (ICP) and midline shift (MLS) will be also considered.

REFERENCES

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