CHAOS Theory and Applications in Applied Sciences and Engineering

e-ISSN: 2687-4539
RESEARCH ARTICLE
Vol.7 / No.1 / 2025 / pp.50-60
https://doi.org/10.51537/chaos.1605529

U-Net-Based Models for Precise Brain Stroke Segmentation

Suat Ince [*,1], **Ismail Kunduracioglu** [α,2], **Bilal Bayram** [β,3] **and Ishak Pacal** [α, §,4]

[*]Department of Radiology, University of Health Sciences, Van Education and Research Hospital, 65000, Van, Turkiye, [α]Department of Computer Engineering, Faculty of Engineering, Igdir University, 76000, Igdir, Turkiye, [β]Department of Neurology, University of Health Sciences, Van Education and Research Hospital, 65000, Van, Turkiye, [§]Department of Electronics and Information Technologies, Faculty of Architecture and Engineering, Nakhchivan State University, AZ 7012, Nakhchivan, Azerbaijan.

ABSTRACT Ischemic stroke, a widespread neurological condition with a substantial mortality rate, necessitates accurate delineation of affected regions to enable proper evaluation of patient outcomes. However, such precision is complicated by factors like variable lesion sizes, noise interference, and the overlapping intensity characteristics of different tissue structures. This research addresses these issues by focusing on the segmentation of Diffusion Weighted Imaging (DWI) scans from the ISLES 2022 dataset and conducting a comparative assessment of three advanced deep learning models: the U-Net framework, its U-Net++ extension, and the Attention U-Net. Applying consistent evaluation criteria specifically, Intersection over Union (IoU), Dice Similarity Coefficient (DSC), and recall the Attention U-Net emerged as the superior choice, establishing record high values for IoU (0.8223) and DSC (0.9021). Although U-Net achieved commendable recall, its performance lagged behind that of U-Net++ in other critical measures. These findings underscore the value of integrating attention mechanisms to achieve more precise segmentation. Moreover, they highlight that the Attention U-Net model is a reliable candidate for medical imaging tasks where both accuracy and efficiency hold paramount importance, while U Net and U Net++ may still prove suitable in certain niche scenarios.

KEYWORDS
Medical image analysis
Ishemic stroke
Brain stroke
Segmentation
U-Net
Deep learning

INTRODUCTION

Stroke is an acute brain vascular disease that occurs as a result of interruption of the blood supply due to blockage of the various arteries or veins supplied to the brain. The phrase "time is brain" just implies that there is a need to spend more time in the diagnosis and treatment of such illnesses (Saver 2006). Fortunately, stroke is a preventable condition and is ranked among the leading causes of mortality and disability globally because the prevalence of the condition is high and the number of people with chronic diseases is rising (Lee *et al.* 2023). It is broadly classified into two main types: ischemic stroke (IS), with a global prevalence of 87%, and hemorrhagic stroke (Clèrigues *et al.* 2020; Roth *et al.* 2018). Ischemic stroke is characterized by hypoxic tissue injury due to arterial obstruction and leads to necrosis of the affected neuronal cells (The GBD 2018). While ischemic strokes are more prevalent and occur when blood clots block flow in the brain, hemorrhagic strokes are caused by conditions resulting in high blood pressure, aneurysms, or bleeding within and around the brain (Chen *et al.* 2017).

Currently, accurate diagnosis plays an essential role in stroke management, as interventions performed during the initial hours can significantly influence patient outcomes (Huang *et al.* 2022). Imaging modalities such as CT-scan (Computed Tomography) and MRI (Magnetic Resonance Imaging) form crucial constituents of the work in stages for stroke typing. Care was taken to select diagnostic tests that were popular with patients and referring clinicians owing to rapid throughput and lower costs compared to CT imaging; however, MRI provided a more detailed definition of the structural topography of the scans, and for differentiating the most recent acute ischaemic injury (Tursynova and Omarov 2021; Zhuang and Shen 2016). Among all MRI techniques, DWI (Diffusion Weighted Imaging) has been reported to be particularly important for the early diagnosis of ischemic strokes due to DWI's high sensitivity and quantitative reliability (Edlow *et al.* 2017; Jauch *et al.* 2013).

Moreover, the use of DWI in combination with ADC (Apparent Diffusion Coefficient) information helps the next step of lesion characterization and the final classification of the disease (Kim *et al.* 2019; Wong *et al.* 2022). Although the gold standard in manual segmentation of stroke lesions has been utilized in the present study, the process is still slow and surprisingly subjective due to the complexity of the human brain (Kumar *et al.* 2021). To overcome these limitations methods based on deep-learning-based automated segmentation methods give the solution to reduce the load and outcome of the diagnostic time (Nielsen *et al.* 2018). For example, the

Manuscript received: 22 December 2024,
Revised: 20 January 2025,
Accepted: 29 January 2025.

[1]suatdr65@gmail.com
[2]ismail.kunduracioglu@igdir.edu.tr (**Corresponding author**)
[3]bayrambilal3@gmail.com
[4]ishak.pacal@igdir.edu.tr

U-net and all of its derived structures with the encoder-decoder have been solely applied broadly to achieve the right segmentation of stroke lesions (Ronneberger *et al.* 2015). These methods are most appropriate in the analysis of stroke because they are less sensitive to global signal changes and are more precise in voxel and lesion level extraction (Hernandez Petzsche *et al.* 2022).

Deep learning models have been widely used in many areas in recent years thanks to their high accuracy and automation capabilities; these areas include disease diagnosis and crop efficiency analysis in the agriculture and farming sectors (Paçal and Kunduracıoğlu 2024), image processing and threat detection in the defense industry (Wang *et al.* 2023), cancer diagnosis in the medical field (Ozdemir and Pacal 2025), analysis of brain diseases and prediction of genetic mutations (Pacal 2025), as well as many different applications such as education, social analysis (Celik *et al.* 2025), financial data analytics (Alkan *et al.* 2023), natural language processing and even space exploration. There may also exist several issues in applying conventional CNNs (Convolutional Neural Networks) for the learning of both local and global features that are crucial to enhancing the understanding of different lesions (Bal *et al.* 2019; Kunduracioglu 2024a; Schlemper *et al.* 2019).

The above limitations have however in recent years been addressed by blends of CNNs and Transformative models (Kunduracioglu and Pacal 2024). These models take the top-level global contextual information because of the self-attention mechanism of Transformers which boosts the segmentation process (Dosovitskiy *et al.* 2020; Paçal and Kunduracıoğlu 2024). Additionally, two-path 3D CNNs provide a proper means of addressing the MRI slices with localized and generalized features to erase imbalances in data and improve the equalization of the segmentation process (Çiçek *et al.* 2016; Kench and Cooper 2021). Incorporation of data from different MRI options with DWI and ADC accessories provides better outcomes in terms of specificity and sensitivity (Sarvamangala and Kulkarni 2022). These approaches cooperate in aligning data across multiple modalities and thereby improve the ability of the model to properly disentangle the location of stroke lesions regardless of whether they are ill-defined (Ding *et al.* 2022). For example, the 3D ResU-Net and GAN-based methods can maintain the structures, and address the issue of the blurred features of lesions for the multispectral images, which can be very helpful in the diagnosis of complex neuronal diseases (Hossain *et al.* 2021).

The present segmentations have also been improved in other ways, and another successful attempt made was to enforce the use of transfer learning techniques. The models trained on the dataset like ISLES, which contain the brain tumor's images, can be returned as a special model to boost the result of the stroke segmentation job (Liu *et al.* 2021). There is also a desire to work with attention mechanisms and with pyramid-atrous convolutional networks to improve both, the segmentation and the classification models (Ansari *et al.* 2022). These innovations make it possible to detect not only the large-scale lesions but also the smaller lesion regions. The current deep learning-based models' performances are assessed with metrics that estimate lesion mask matching with the ground truth (Hernandez Petzsche *et al.* 2022). However, lesion size, location, and shape are being incorporated more and more into more detailed evaluation of clinically relevant performance metrics (Hernandez Petzsche *et al.* 2022; Maier *et al.* 2017). This is particularly the case in instances where the lesion is large, and lesion-load contrasts contribute significantly toward accurate lesion margin delineation.

Advanced imaging techniques and the application of artificial intelligence (AI) hold great promise for the detection and segmentation of acute ischemic stroke (AIS) lesions. However, clinical studies in this area remain limited in number and are often hindered by small sample sizes and methodological constraints. Despite these challenges, these studies bridge the gap between experimental methodologies and real-world medical applications, highlighting both the potential and the difficulties of implementing AI-driven solutions in stroke care. In a study explored AIS lesion detection using 2D and 3D U-Net models with multimodal MRI data. The 2D multimodal U-Net model, which combined DWI and FLAIR data, achieved a Dice score of 73.7%, outperforming other methods (Moon *et al.* 2022).

However, the small and homogenous dataset limited the generalizability of the results. The study also identified a lack of longitudinal data to track lesion progression and the absence of integrated clinical-demographic information as key limitations. Another study developed an ultrafast MRI protocol using DWI, FLAIR, and SWI/T2 modalities to compare its performance with traditional AIS detection protocols (Verclytte *et al.* 2023). While the ultrafast protocol showed excellent agreement with traditional methods in detecting AIS, its performance in detecting thrombus and hemorrhagic transformation was limited. The study suggested that future research with larger patient groups and more diverse clinical scenarios could enhance the accuracy of the protocol. Focused on machine learning models that utilized radiomic features from MRI data to classify stroke onset time (Zhang *et al.* 2022).

The DWI/ADC radiomic model demonstrated the best performance, with high sensitivity (95.2%) and positive predictive value (76.9%). However, the small sample size and data from a single medical center limited the model's applicability. Study on segment AIS lesions, developed a model using U-Net architecture and predict functional outcomes (Wong *et al.* 2022). This model achieved a Dice score of 85% on a test set of 875 AIS patients and demonstrated high accuracy in predicting 90-day Modified Rankin Scale (mRS) outcomes. The study emphasized the need for validation with larger, more diverse populations, as the dataset was sourced from a single center.

These studies demonstrate the effectiveness of U-Net architectures, radiomic-based machine learning models, and innovative imaging protocols in detecting and segmenting AIS lesions. However, common limitations such as small sample sizes, limited data diversity, and the need for validation across different clinical settings remain. Collectively, these findings underscore the significant potential of AI-driven techniques in improving AIS diagnosis and clinical decision support systems. Aslan and Ozupak (2025) demonstrates the effectiveness of the Edge U-Net architecture in road extraction from satellite images, showing remarkable performance with a global accuracy of 98.1% and an mIoU of 96.53%. These results surpass other existing methods and highlight the advantages of deep learning techniques in this domain. Aslan (2024) found that the proposed LSTM-ESA model outperformed the standard ESA model, achieving an accuracy rate of 98.1%. This result demonstrates higher success compared to similar studies in the literature.

This research significantly advances the domain of ischemic stroke segmentation by systematically evaluating three cutting-edge deep learning models; U-Net, U-Net++, and Attention U-Net, using consistent performance measures (IoU (Intersection over Union), DSC (Dice Similarity Coefficient), and Recall) and a carefully curated subset of 998 DWI scans from the ISLES 2022 dataset. The results highlight the Attention U-Net's exceptional performance in achieving high-precision segmentation, thereby emphasizing the critical importance of attention mechanisms in refining model accuracy. By employing a more targeted image selection strategy, this work not only yields more robust outcomes but also establishes a dependable methodological framework for precise lesion delineation in clinical stroke imaging.

RELATED WORKS

Stroke lesion segmentation has garnered substantial attention due to its clinical significance. Earlier on, segmentation techniques were based on manual feature extraction, where features are extracted before being classified by machine learning approaches (Kamnitsas *et al.* 2017). However, the limitation of the generalization capability of hand-crafted features due to which there is a variation in performance across datasets has paved the way for deep learning-based methods (Kamnitsas *et al.* 2017; Salvi *et al.* 2021). These approaches seem to learn features by themselves as they perform high-level image processing tasks for medical images which include tumor and stroke lesion segmentation (Goel *et al.* 2023; Salvi *et al.* 2021). On account of their capability of learning hierarchical features, Convolution Neural Networks (CNNs) have proved efficient for the segmentation of stroke lesions. U-Net and its derivatives have been developed especially (Chen *et al.* 2023; Xiao *et al.* 2018). For instance, Clèrigues *et al.* (2020) suggested a 3D U-Net for segmenting stroke lesions from MRI data, to solve the class imbalance issue, weight reduction was applied dynamically, and overlapping patches were used. However, because of the single-type, larger patches, the local features were not extracted optimally, and the analysis was majorly confined to the global characteristics. Similarly, another study expanded the U-Net structure without using 3D kernels; therefore, the inter-slice connection and segmentation of minute lesions were limited (Tursynova and Omarov 2021).

To overcome the architectural constraints, Zhao *et al.* (2019) proposed a multi-feature map fusion network for dealing with features coming from different paths. Even though they used fully and weakly labeled data, their model had a higher time complexity than the other two approaches. Zhang *et al.* (2020) used FPN-ResNet101 for the fusion of multi-plane information and encountered difficulties in integrating multiple manners of MRI data and thereby were constrained in overall performance. One major advancement in stroke lesion segmentation has come from the use of attention mechanisms, they help to bring priority to the right inputs (Woo *et al.* 2018; Yang *et al.* 2019).Yang *et al.* (2019) designed the framework as a CLCI-Net that uses hierarchical feature fusion and LSTM for improving plaque info location in gray-scale.

Likewise, Alshawi *et al.* (2023) integrated spatial and channel attention into a dual-attention U-Net to enhance feature dependency modeling and acquire higher accuracy of semantic segmentation. Moreover, for CNN-based methods, to overcome the drawback of CNN cross-attention mechanisms have been included in the hybrid architecture. For example, Wang *et al.* (2020) employed attention to obtain lesion similarities across the modalities. However, most attention-based methods are still confined to the region of interest, or local context, and hence may not capture the global context effectively (Woo *et al.* 2018). The transformers that were first incorporated for natural language processing applications have shown great promise in medical image segmentation (Pacal *et al.* 2024). Unifications of CNNs with transformer architectures are present in the Vision Transformer (ViT) and Swin-Unet, which exploits both local and global information (Yuan *et al.* 2023). Chen *et al.* (2021) introduced TransUNet which employs CNN for capturing local features and transformers for capturing global context information and reported impressive performance of organ segmentation. In stroke lesion segmentation, Wu *et al.* (2023) use multi-scale transformers to localize boundary area and improve the feature completeness.

Encoder-decoder architecture has also received massive improvement in its development. Liu *et al.* (2021) proposed a new hybrid contextual semantic module that can produce enhanced contextual features within such frameworks. Apart from CNNs, transformers were used in vision tasks, which were originally introduced for language modeling (Bayram *et al.* 2025; Burukanli and Yumuşak 2024). Dosovitskiy *et al.* (2020) Vision Transformer received great attention in image recognition by efficiently capturing global context by replacing convolutions with linear transformations. Other recent works in stroke segmentation using a transformer-based approach have produced state-of-the-art performance but still pose issues because of the missing inductive bias like locality that is already incorporated into CNNs (Li *et al.* 2022; Xie *et al.* 2021; Yuan *et al.* 2023). To overcome this, architectures that combine both CNNs and transformers have been discussed. These models are still based on the strengths of the CNNs in the local feature extraction and transformers for the global context modeling where a balance between the two is improved to pave the way for better segmentation (Wu *et al.* 2023, 2024; Yuan *et al.* 2023). Such approaches show how it is possible to use the strength of other paradigms to improve medical image segmentation beyond what is traditionally achieved.

The study of combining CNN and transformer architecture hybrids is quite encouraging. For example, Wu *et al.* (2024); Yuan *et al.* (2023), have designs of nets that will combine local and global features that do not have inductive bias of transformers. All the above-mentioned methods highlight the need to integrate two complementary skills to achieve strong results in segmentation. Several problems persist, however, even with the development of deep learning-based approaches. Previous approaches face difficulties in achieving stability between computational time and considering all the features (Yalçın and Vural 2022; Zhao *et al.* 2019). It is found that several architectures are unable to address local and global features together and as a result, there is a performance gap for small lesion segmentation (Alshawi *et al.* 2023; Tomita *et al.* 2020).

METHODOLOGY

ISLES2022 dataset

Data quality plays a pivotal role in deep learning success, as the dataset itself significantly influences model performance (Kunduracioglu 2024b). High-quality, balanced, and accurately annotated data minimize the likelihood of misclassification, thereby enabling the model to comprehensively learn its environment and operate as intended through iterative training. In this research, the ISLES 2022 dataset was employed, and its specific characteristics were thoroughly examined and discussed (Hernandez Petzsche *et al.* 2022; Maier *et al.* 2017). The datasets of the ISLES are available under an open database license for scientific purposes in the field of medical image processing and can be visualized in axial, coronal, and sagittal planes in the NIfTI (Neuroimaging Informatics Technology Initiative) format.

ISLES 2022 is particularly based on the segmentation of stroke lesions in multimodal MRI images (Li *et al.* 2024; Maier *et al.* 2017). ISLES 2022 has multimodal MRI scans of 250 patients with high variability in lesions in size and location because images from multiple centers are used (Li *et al.* (2024)). The distribution within these datasets leads to a problem such as class imbalance but the model is fair when evaluated in clinical conditions (Hernandez Petzsche *et al.* 2022; Maier *et al.* 2017). In the preprocessing steps, the obtained ISLES datasets were transformed into MNI (Montreal Neurological Institute) space by registering DWI, FLAIR, and ADC images. Among them, DWI modalities seem to be most effective for stroke lesion detection and therefore were addressed in the experiments. DWI images and masks are shown in Figure (1).

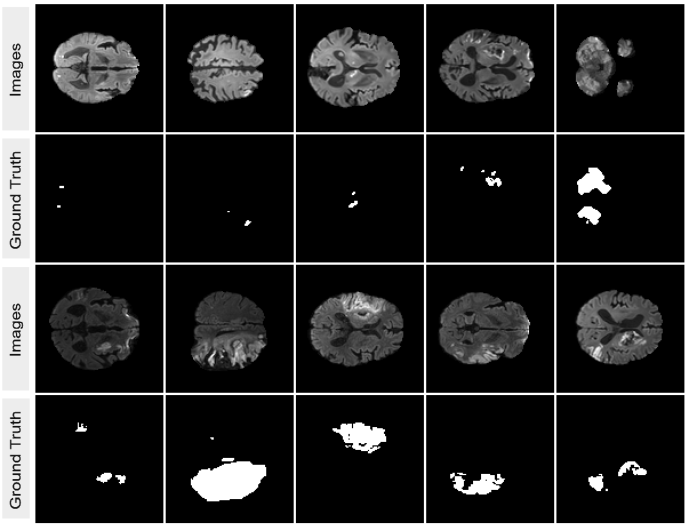

Figure 1 ISLES 2022 samples of DWI images and masks

To perform the experiments the resolution of each sample was reduced to 128x128x128 and then divided into three splits: training, validation, and test splits; 80% of samples were used for training, and the remaining 20% for testing (Kilicarslan and Pacal 2023). In conclusion, the ISLES datasets are useful in the benchmarking of automated approaches aimed at segmenting stroke lesions. The variety of sources for the data guarantees that the textures of datasets are genuine clinical circumstances and that the environment is appropriate for evaluating capabilities for generalization of models (Maier *et al.* 2017).

U-Net

The U-Net architecture is a perfect neural network often applied in the processes of image segmentation. This model consists of two main components: a contracting path encoder and an expansive path decoder. The encoder extracts the low-level feature vectors from the input image and the decoder utilizes these features to come up with real segmentation maps (Abdmouleh *et al.* 2022; Sacco *et al.* 2013). Because the decoding and encoding processes of the network are quite similar, it has a form of a "U" (Ashburner and Friston 2005). The U-Net architecture extends the "fully convolutional network" model. It optimizes it to perform well even with comparatively small sets of training data and, at the same time, provides better means of segmenting images (Figure (2)). Unlike the FCN (Fully Convolutional Network), for example, U-Net has layers in which ashamed of the polluted function will be utilized to increase the resolution of the output. Detailed features found at the contracting path are concatenated to assist in localization with the up-sampled outputs. A convolutional layer then takes this merged data to produce even more accurate outcomes.

The encoder is organized from 3 x 3 convolutions layered with rectified linear units (ReLU) and 2 x 2 max-pooling layers that are repeated. The number of feature channels increases at each pooling step, and doubles (Sacco *et al.* 2013). The decoder, on the

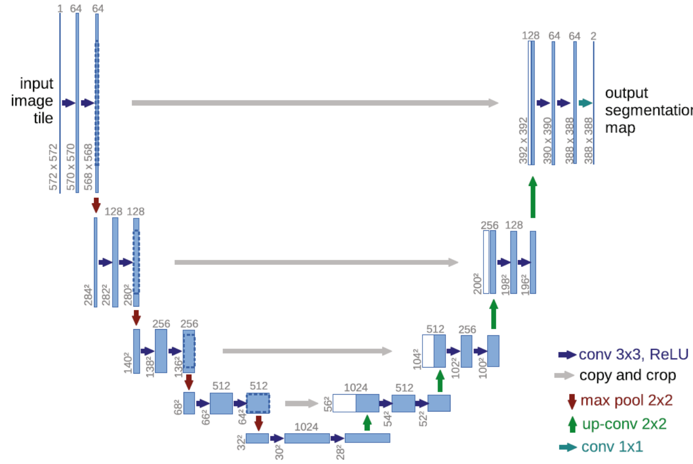

Figure 2 U-Net architecture. Figure from (Ronneberger *et al.* 2015).

other hand, has 2 x 2 up-convolutions to up-sample the feature maps but the number of channels is also reduced. Further, it also concatenates the feature map with the cropped version of the similar feature map from the encoder (Ashburner and Friston 2005; Sacco *et al.* 2013). U-Net is particularly applicable for handling large amounts of medical images. The data in medical images might have to be partitioned into several patches to be accepted by the network. Nevertheless, through the overlapping tile strategies, U-Net is in a position to accept images of any size in the network. These strategies allow attaining the higher resolution segmentation since the GPU memory-bound problem is solved (Karani *et al.* 2021). The energy function E serves as a loss function, evaluating the difference between the predicted probability distribution of each pixel and its corresponding true label. To enhance the training process, this function incorporates a weight map that assigns varying levels of importance to different pixels. The function is defined mathematically as:

$$E = \sum_{x \in \Omega} w(x) \log p_{l(x)}(x) \tag{1}$$

Where Ω is the set of vectors that can define a generic position in the image. The weight map $w(x)$ enables certain pixels to be prioritized during training, $l(x)$ signifies the true class of a pixel x, and $p_{l(x)}(x)$ refers to the probability, as estimated by the computer, that a certain pixel x belongs to its actual class. This loss function strengthens $p_{l(x)}(x)$ with an aim of increasing the model' s accuracy in its predictions by penalizing deviations of the value from 1 (Ronneberger *et al.* 2015).

In calculating separation boundaries, the family of morphological operations is used while for the formulation of the weight map, the family takes into consideration class imbalance and geometrical characteristics. The weight map contains variables for distributing class frequencies and will contain exponential terms to the first and second nearest cell border. Specifically, the map is expressed as:

$$w(x) = w_c(x) + w_0 \exp\left(-\frac{(d_1(x) + d_2(x))^2}{2\sigma^2}\right) \tag{2}$$

Where $w_c : \Omega \to \mathbb{R}$ as class frequencies are measuring, $d_1 : \Omega \to \mathbb{R}$ and $d_2 : \Omega \to \mathbb{R}$ represent the distances to the nearest border of the cell and the second nearest. This formulation makes certain that the points the model uses to focus while training consider both the spatial aspects and class concerns. Weight initialization is a critical factor for deep neural networks, particularly convolutional architectures with many layers and the U-Net is one of such complex pathways. Some authors pointed out that due to poor initialization, some parts of the network compute large activity whereas others compute very small activity during the training phase. To avoid this, the initial weights must be generated from a Gaussian distribution of mean zero and standard deviation of $\sqrt{\frac{2}{N}}$ for N, the number of input neurons per each neuron. This approach that incorporated Moment's normalization guarantees that every feature map within the network has a variance of nearly one; making the learning process balanced in the network.

U-Net is a modified version of the fully convolutional network model that can work with considerably fewer training images and give more precise segmentation. This structure eliminates the overall contraction network and uses one layer after another, so down-sampling is interconnected with up-sampling to increase the stability of output resolution. Another important aspect, that is implemented in the suggested architecture, is the possibility of having many more feature channels in the up-sampling section than in the corresponding down-sampling section, providing contextual data to the higher-resolution layers. This mechanism helps to get an accurate segmentation with the help of pixel-level (Johnson *et al.* 2024).

U-Net++

The developed U-Net++ an extension of the U-Net architecture with attention gives equally high accuracy and precision for tasks that demand it, such as medical image segmentation (Zhou *et al.* 2018). This architecture refines the inter-dependencies of the encoder and decoder structures heavily, decreases the semantic gap, and allows for efficient merging of multi-scale features. Here, the skip connections are implemented with dense convolutional blocks that sum feature maps of previous layers which improve semantic similarity and ensure better gradients flow. Consequently, the suggested model segments more accurately and efficiently while learning. In the U-Net++ model, one of the most important forms of modification is that of attention mechanisms, which would enable the model to pay heed only to a specific area. This affords a significant improvement, especially for scenes where images contain small or scattered structures such as body elements in medical images. Moreover, deep supervision is introduced into the architecture to provide the output of all the semantic levels. This not only gives a very fine-grained segmentation but also allows steps to be taken to minimize the network complexity where this is necessary. Through the use of the hybrid loss function, difficult issues like the imbalance of classes are sufficiently handled.

U-Net++ architecture is an extension of the U-Net model, which involves connecting the decoders in a way that creates densely connected skip connections. These connections facilitate the dense propagation of features through the skip connections, allowing for more flexible fusion of features at the decoder nodes. Consequently, each decoder node in U-Net++, from a horizontal viewpoint, combines multi-scale features from all its preceding nodes at the same resolution, while from a vertical perspective, it integrates multi-scale features from different resolutions across its preceding nodes (Figure (3)).

This architecture has a very tight coupling between the encoder and the decoder parts and it can use not only the feature maps corresponding to the same scale but also the features at the lower scales (Zhou *et al.* 2020). Consequently, this design helps to per-

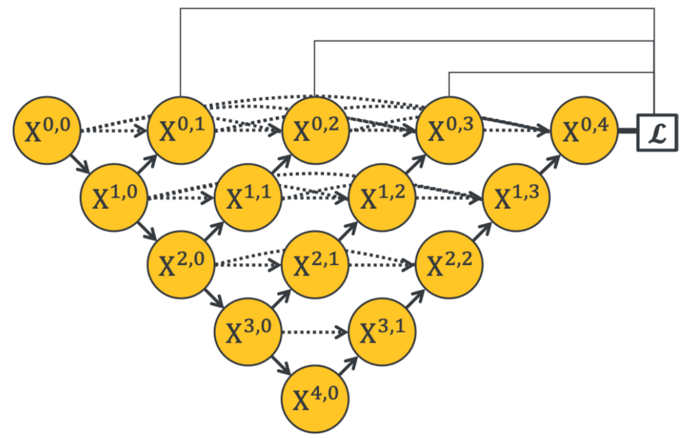

Figure 3 U-Net++ architecture. Figure from (Zhou *et al.* 2020)

ceive richer and more meaningful features and bears superiority over the U-Net and other of its versions in medical image processing tasks, in terms of accuracy and time consumption. Experiments have proved that U-net++ is helpful, especially for medical segmentation problems.

Attention U-Net

Attention U-Net is a type of deep learning that is particularly appropriate for difficult applications and is commonly used in medical contexts for instance aged image segmentation. It is a modification of the U-Net architecture where the focus mechanism is made more task-specific we call it the 'Attention Gate' (AG). Another that U-Net has is its capability to obtain feature maps of various resolutions preserving the global and local information. But in the standard U-Net, there is a problem of unnecessary activations and false positives in background areas. Attention U-Net complies with this problem because AGs are used to highlight only those activations that are important for the task and leave out all irrelevant ones (Oktay *et al.* 2018). In the encoder part of the model, the input image is necessarily passed through a series of filters and then down sampling by 2 at each scale level. Nc represents the total number of classes. Coefficients transmitted through the skip connections are passed through a number of AGs. In these mechanisms, feature selection is done by using context information derived from rougher resolution scales (Figure (4)).

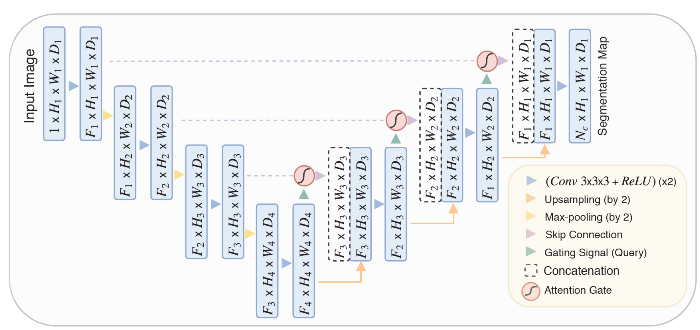

Figure 4 Attention U-Net architecture. Figure from (Oktay *et al.* 2018).

The details of the computation of an attention coefficient are that each pixel in the input feature maps are coupled with respective contextual information. These coefficients are used through element-wise multiplication with the feature maps which means that the focus is placed only on significant areas. The use of the described approach enables accurate division of tissue samples, especially in cases when the specimens are small or contain morphologically diverse structures (Oktay *et al.* 2018). Further, the incorporation of the AGs helps to reduce the training of several models, making training easier.

This research has shown that the proposed Attention U-Net can resolve many of the limitations of other current medical image segmentation techniques, including the challenging organ boundaries of the pancreas (Oktay *et al.* 2018). The presented architecture seems to yield higher Dice scores and lower surface distances when tested in comparison with the standard U-Net. In addition to this, the model's AGs guard against deviations from normal performance even with limited training data. It helps the architecture to learn only meaningful activations for given tasks and reduces the impact of background regions during the process of updating its parameters. Due to these features, Attention U-Net can become a valuable tool for the analysis of medical images.

Performance metrics

In automated segmentation methods, both accuracy and reproducibility aspects are crucial because they are the building blocks of the validity of segmentation. The performance of an algorithm is measured with its output against the ground truth dataset and is compared using metrics like true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Key performance metrics for assessing segmentation include:

Dice Similarity Coefficient (DSC): This measure represents the similarity of the established segmentation and segmentation referred to as reference segmentation. The closer the value to 0, it means there is no overlapping, a value of 1 means perfect overlapping (Dice 1945).

$$\mathrm{DSC} = \frac{2 \cdot TP}{FP + FN + 2 \cdot TP} \tag{3}$$

Intersection over Union (IoU) metric is used to measure the overlap ratio between the predicted segmentation area of a model and the ground truth area (Everingham and et al. 2010).

$$\mathrm{IoU} = \frac{TP}{TP + FP + FN} \tag{4}$$

Recall (Sensitivity, R) determines the percentage of instances that were identified as relevant and that are common to both the computed segmentation and the reference segmentation (van Rijsbergen 1979).

$$\mathrm{Recall} = \frac{TP}{TP + FN} \tag{5}$$

Precision (P) indicates the degree of similarity between the actual computed segmentation solution and the reference segmentation that has a significant positive prediction value (van Rijsbergen 1979).

$$\mathrm{Precision} = \frac{TP}{TP + FP} \tag{6}$$

Together these metrics provide a rounded evaluation of an automated segmentation algorithm as the measures of precision, coverage, and reliability are compared.

RESULTS

Implementation details

A system with the Ubuntu 22.04 operating system, an NVIDIA RTX 4090 graphics card, and an Intel Core i9 processor was used for this research. The experiments were conducted using the latest PyTorch framework and NVIDIA CUDA, commonly used for evaluating deep learning models. The optimization process was carried out using the Stochastic Gradient Descent (SGD) algorithm with a momentum of 0.9 and a learning rate of 0.01. Model updates were made using a batch size of 32 and 5 warm-up epochs to prevent large steps during training.

Data processing

Within the ISLES 2022 dataset, the initial and final images obtained from the same patient cohort often lacked discernible lesions, thereby diminishing their clinical and diagnostic utility. To refine the quality of dataset and ensure its clinical relevance, two experienced radiologists were consulted. Guided by their expertise, all non-informative images and those lacking appropriate segmentation masks were systematically excluded, resulting in a more diagnostically meaningful collection.

After this expert-driven curation, the dataset comprised 998 clinically and methodologically suitable images. For uniformity in subsequent segmentation tasks, all selected images were resampled to 256x256 resolution. To enhance the robustness and generalizability of the models, data augmentation was applied online during training, incorporating a diverse range of transformations; namely rotation, elastic deformation, horizontal flipping, scaling, random cropping, Gaussian blur, Gaussian noise, brightness and contrast adjustments, and random gamma transformations. These controlled augmentations aimed to simulate realistic variations encountered in clinical practice, thereby enabling the models to learn more generalizable features.

Following the augmentation and preparation steps, the dataset was divided into training and testing subsets, with 80% allocated for model training and the remaining 20% for performance evaluation. This rigorous approach, combining expert image selection, standardized preprocessing, and comprehensive online augmentation, was designed to improve the reliability, clinical applicability, and overall interpretability of the resulting segmentation models.

Experimental results

The paper also compares the results of the different models including U-Net, U-Net++, and Attention U-Net based on different evaluation measures. The presented outcomes show that, except for the number of parameters, Attention U-Net has higher scores in all other evaluation criteria (Table 1). Unexpectedly, the evaluation metrics, IoU, DSC, precision and F1-Score, which are closely related to the segmentation quality, reveal that Attention U-Net outperforms other methods. However, while U-Net achieves higher scores in some metrics, the recall index proves that the stability of this model is quite strong. However, in most cases, U-Net++ lags behind the other two models. This shows that the unique design of U-Net++ provides certain advantages, but it may fall short of its counterparts in terms of overall accuracy and efficiency.

The loss metric which shows how much error built up during training shows that U-Net has the least value of 0.3196 meaning that it made the fewest errors. Altogether, U-Net++ contains a higher loss value equal to 0.3671, but Attention U-Net and U-Net are closer to each other with a loss value of 0.3353. This implies that the attention mechanism in Attention U-Net does not disrupt the learning process while U-Net++ significantly improves the error

Table 1 Comparative performance metrics on U-Net architectures

Metric	U-Net	U-Net++	Attention U-Net
Loss	0.3196	0.3671	0.3353
IoU	0.8186	0.8004	0.8223
DSC	0.8999	0.8886	0.9021
Recall	0.9027	0.8919	0.8975
Precision	0.8974	0.8856	0.9072

rates. This is a representation of the IoU metric that measures how much the predicted segmentation of MR images by the different models corresponds to the ground truth an evaluation of the results shows that, for the Attention U-Net model, the IoU benefit reaches 0.8223 while for the U-Net model reaches 0.8186. U-Net++ has the lowest rate of 0.8004. This highlights that Attention U-Net has a higher segmentation accuracy than U-Net which causes the latter to seem to struggle in providing good segmentation. Dice Similarity Coefficient (DSC) familiar to IoU, estimates the overlap between the predicted and actual outputs. Attention U-Net starts the comparison with an accuracy of 0.9021, while U-Net receives slightly lower results with 0.8999. Here, only U-Net++ reaches a slightly lower score of 0.8886. Such outcomes support the usefulness of Attention U-Net, especially for processing difficult and small structures in segmentation Figure (5).

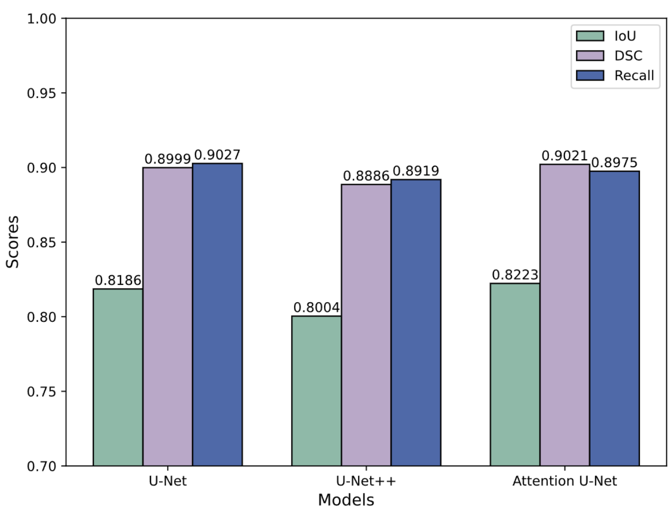

Figure 5 IoU, DSC, and Recall scores across models

Remember, that all calculates the sharpness of the model concerning positively labeled data: thus, the highest value of 0.9027 belongs to the U-Net model. Attention U-Net achieved the second highest recall with 0.8975 while U-Net++ has the lowest recall metric with 0.8919. This suggests that in segmentation problems U-Net is better suited for detecting positive samples in a precise manner. Precision, which signifies the extent of positive instance identification, placed Attention U-Net at the top bit with a measure of 0.9072. U-Net is followed by 0.8974 and U-Net++ is the lowest at 0.8856. This means that the predicted false positive regions are reduced in Attention U-Net, which has a significant benefit for capturing slim structures.

Figure (6) presents the segmentation results of the U-Net, U-Net++, and Attention U-Net models on a representative DWI brain image selected from the ISLES 2022 dataset. In addition, the Figure (6) includes four panels for each model: the original image, the ground-truth mask, the predicted mask, and an overlay combining the predicted mask with the original image. This structured presentation enables a clear, comprehensive, and academic comparison of the models' segmentation performances.

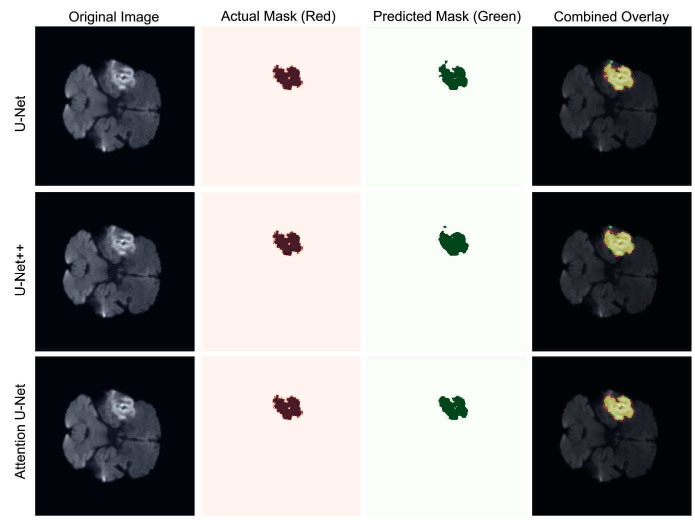

Figure 6 Comparative visualization of segmentation results for U-Net, U-Net++, and Attention U-Net models on a sample DWI brain image

For the purpose of comparison, the original image is presented in the first column and the results are obtained using the corresponding model. It is possible to distinguish a tumor region in the image compared to the default areas, which allows us to assess the segments used by the segmentation models. The real mask is aligned with two radiologists's annotation of the tumor location in red areas and is the ground for all models being compared here. The second image is the predicted mask panels where we see the segmentation results of each model. The authors concluded that the U-Net model has a high ability to detect the entire tumor area, but there are slight deviations at the edges. On the other hand, the U-Net++ model needs improvement in outlining the tumor region or boundary. It seems that the predicted mask for this model seems relatively smaller compared to the actual region of the tumor. Thus, through the aided assessment of the Attention U-Net model, it is evident that the generated predicted mask accurately targets more areas of the outlines compared with other findings and better segments the tumor.

In the combined overlay, the current mask, green, and the future mask, red are placed side by side on the working image. Yellow areas represent the places where the predicted mask and ground truth mask are the same, that is, there is agreement. When looking at the density of the yellow areas, the model is reasonably significant since large yellow areas of data points are observed but green areas of over-prediction and red areas of under-prediction are also noticeable. It is noticeable that red areas are present in greater numbers and the yellow regions are narrower in the U-Net++ model and are not able to capture all the regions of the tumor. In contrast, the Attention U-Net model yields a large number of yellow zones that conform to the actual mask and reduces mispredictions in red or green fields.

These results provide visual representations of the segmentation performance of the models. The prediction is especially accurate when the Attention U-Net model is used, as the larger areas marked in yellow and fewer mistakes based on the actual mask are demonstrated. The U-Net model is also high-performing but ranks a little low than the Attention U-Net. On the other hand, the U-Net++ has displayed poor performance in outlining the edges of the tumor. This work establishes that Attention U-Net is the best architecture for high precision and low loss rate tasks such as medical image segmentation. However, they depend on the specific application needs of a particular organization, company, or researcher in addition to the available resources.

For instance, U-Net has benefits for aspects such as simplicity while having higher sensitivity compared to other networks providing it with stability for specific operations. However, for those, who might be interested in the model with different optimization strategies, U-Net++ might be more suitable despite having lower general performance. However, the study also has some limitations. The dataset used contains a limited number of images, and the accuracy of the model could be further improved with a larger dataset. Additionally, integrating different deep learning architectures and applying optimization techniques could enhance the performance of models. Apart from the metrics considered in the study, testing the model with more diverse and complex data under real-world conditions could improve its generalizability.

DISCUSSION

In this study, the performances of three deep learning models namely U-Net, U-Net++, and Attention U-Net were considered to segment medical images using the ISLES 2022 dataset. The outputs were then evaluated with several performance indicators such as Loss, IoU, DSC, Recall, and Precision. These metrics give an overall evaluation of each model on how correctly they segment the tumor regions from medical images. Although the Loss and Recall metric is higher in the U-Net model than that of Attention U-net, attention U-Net performs slightly better in IoU, DSC, and Precision scores. In U-Net++, a similar but slightly lower performance for most of the proposed metrics. The key claim of the Attention U-Net is that the exact attention will enable the model to pay more attention to parts of the image that are essential for precise segmentation maps. This makes Attention U-Net the best-performing model for several tasks where high precision is essential in medical image segmentation for diagnosis or treatment planning.

In particular, all the considered models show high performance in terms of segmentation; however, based on the analysis of the results and the time needed to train and make a prediction, the Attention U-Net model can be officially recognized as the most effective for implementing high-precision segmentation of tumors. Nevertheless, the selection of the model might still be based on certain application requirements or resources. For example, U-Net is simpler and has higher recall; that is why it may be used in situations where more particular focus on tumor regions' detection is needed, including potential false-positive regions. Likewise, generalizing from this, there may be places where U-Net++ may be useful because it will be necessary to work with more complex models in such scenarios though the overall accuracy might be slightly less.

CONCLUSION

In this work, we investigated the U-Net, U-Net++, and Attention U-Net in context to the segmentation of brain tumors and achieved high accuracy scores with the DWI images of the ISLES 2022 dataset. These metrics show that the Attention U-Net method outperforms the other in segmentation accuracy and is in line with the results, especially for the IoU, DSC, and F1-Score essential measures of segmentation. Regarding computational costs, U-Net can directly attend to salient regions through its attention mechanisms the control of which is particularly beneficial when focusing on small or complex structures in medical images. Despite its unique approach to the architecture, U-Net++ was observed to be less accurate in all the evaluated metrics apart from recall which makes U-Net accurate in detecting positives. The analysis of loss values also highlights the stability of Attention U-Net during training, which ended with a loss that is almost as low as the one of U-Net, and considerably lower than of U-Net++.

The integration of advanced imaging techniques and deep learning algorithms has revolutionized stroke diagnosis and management. These innovations have not only streamlined the diagnostic process but also enhanced the precision of lesion characterization, contributing to improved clinical outcomes. Future research should focus on refining these methodologies, expanding multimodal integration, and exploring novel architectures to further advance the field of stroke diagnostics. Therefore, Attention U-Net is the algorithm that performs the best in cases when segmentation precision and the absence of errors are critical, and it should be demanded for medical image analysis. Nevertheless, the selection of the model should correspond to the presence of particular requirements and available resources. In general, U-Net is both simple and reliable, which can be useful if nothing else is known; however, U-Net++ may be more interesting to researchers who wish to investigate other optimization methods even though an evaluation showed it to be slightly less effective. Future work can improve them or propose different approaches for medical image segmentation since the presented models have some limitations.

Acknowledgments

This work was supported by the grant provided by TUSEB under the '2023-C1-YZ 'call and Project No: '33934'. We would like to thank TUSEB for their financial support and scientific contributions. Experimental computations were carried out on the computing units at Igdir University's Artificial Intelligence and Big Data Application and Research Center.

Availability of data and material

ISLES 2022 is an open-access dataset.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

LITERATURE CITED

Abdmouleh, N., A. Echtioui, F. Kallel, and A. B. Hamida, 2022 Modified u-net architeture based ischemic stroke lesions segmentation. In *2022 IEEE 21st International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA)*, pp. 361–365.

Alkan, T., Y. Dokuz, A. Ecemiş, A. Bozdağ, and S. S. Durduran, 2023 Using machine learning algorithms for predicting real estate values in tourism centers. Soft Computing **27**: 2601–2613.

Alshawi, R., M. T. Hoque, M. M. Ferdaus, M. Abdelguerfi, K. Niles, *et al.*, 2023 Dual attention u-net with feature infusion: Pushing the boundaries of multiclass defect segmentation. Unpublished .

Ansari, M. Y., Y. Yang, S. Balakrishnan, J. Abinahed, A. Al-Ansari, *et al.*, 2022 A lightweight neural network with multiscale feature enhancement for liver ct segmentation. Scientific Reports **12**: 14153.

Ashburner, J. and K. J. Friston, 2005 Unified segmentation. NeuroImage **26**: 839–851.

Aslan, E., 2024 LSTM-ESA Hibrit Modeli ile MR Goruntulerinden Beyin Tumorunun Siniflandirilmasi. Adiyaman Universitesi Muhendislik Bilimleri Dergisi **11**: 63–81.

Aslan, E. and Y. Ozupak, 2025 Detection of road extraction from satellite images with deep learning method. Cluster Computing **28**: 72.

Bal, A., M. Banerjee, P. Sharma, and M. Maitra, 2019 An efficient wavelet and curvelet-based pet image denoising technique. Medical & Biological Engineering & Computing **57**: 2567–2598.

Bayram, B., I. Kunduracioglu, S. Ince, and I. Pacal, 2025 A systematic review of deep learning in mri-based cerebral vascular occlusion-based brain diseases. Neuroscience .

Burukanli, M. and N. Yumuşak, 2024 Tfradmcov: a robust transformer encoder based model with adam optimizer algorithm for covid-19 mutation prediction. Connection Science **36**: 2365334.

Çiçek, Ö., A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, 2016 3d u-net: Learning dense volumetric segmentation from sparse annotation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pp. 424–432.

Celik, M., A. S. Dokuz, A. Ecemis, and E. Erdogmus, 2025 Discovering and ranking urban social clusters out of streaming social media datasets. Concurrency and Computation: Practice and Experience **37**: e8314.

Chen, G., Z. Li, J. Wang, J. Wang, S. Du, *et al.*, 2023 An improved 3d kiu-net for segmentation of liver tumor. Computers in Biology and Medicine **160**: 107006.

Chen, J., Y. Lu, Q. Yu, X. Luo, E. Adeli, *et al.*, 2021 Transunet: Transformers make strong encoders for medical image segmentation. Unpublished .

Chen, L., P. Bentley, and D. Rueckert, 2017 Fully automatic acute ischemic lesion segmentation in dwi using convolutional neural networks. NeuroImage: Clinical **15**: 633–643.

Clèrigues, A., S. Valverde, J. Bernal, J. Freixenet, A. Oliver, *et al.*, 2020 Acute and sub-acute stroke lesion segmentation from multimodal mri. Computer Methods and Programs in Biomedicine **194**: 105521.

Dice, L., 1945 Measures of the amount of ecologic homeostasis. Science **113**: 297–302.

Ding, Y., W. Zheng, J. Geng, Z. Qin, K.-K. R. Choo, *et al.*, 2022 Mvfusfra: A multi-view dynamic fusion framework for multimodal brain tumor segmentation. IEEE Journal of Biomedical and Health Informatics **26**: 1570–1581.

Dosovitskiy, A., L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, *et al.*, 2020 An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929 .

Edlow, B. L., S. Hurwitz, and J. A. Edlow, 2017 Diagnosis of dwi-negative acute ischemic stroke. Neurology **89**: 256–262.

Everingham, M. and et al., 2010 The pascal visual object classes (voc) challenge. International Journal of Computer Vision **88**: 303–338.

Goel, A., A. K. Goel, and A. Kumar, 2023 The role of artificial neural network and machine learning in utilizing spatial information. Spatial Information Research **31**: 275–285.

Hernandez Petzsche, M. R., E. de la Rosa, U. Hanning, R. Wiest, W. Valenzuela, *et al.*, 2022 Isles 2022: A multi-center magnetic resonance imaging stroke lesion segmentation dataset. Scientific Data **9**: 762.

Hossain, M. S., J. M. Betts, and A. P. Paplinski, 2021 Dual focal loss to address class imbalance in semantic segmentation. Neurocomputing **462**: 69–87.

Huang, B., G. Tan, H. Dou, Z. Cui, Y. Song, *et al.*, 2022 Mutual gain adaptive network for segmenting brain stroke lesions. Applied Soft Computing **129**: 109568.

Jauch, E. C., J. L. Saver, H. P. Adams, A. Bruno, J. J. B. Connors, *et al.*, 2013 Guidelines for the early management of patients with acute ischemic stroke. Stroke **44**: 870–947.

Johnson, L., R. Newman-Norlund, A. Teghipco, C. Rorden, L. Bonilha, *et al.*, 2024 Progressive lesion necrosis is related to increasing aphasia severity in chronic stroke. NeuroImage: Clinical **41**: 103566.

Kamnitsas, K., C. Ledig, V. F. J. Newcombe, J. P. Simpson, A. D. Kane, *et al.*, 2017 Efficient multi-scale 3d cnn with fully connected crf for accurate brain lesion segmentation. Medical Image Analysis **36**: 61–78.

Karani, N., E. Erdil, K. Chaitanya, and E. Konukoglu, 2021 Test-time adaptable neural networks for robust medical image segmentation. Medical Image Analysis **68**: 101907.

Kench, S. and S. J. Cooper, 2021 Generating 3d structures from a 2d slice with gan-based dimensionality expansion. Nature Machine Intelligence .

Kilicarslan, S. and I. Pacal, 2023 Domates yapraklarıında hastalık tespiti için transfer ogrenme metotlarınn kullanılması. Mühendislik Bilimleri ve Araştırmaları Dergisi **5**: 215–222.

Kim, Y.-C., J.-E. Lee, I. Yu, H.-N. Song, I.-Y. Baek, *et al.*, 2019 Evaluation of diffusion lesion volume measurements in acute ischemic stroke using encoder-decoder convolutional network. Stroke **50**: 1444–1451.

Kumar, A., P. Chauda, and A. Devrari, 2021 Machine learning approach for brain tumor detection and segmentation. International Journal of Organizational and Collective Intelligence **11**: 68–84.

Kunduracioglu, I., 2024a Cnn models approaches for robust classification of apple diseases. Computer and Decision Making: An International Journal **1**: 235–251.

Kunduracioglu, I., 2024b Utilizing resnet architectures for identification of tomato diseases. Journal of Intelligent Decision Making and Information Science **1**: 104–119.

Kunduracioglu, I. and I. Pacal, 2024 Advancements in deep learning for accurate classification of grape leaves and diagnosis of grape diseases. Journal of Plant Diseases and Protection .

Lee, K.-Y., C.-C. Liu, D. Y.-T. Chen, C.-L. Weng, H.-W. Chiu, *et al.*, 2023 Automatic detection and vascular territory classification of hyperacute staged ischemic stroke on diffusion weighted image using convolutional neural networks. Scientific Reports **13**: 404.

Li, T., X. An, Y. Di, C. Gui, Y. Yan, *et al.*, 2024 Srsnet: Accurate segmentation of stroke lesions by a two-stage segmentation framework with asymmetry information. Expert Systems with Applications **254**: 124329.

Li, Z., D. Li, C. Xu, W. Wang, Q. Hong, *et al.*, 2022 Tfcns: A cnn-transformer hybrid network for medical image segmentation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pp. 781–792.

Liu, Y., W. Cui, Q. Ha, X. Xiong, X. Zeng, *et al.*, 2021 Knowledge transfer between brain lesion segmentation tasks with increased model capacity. Computerized Medical Imaging and Graphics **88**: 101842.

Maier, O., B. H. Menze, J. von der Gablentz, L. Häni, M. P. Heinrich, *et al.*, 2017 Isles 2015 - a public evaluation benchmark for ischemic stroke lesion segmentation from multispectral mri. Medical Image Analysis **35**: 250–269.

Moon, H. S., L. Heffron, A. Mahzarnia, B. Obeng-Gyasi, M. Holbrook, *et al.*, 2022 Automated multimodal segmentation of acute ischemic stroke lesions on clinical mr images. Magnetic Resonance Imaging **92**: 45–57.

Nielsen, A., M. B. Hansen, A. Tietze, and K. Mouridsen, 2018 Prediction of tissue outcome and assessment of treatment effect in acute ischemic stroke using deep learning. Stroke **49**: 1394–1401.

Oktay, O., J. Schlemper, L. L. Folgoc, M. Lee, M. Heinrich, *et al.*, 2018 Attention u-net: Learning where to look for the pancreas. Medical Image Analysis **53**: 197–207.

Ozdemir, B. and I. Pacal, 2025 An innovative deep learning framework for skin cancer detection employing convnextv2 and focal self-attention mechanisms. Results in Engineering **25**: 103692.

Pacal, I., 2025 Investigating deep learning approaches for cervical cancer diagnosis: a focus on modern image-based models. European Journal of Gynaecological Oncology **46**: 125–141.

Pacal, I., I. Kunduracioglu, M. H. Alma, M. Deveci, S. Kadry, *et al.*, 2024 A systematic review of deep learning techniques for plant diseases. Artificial Intelligence Review **57**: 304.

Paçal, I. and I. Kunduracıoğlu, 2024 Data-efficient vision transformer models for robust classification of sugarcane. Journal of Soft Computing and Decision Analytics **2**: 258–271.

Ronneberger, O., P. Fischer, and T. Brox, 2015 U-net: Convolutional networks for biomedical image segmentation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pp. 234–241.

Roth, G. A., D. Abate, K. H. Abate, S. M. Abay, C. Abbafati, *et al.*, 2018 Global, regional, and national age-sex-specific mortality for 282 causes of death in 195 countries and territories, 1980-2017: a systematic analysis for the global burden of disease study 2017. The Lancet **392**: 1736–1788.

Sacco, R. L., S. E. Kasner, J. P. Broderick, L. R. Caplan, J. J. B. Connors, *et al.*, 2013 An updated definition of stroke for the 21st century. Stroke **44**: 2064–2089.

Salvi, M., U. R. Acharya, F. Molinari, and K. M. Meiburger, 2021 The impact of pre- and post-image processing techniques on deep learning frameworks: A comprehensive review for digital pathology image analysis. Computers in Biology and Medicine **128**: 104129.

Sarvamangala, D. R. and R. V. Kulkarni, 2022 Convolutional neural networks in medical image understanding: a survey. Evolutionary Intelligence **15**: 1–22.

Saver, J. L., 2006 Time is brainâĂŤquantified. Stroke **37**: 263–266.

Schlemper, J., O. Oktay, M. Schaap, M. Heinrich, B. Kainz, *et al.*, 2019 Attention gated networks: Learning to leverage salient regions in medical images. Medical Image Analysis **53**: 197–207.

The GBD, . L. R. O. S. C., 2018 Global, regional, and country-specific lifetime risks of stroke, 1990 and 2016. New England Journal of Medicine **379**: 2429–2437.

Tomita, N., S. Jiang, M. E. Maeder, and S. Hassanpour, 2020 Automatic post-stroke lesion segmentation on mr images using 3d residual convolutional neural network. NeuroImage: Clinical **27**: 102276.

Tursynova, A. and B. Omarov, 2021 3d u-net for brain stroke lesion segmentation on isles 2018 dataset. In *2021 16th International Conference on Electronics Computer and Computation (ICECCO)*, pp. 1–4.

van Rijsbergen, C. J., 1979 *Information Retrieval*. Butterworth.

Verclytte, S., R. Gnanih, S. Verdun, T. Feiweier, B. Clifford, *et al.*, 2023 Ultrafast mri using deep learning echoplanar imaging for a comprehensive assessment of acute ischemic stroke. European Radiology **33**: 3715–3725.

Wang, G., T. Song, Q. Dong, M. Cui, N. Huang, *et al.*, 2020 Automatic ischemic stroke lesion segmentation from computed tomography perfusion images by image synthesis and attention-based deep neural networks. Medical Image Analysis **65**: 101787.

Wang, Z., B. Wang, C. Zhang, and Y. Liu, 2023 Defense against adversarial patch attacks for aerial image semantic segmentation by robust feature extraction. Remote Sensing **15**: 1690.

Wong, K. K., J. S. Cummock, G. Li, R. Ghosh, P. Xu, *et al.*, 2022 Automatic segmentation in acute ischemic stroke: Prognostic significance of topological stroke volumes on stroke outcome. Stroke **53**: 2896–2905.

Woo, S., J. Park, J.-Y. Lee, and I. S. Kweon, 2018 Cbam: Convolutional block attention module. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 3–19.

Wu, Z., X. Zhang, F. Li, S. Wang, L. Huang, *et al.*, 2023 W-net: A boundary-enhanced segmentation network for stroke lesions. Expert Systems with Applications **230**: 120637.

Wu, Z., X. Zhang, F. Li, S. Wang, and J. Li, 2024 A feature-enhanced network for stroke lesion segmentation from brain mri images. Computers in Biology and Medicine **174**: 108326.

Xiao, X., S. Lian, Z. Luo, and S. Li, 2018 Weighted res-unet for high-quality retina vessel segmentation. In *2018 9th International Conference on Information Technology in Medicine and Education (ITME)*, pp. 327–331.

Xie, Y., J. Zhang, C. Shen, and Y. Xia, 2021 Cotr: Efficiently bridging cnn and transformer for 3d medical image segmentation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pp. 171–180.

Yalçın, S. and H. Vural, 2022 Brain stroke classification and segmentation using encoder-decoder based deep convolutional neural networks. Computers in Biology and Medicine **149**: 105941.

Yang, H., W. Huang, K. Qi, C. Li, X. Liu, *et al.*, 2019 Clci-net: Cross-level fusion and context inference networks for lesion segmentation of chronic stroke. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pp. 266–274.

Yuan, F., Z. Zhang, and Z. Fang, 2023 An effective cnn and transformer complementary network for medical image segmentation. Pattern Recognition **136**: 109228.

Zhang, L., R. Song, Y. Wang, C. Zhu, J. Liu, *et al.*, 2020 Ischemic stroke lesion segmentation using multi-plane information fusion. IEEE Access **8**: 45715–45725.

Zhang, Y. Q., A. F. Liu, F. Y. Man, Y. Y. Zhang, C. Li, *et al.*, 2022 Mri radiomic features-based machine learning approach to classify ischemic stroke onset time. Journal of Neurology pp. 1–11.

Zhao, B., S. Ding, H. Wu, G. Liu, C. Cao, *et al.*, 2019 Automatic acute ischemic stroke lesion segmentation using semi-supervised learning. Neurocomputing .

Zhou, Z., M. M. Rahman Siddiquee, N. Tajbakhsh, and J. Liang, 2018 Unet++: A nested u-net architecture for medical image segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 3–11.

Zhou, Z., M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, 2020 Unet++: Redesigning skip connections to exploit multiscale features in image segmentation. IEEE Transactions on Medical Imaging **39**: 1856–1867.

Zhuang, X. and J. Shen, 2016 Multi-scale patch and multi-modality atlases for whole heart segmentation of mri. Medical Image Analysis **31**: 77–87.

How to cite this article: Ince, S., Kunduracioglu, I., Pacal, I., and Bayram, B. U-Net-Based Models for Precise Brain Stroke Segmentation. *Chaos Theory and Applications*, 7(1), 50-60, 2025.