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Original Article

Intelligent Segmentation of Brain Parenchymal Involvement in Patients With Acute Ischemic Stroke Using Deep Learning Algorithms

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Abstract

Background: Ischemic stroke is the most common type of stroke. In the context of ischemic stroke imaging, automated segmentation methods facilitate deeper exploration of imaging data by providing consistent measurements and quantitative analyses, thereby reducing human errors while enhancing physician efficiency. This study presents a specific type of convolutional neural network (NN) to automate the segmentation of ischemic stroke lesions.

Methods: A deep NN called U-Net was developed for the automatic segmentation of ischemic stroke lesions using a U-shaped architecture. Then, the He-normal initialization algorithm was employed to address the issues of gradient explosion or vanishing gradients.

Results: The U-Net model was evaluated on a separate dataset consisting of samples collected from Tabriz University of Medical Sciences, which included 837 images of patients with acute ischemic stroke who sought treatment interventions at the center during 2021 and underwent magnetic resonance imaging (MRI). The obtained Dice coefficient (DC) values varied, depending on different images and their complexities (0.89–0.98). Notably, most images exhibited an average DC of 0.96, with approximately 70% of the images achieving a value of 0.96. Moreover, the annotation time for the network was reported to be 7 seconds for 10 images, while a radiologist took approximately 4 minutes for the same set of images.

Conclusion: Overall, the U-Net algorithm could enhance the speed and quality of service delivery, thereby reducing the time for patient care. Consequently, this improvement is likely to result in better patient outcomes and a decrease in stroke-associated complications.

Keywords: Ischemic stroke, Convolutional network, MRI lesion segmentation, Deep learning algorithm

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Background

Ischemic stroke is considered the most prevalent type of stroke, accounting for 87% of all stroke cases. It occurs due to reduced blood supply to brain tissue.[1] In addition, this condition is a major cause of disability and the second leading cause of mortality worldwide.[2] In the acute phase of stroke, early diagnosis and identification of the location and extent of infarction within a short time frame are crucial for treatment, particularly for administering thrombolytic drugs and performing surgical interventions aimed at preserving the affected area and mitigating stroke-associated risks.[3,4] Standard medical treatment for acute ischemic stroke is effective only within 4.5 hours after the onset of symptoms.[5] Therefore, the success of treatment is closely related to the time elapsed between the onset of symptoms and successful intervention.[6]

The brain parenchyma refers to the functional tissue of the brain, and ischemic lesions can appear at any point within this parenchyma. The morphology and signal intensity of these lesions can vary not only between stages of the disease but also within them, with this variability increasing over time following the onset of the stroke.[7] While many clinical centers utilize computed tomography (CT) as the first imaging modality for stroke due to its accessibility and rapidity, magnetic resonance imaging (MRI) remains the gold standard for identifying and quantifying ischemic lesions.[6] This is because MRI facilitates the early detection of lesion size and location in patients with acute stroke by assessing the functional and metabolic parameters of the brain.[8-10] Currently, medical images are analyzed by radiologists, who often work under conditions of fatigue and limited experience, leading

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to slower processing times.[11] Furthermore, the manual identification and diagnosis of lesions are particularly challenging due to the similarities and ambiguous borders between normal tissue and infarcts.[12]

In this context, automated segmentation methods are urgently needed to provide consistent measurements and quantitative analyses.[13] Lesions in imaging may exhibit diverse morphological characteristics, potentially leading to oversight by healthcare providers. The degree of differentiation between lesions and normal tissues is based on varying intensities, making the identification of their boundaries relatively complex.[14] The challenge of segmenting ischemic stroke lesions began in 2015 to establish a fair and direct comparison framework for automated methods.[15] Consequently, machine learning (ML) has emerged as one of the most effective solutions for integrating, analyzing, and predicting large and heterogeneous datasets .[8] With significant advancements, deep learning (DL) algorithms have demonstrated the capability to produce results comparable to, or sometimes surpassing, those of human specialists. DL in the context of ischemic stroke imaging can facilitate intelligent segmentation, focus detection, image analysis, prediction, and treatment of ischemic stroke by exploring deeper imaging data, thereby decreasing human errors while improving physician efficiency.[4]

Currently, research on artificial intelligence (AI), including DL and diverse imaging techniques, serves as a vital tool for studying the brain. More precisely, it assists physicians in optimizing time-consuming tasks related to the diagnosis and segmentation of brain abnormalities, as well as in improving the interpretation of brain images and the complex analysis of imaging data. Additionally, sophisticated ML algorithms support clinicians in identifying effective diagnostic patterns.[16] This study employs DL algorithms capable of quantifying features of brain images, aiding physicians and researchers in diagnosing cerebral infarcts and enhancing the understanding of brain parenchyma.

The investigation is based on MRI imaging data, which is a well-established method for obtaining high-contrast brain images. The quantitative analysis of medical images or volume measurements necessitates an examination of anatomical structures, a process accomplished through segmentation, which considerably influences the efficiency of medical image analysis. It should be noted that even minor inaccuracies in segmentation can cause failures in subsequent analysis stages (e.g., feature extraction, measurement, and visualization of target regions). Moreover, accurate disease diagnosis is crucial in medical contexts; therefore, segmentation is a vital step in image analysis. Utilizing DL models can lead to time saving and improved accuracy [17]. Recent DL applications in the medical field have shown promising results.[18] Among the well-known DL algorithms, convolutional neural networks (CNNs) stand out as the most successful for image segmentation, offering high objectivity and efficiency compared to other ML algorithms.[19] These networks are also capable of segmenting infarct lesions in MRI images, thereby enabling more accurate predictions regarding patient status by integrating lesion volume and location.

It is important to note that segmentation is the most critical step in identifying and diagnosing lesions. Subsequent classification cannot be accurately performed without proper segmentation.[11] In this study, a specific type of CNN is employed to automate the segmentation process. This algorithm will assist healthcare providers in expediting decision-making and delivering the best treatment protocols in the absence of specialist physicians. The findings of this research are significant, as they provide accessible and precise methods for the automatic extraction of data from images for academic, educational, and healthcare institutions aiming to enhance clinical care.

Methods

This research is divided into several sections. It should be noted that no clinical trial number was applicable in this research.

Data Collection (Dataset)

The first step in ML projects is the process of gathering training samples [20, 21]. In this study, the source of the raw data was MRI images from the PACS system at the Imam Reza Educational and Treatment Center of Tabriz University of Medical Sciences, prepared in collaboration with the Neuroscience Research Center. A total of 837 DICOM-format MRI images were extracted, which belonged to patients who were diagnosed with ischemic stroke. To obtain more precise information, all image views were examined, and ultimately, the axial view was selected for analysis.

Preprocessing

For annotating the MRI images, DICOM files were converted from various formats to PNG format. This format is capable of preserving details and high-contrast graphics, as well as providing extremely precise displays without pixel compression. In this study, preprocessing was conducted twice. First, additional information (e.g., demographic details) was removed from the images, and then the brain region was centered in all MRI slices prior to annotation. The second preprocessing step involved selecting all MRI slices that contained ischemic stroke lesions. The number of slices affected by ischemic brain injury varied by method, yielding 60 slices for analysis.

To isolate images containing ischemic lesions, specific masks created by physicians during the annotation process were utilized, and each mask was associated with the corresponding two-dimensional (2D) image of the stroke lesion. On average, approximately 19 image slices were extracted for each sample. In the final preprocessing stage, all stroke images and their corresponding masks, stored in PNG format, were selected and converted into

2D Numpy arrays.

Data Annotation

Data labeling and annotation are fundamental steps in ML. It is noteworthy that labeling it is a time-consuming process since it heavily relies on manual work and must be performed by field specialists. In the present study, the data were annotated after file format conversion and the first preprocessing stage, with the assistance of a radiology expert from Tabriz University of Medical Sciences. They annotated the stroke lesions in each slice of the MRI images using Sefexa software (version 1.1.2). Regardless of the presence or absence of lesions, this software generated a mask for each 2D slice, which was saved in PNG format. The values of the generated masks were either 1 or 0, indicating either the stroke lesion tissue (1) or healthy tissue (0).

Setting up the Google Colab Environment

To enhance the accuracy and speed of NN computations and improve accessibility and efficiency, the U-Net deep NN was designed and implemented on a graphics processing unit platform. Google Colab was selected as an online host for implementing the network code. The capabilities of this platform eliminated the need for a dedicated server and provided access to hardware with 52 GB of RAM and 16 GB of graphics processing unit, thereby facilitating faster model development and evaluation while reducing overall processing time.

Connecting Google Colab to Google Drive

Using Python coding, a connection was established between Google Colab and Google Drive. The deep NN then read all the original images and their corresponding masks from Google Drive for processing. At this stage, the connection between Google Colab and Google Drive was established by mounting the coding environment to the virtual drive in Google Drive. After executing the mount command to facilitate the connection, a message appeared requesting permission to access Google Drive. The connection was successfully established following confirming and selecting the desired Gmail account. To enable this connection while performing deep NN computations in the cloud, project data were stored in the Google Drive virtual space under the name "my_drive," and the link to Google Colab was established.

Library Imports

After completing the previous steps, all necessary libraries and packages were imported and categorized into four groups: system and standard libraries, image processing libraries, libraries for numerical computations, visualization, and file handling, and libraries related to the design and implementation of deep NNs.

Design and Training

To configure the image parameters, the size of the images was adjusted from 192×192 to 128×128 pixels. Based on the architecture of the U-Net NN, the optimal standard for image dimensions for training the NN is 128×128 with a single channel. The selected images were converted to a single-channel format. In addition, the access paths for the images were designated during the training and testing phases within Google Drive. A total of 700 training images were allocated, indexed from 1 to 700 in the specified path, while 137 testing images were indexed from 701 to 837.

Modification and Retrieval of Training Images and Corresponding Masks

The size of the images was adjusted to 128×128 pixels to ensure the optimal dimensions for input into the NN while preserving the relevant features. Additionally, the input images for the network were selected in grayscale format as single-channel images, resulting in a 2D matrix when dealing with the grayscale images in this project.

Results

The proposed architecture, its characteristics, and the results derived from deep learning modeling are examined.

The Proposed Network Architecture

Building the U-Net Neural Network Model

A deep NN, known as U-Net, was presented for the automatic segmentation of ischemic stroke lesions. This NN reduces the number of network parameters and mitigates the risk of overfitting. As illustrated in Figure 1, the architecture is primarily U-shaped and consists of two main components: the encoding path and the decoding path. The encoding path is composed of two convolutional layers, each utilizing a 3×3 kernel. Each of these convolutional layers employs a rectified linear unit (ReLU) activation function and a 2×2 max-pooling algorithm to reduce feature map sampling.[22] The decoding path, on the other hand, reconstructs the image to its original size through convolutional and pooling layers, playing a crucial role in facilitating the precise localization of objects. The U-Net architecture incorporates 23 convolutional layers.

Encoder Path

In the encoding layer during the feature extraction phase, the first layer was defined with 16 kernels of size 3×3, utilizing the ReLU activation function to learn complex data and produce acceptable predictions at the output. The exponential linear unit activation function was also employed to address the issue of neuron death for negative values in the ReLU function. In addition, the He-normal initialization algorithm was applied to mitigate the problems of gradient explosion and vanishing gradients. In the convolution process, kernels were utilized for feature extraction. A kernel size of 3×3 was chosen, given that larger kernels entail high computational costs.

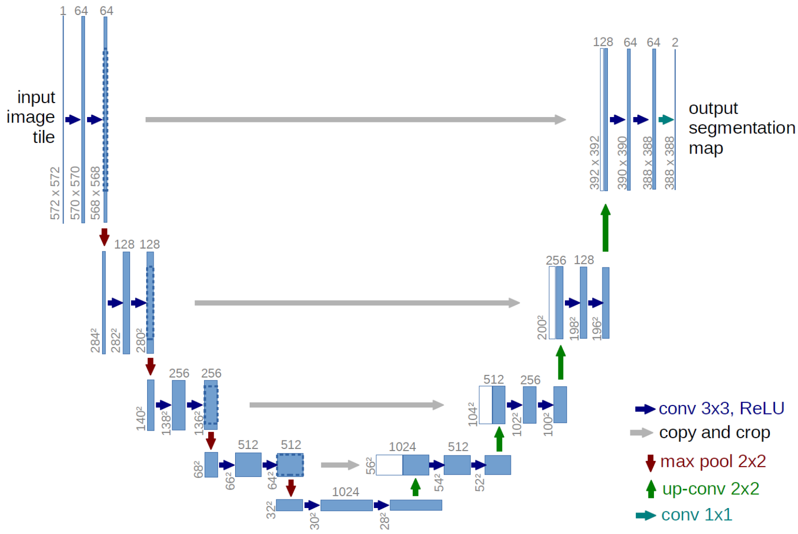

Figure 1. The Proposed U-Net Architecture for Semantic Image Segmentation. *Note*. ReLU: Rectified linear unit

Subsequently, the second layer was constructed with 32 kernels of size 3×3, followed by the third layer with 64 kernels, the fourth layer with 128 kernels, and the fifth layer with 256 kernels.

Decoder Path

After completing the encoding path, the features were transformed into a mask representation in the final layer using Softmax. This was achieved through pooling and convolutional layers that resize the output back to its original dimensions, with the features presented as masks. To prevent network errors due to the loss of image information, concatenation was performed at four stages. The input (original images) and output (image masks) were read using the model command. The system loss was calculated through the Adam optimization function, utilizing "binary_crossentropy" as the loss function.

Network Training

During the model training process, due to the high number of images, 15% of the data was set aside as validation data. The batch size was set to 1. To enhance the model's accuracy, the number of epochs was determined to be 100. The loss decreased from 0.034 in the first epoch to 0.0085 by the hundredth epoch, while the validation loss (val_loss) changed from 0.028 to 0.0097.

Evaluation

Evaluation and Comparison of the Designed Algorithm With Medical Diagnosis

The Dice coefficient (DC) was employed to assess the segmentation results of the model. In the context of image segmentation, the DC was utilized to evaluate the similarity between the predicted mask generated by the AI and the corresponding ground truth mask. The DC ranges from 0 to 1, indicating no overlap or complete overlap and agreement, respectively. The Dice index was calculated using the following formula:

$$DCS = \frac{2|X \cap Y|}{|X| \cup |Y|} \qquad or \qquad DCS = \frac{2|X \cap Y|}{|X| + |Y|}$$

In this context:

- |X∩Y| denotes the number of common elements between sets X and Y.
- |X| represents the number of elements in set X, and |Y| is the number of elements in set Y.

The U-Net model was evaluated on a separate dataset comprised of samples collected from Tabriz University of Medical Sciences. Figure 2 shows a sample of dataset and the segmentation result by the proposed model. This dataset included 837 images from patients with acute ischemic stroke who visited the aforementioned center for therapeutic interventions from the beginning to the end of the year 2021 and underwent MRI. The DC was utilized for model evaluation, as it is one of the most important assessment metrics for segmentation studies. This coefficient calculates the similarity between two sets, quantifying the overlap space between the segmentation map and the true label of each image. In this study, the DC values varied based on different images and their complexities, ranging from 0.89 to 0.98. Notably, the majority of images had an average DC of 0.96, with approximately 70% of the images yielding a DC of 0.96. The results indicated that the annotation time for the network for 10 images was reported to be 7 seconds, whereas the same number of images took approximately 4 minutes for the radiologist to annotate.

Discussion

Importance of Data Collection and Preparation in Stroke Diagnosis

Data collection and preparation results revealed that the availability and lower cost of CT scans compared to MRI lead to many patients exhibiting a number of clinical symptoms (e.g., diplopia, dizziness, and weakness) being initially subjected to CT imaging. However, due to the superior ability of MRI to display details of soft tissue and high-quality images, patients with ischemic stroke are referred for MRI, especially for the diagnosis of the lesion's location and extent.

Imaging techniques (e.g., MRI with perfusion-weighting and diffusion-weighting) are integral components of the diagnostic process in acute ischemic stroke conditions. The visual interpretation of these data is the most likely method for triaging stroke patients and can facilitate timely reperfusion therapy. Time is critical in stroke diagnosis; the sooner a diagnosis is made and appropriate treatment initiated, the better the outcomes for patients. Therefore, the development of automated methods for measuring and identifying stroke lesions can significantly enhance assessment accuracy.[23-25]

The Role of Deep Learning in Stroke Diagnosis

Given global statistics, stroke remains a leading cause of morbidity and mortality. The accurate identification of lesion location and volume, particularly through early diagnosis, can improve clinical outcomes, thereby reducing disability. However, stroke identification is often challenging and heavily relies on the speed and accuracy of imaging data interpretation. In this context, DL has emerged as an effective tool for analyzing medical images.

DL models (e.g., U-Net and autoencoder) have achieved remarkable success in medical imaging. These models are specifically designed for the segmentation and identification of lesions in images and can expedite the diagnostic process. Moreover, DL algorithms, due to their ability to extract complex features from data, can effectively facilitate the identification and analysis of ischemic stroke.

Distinction of This Research From Other Studies

This study differentiates itself from previous research in several key aspects. Firstly, while many prior studies focused on stroke identification based on clinical features and imaging, this study emphasized the application of deep NNs for the precise segmentation of stroke lesions. Furthermore, this research utilized high-quality MRI images rather than CT scan data, providing greater accuracy in identifying and analyzing brain lesions.

Additionally, the performance evaluation results of the designed algorithm in this study demonstrated high segmentation accuracy and a faster response time compared to manual methods. While many studies rely on considerable time and human resources for image analysis, this study confirmed that the designed algorithm can segment an image in an average of 7 seconds, whereas a radiologist would typically require about 4 minutes for the same task.

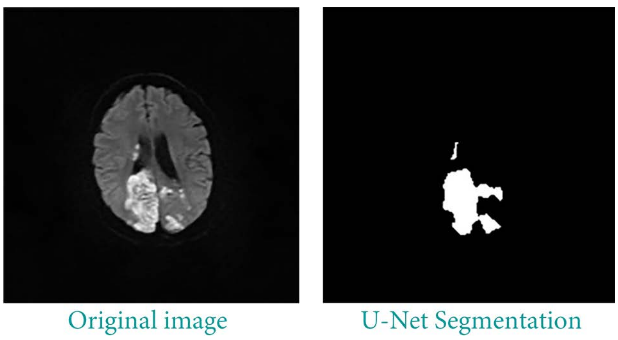

Figure 2. Original Grayscale Brain Scan, Highlighting Anatomical Structures, Potential Abnormalities, and the U-Net-Generated Segmentation Mask

Performance Evaluation of the Algorithm

In the performance evaluation, the use of the intersection over union (IoU) metric as a measure of accuracy clearly illustrated the advantages of this approach compared to traditional algorithms (Table 1). A minimum IoU value of 0.48 was achieved in this study, indicating a commendable level of accuracy in lesion segmentation, which contradicts the results of numerous previous studies that faced significant challenges in achieving high accuracy under complex conditions.

The development of DL algorithms in this domain can lead to further advancements in stroke diagnosis and treatment, enhancing the quality of healthcare services in this area. Ultimately, our findings demonstrated that the integration of DL techniques for stroke diagnosis can alleviate the workload of healthcare providers and improve clinical outcomes for patients.

Conclusion

DL techniques have been utilized in diagnostic imaging to address many existing challenges in modern healthcare environments. These techniques provide tools that assist physicians in making more confident decisions when faced with growing patient lists while also helping to streamline workflows and optimize the deployment of personnel and equipment resources. Additionally, they contribute to reducing daily stress and pressure on healthcare professionals' well-being.

The outcome of this research was the development of a DL algorithm for patients with acute ischemic stroke, designed as an AI-based model. Our findings indicated

Table 1. Performance Comparison of Deep Learning Models for Image Segmentation

Reference	Model Architecture	DSC	IoU
Sales B[12]	U-Net-based CNN	0.84 ± 0.31	-
Nishio M[19]	U-Net-based CNN	0.6684	-
Clèrigues A[16]	CNN	0.8503	-
Lundervold AS[11]	FCN	Training = 0.8652 Validation = 0.74 Testing = 0.63	-
Kim YC[8]	VoxResNet	0.8491	-
Valverde JM[25]	CNN	0.73	-
Castillo D[17]	CNN-Res	0.8543	
Our model	U-Net-based CNN	0.96	0.48

Note. CNN: Convolutional neural network; FCN: Fully convolutional network; VoxResNet: Voxelwise residual neural network; DSC: Dice similarity coefficient; IoU: Intersection over union.

that the developed algorithm could successfully enhance the speed and quality of service delivery. The results further demonstrated that, due to the efficiency and high speed of the proposed algorithm compared to human performance, the time required to provide care to patients was reduced, ultimately leading to an improvement in patient outcomes and a decrease in complications associated with strokes.

As previously mentioned, this study presented a clinical decision-making model utilizing deep NNs known as U-Net-based CNNs for the automatic segmentation of ischemic stroke lesion tissue from MRI images. In other words, this study introduced a novel approach for segmenting MRI medical images using advanced deep NN architectures, specifically the U-Net, which directly generates segmentation maps from the raw input image pixels. To overcome the limited local data availability and Architectural Constraints of present study and enhance the segmentation process, several actions are recommended, including collecting additional local data, integrating MRI techniques to acquire extra metadata and better positional data, utilizing 3D convolutional layers, incorporating embedded layers between skip connections, and applying translated convolutional layers instead of expanding layers. Moreover, it is suggested that future researchers employ hybrid methodologies in their studies.

Furthermore, to achieve a successful outlook for the designed segmentation algorithms in the DL framework, addressing gaps, such as the lack of sufficient studies in this field and the absence of healthcare specialists' involvement in the model development stages, as well as the scarcity of commercially applicable models in healthcare service centers in the country, is of significant importance.

Authors' Contribution

Conceptualization: Mahdi Farhoudi, Mahdis Abbasi.
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Methodology: Mahdis Abbasi, Taha Samad-Soltani.
Project administration: Taha Samad-Soltani.
Resources: Parya Vojdani.
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Visualization: Mahdis Abbasi.
Writing–original draft: Mahdis Abbasi, Taha Samad-Soltani.
Writing–review & editing: Parya Vojdani.

Competing Interests

The authors declare they have no personal, professional, or financial conflict of interests.

Consent for Publication

All participants were informed about the study's objectives. They signed a form and announced their consent for publication.

Data Availability Statement

All data generated or analyzed during this study are included in this published article. The datasets used and/or analyzed during the current study are available upon reasonable request from the corresponding author.

Ethical Approval

All the methods were performed in accordance with relevant guidelines and regulations, especially in AI-related studies. Before the initiation of the study, all participants received an information statement about the study and provided written consent to participate. In addition, this study was approved by the Ethics Committee of Tabriz University of Medical Sciences (IR.TBZMED.REC.1402.194).

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Intelligence Use Disclosure

The authors used GPT-5 for grammar correction and language editing to improve manuscript readability. All AI-generated language suggestions were reviewed and edited by the authors.

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