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Research Article

Deep Learning-Based Ischemic Stroke Segmentation on Brain Computed Tomography Images

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Abstract

Stroke is brain cell death because of either lack of blood flow (ischemic) or bleeding (hemorrhagic) that prevents the brain from functioning properly in both conditions. Ischemic stroke is a common type of stroke caused by a blockage in the cerebrovascular system that prevents blood from flowing to brain regions and directly blocks blood vessels. Computed tomography (CT) scanning is frequently used in the evaluation of stroke, and rapid and accurate diagnosis of ischemic stroke with CT images is critical for determining the appropriate treatment. The manual diagnosis of ischemic stroke can be error-prone due to several factors, such as the busy schedules of specialists and the large number of patients admitted to healthcare facilities. Therefore, in this paper, a deep learning-based interface was developed to automatically diagnose the ischemic stroke through segmentation on CT images leading to a reduction on the diagnosis time and workload of specialists. Convolutional Neural Networks (CNNs) allow automatic feature extraction in ischemic stroke segmentation, utilized to mark the disease regions from CT images. CNN-based architectures, such as U-Net, U-Net VGG16, U-Net VGG19, Attention U-Net, and ResU-Net, were used to benchmark the ischemic stroke disease segmentation. To further improve the segmentation performance, ResU-Net was modified, adding a dilation convolution layer after the last layer of the architecture. In addition, data augmentation was performed to increase the number of images in the dataset, including the ground truths for the ischemic stroke disease region. Based on the experimental results, our modified ResU-Net with a dilation convolution provides the highest performance for ischemic stroke segmentation in dice similarity coefficient (DSC) and intersection over union (IoU) with 98.45 % and 96.95 %, respectively. The experimental results show that our modified ResU-Net outperforms the state-of-the-art approaches for ischemic stroke disease segmentation. Moreover, the modified architecture has been deployed into a new desktop application called *BrainSeg*, which can support specialists during the diagnosis of the disease by segmenting ischemic stroke.

Keywords: Artificial Intelligence, Deep Learning, Ischemic Stroke Disease, Convolutional Neural Network.

Beyin Bilgisayarlı Tomografi Görüntülerinde Derin Öğrenme Tabanlı İskemik İnme Hastalığı Segmentasyonu

Öz

İnme, beyindeki işlevlerin doğru şekilde yerine getirilmesini engelleyen ve kan akışı eksikliği (iskemik) ya da kanama (hemorajik) gibi nedenlerle ortaya çıkan beyin hücre ölümüdür. İskemik inme, kan akışının beyin bölgelerine akmasını önleyen serebrovasküler sistemdeki bir tıkanıklık nedeniyle ortaya çıkan yaygın bir inme türüdür. İnme değerlendirmesinde sıklıkla Bilgisayarlı Tomografi (BT) taraması kullanılmaktadır ve BT görüntüleriyle iskemik inmenin hızlı ve doğru teşhisi, uygun tedavinin belirlenmesi için kritik öneme sahiptir. Uzmanların yoğun programları ve sağlık tesislerine başvuran çok sayıda hastanın olması gibi çeşitli faktörler nedeniyle iskemik inmenin manuel teşhisi hataya açık olabilmektedir. Bu nedenle, bu makalede, BT görüntüleri üzerinden segmentasyon yoluyla iskemik

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inmeyi otomatik olarak teşhis etmek için derin öğrenme tabanlı bir arayüz geliştirilmiş; bu sayede uzmanların teşhis süresi ve iş yükünün azaltılması hedeflenmiştir. Iskemik inme segmentasyonunda otomatik özellik çıkarımını sağlayan Evrişimli Sinir Ağları (CNN'ler), BT görüntülerindeki hastalıklı bölgeleri işaretlemek için kullanılmıştır. U-Net, U-Net VGG16, U-Net VGG19, Attention U-Net ve ResU-Net gibi CNN tabanlı mimariler, iskemik inme hastalığı segmentasyonunu karşılaştırmak için kullanılmıştır. ResU-Net, segmentasyon performansını daha da artırmak için mimarinin son katmanından sonra bir genişletme evrişim katmanı eklenerek modifiye edilmiştir. Ek olarak, iskemik inme hastalığı bölgesi için gerçek referans değerleri de içeren veri setindeki görüntü sayısını artırmak için veri artırma işlemi gerçekleştirilmiştir. Deneysel sonuçlara dayanarak, genişletme evrişimli olarak modifiye edilmiş ResU-Net, zar benzerlik katsayısı (DSC) ve Jaccard benzerlik katsayısı (IoU) açısından sırasıyla 98.45 % ve 96.95 % ile en yüksek performansı sağlamıştır. Deneysel sonuçlar, modifiye edilmiş ResU-Net mimarisinin iskemik inme hastalığı segmentasyonu için modern yaklaşımlardan daha iyi performans sergilediğini göstermektedir. Ayrıca modifiye edilmiş mimari, iskemik inme bölgesini segmente ederek hastalığın teşhisinde uzmanlara destek sağlayabilen yeni bir masaüstü uygulaması olan *BrainSeg*'e entegre edilmiştir.

Anahtar Kelimeler: Yapay Zekâ, Derin Öğrenme, İskemik İnme Hastalığı, Evrişimsel Sinir Ağı.

1. Introduction

Brain disorders affect the daily routine of the individual and appear as severe physical symptoms, including motor function impairments, memory loss, tremors, seizures, vision problems, speech difficulties, and changes in behavior. Brain disorders are caused by a wide range of diseases that gradually disable brain abilities, such as Alzheimer, Parkinson, dementia, brain cancer, stroke, transient ischemic attack, and epilepsy. Among these diseases, stroke, a major abnormality of the brain, is the leading cause of severe long-term disability worldwide. The World Health Organization reports that stroke is responsible for about 11 % of human diseases and is the second leading cause of death worldwide (Khezrpour, Seyedarabi, Razavi, & Farhoudi, 2022). Typically, there are two types of stroke: hemorrhagic and ischemic stroke. A hemorrhagic stroke is caused by a ruptured cerebral blood vessel that bleeds into or around the brain, while an ischemic stroke occurs predominantly due to a lack of blood flow in parts of the brain (Kirshner & Schrag, 2021). Of these two types, ischemic stroke accounts for about 85 % of all strokes, so diagnosing ischemic stroke is vital for the recovery of patients. Several approaches are available to diagnose ischemic stroke, including a cerebral angiogram, echocardiogram, carotid ultrasound, and medical imaging (Karthik, Menaka, Johnson, & Anand, 2020). Among these approaches, medical imaging methods such as computed tomography (CT), X-rays, and magnetic resonance imaging (MRI) have become functional since they visualize the brain, making it easier to diagnose the disease. X-rays produce low-quality imaging, while CT and MRI provide less noisy images for diagnosing ischemic stroke disease. CT is less time-consuming and cost-effective during imaging, making it the primary medical imaging technique. Therefore, CT is widely used in medical centers as it greatly improves the imaging resolution and diagnosis speed of ischemic stroke disease. However, the quality of diagnosis also depends on the expertise of the specialists, causing an increased likelihood of misdiagnosis when manually detecting ischemic stroke disease on CT images due to factors such as lack of awareness or overwork. Besides detecting the presence of ischemic stroke disease, the specific region affected on a CT image is crucial in the diagnostic process. An automated system that can accurately diagnose the disease region can help specialists and ease their workload. Therefore, artificial intelligence-based approaches such as machine learning and deep learning have been proposed to detect ischemic stroke disease (Tursynova, Omarov, Sakhipov, & Tukenova, 2022). Machine learning approaches can perform a task utilizing manually extracted features with small-scale datasets (Doğan, Isık, Kılıç, & Horzum, 2022; Doğan, Yüzer, Kılıç, & Şen, 2021; Gölcez, Kilic, & Şen, 2021; V. Kilic & Şen, 2019). In contrast, deep learning approaches have advanced structures that perform automatic feature extraction in various complex tasks, including segmentation and classification (Castiglioni et al., 2021; Volkan Kılıç, Mercan, Tetik, Kap, & Horzum, 2022). The automatic extraction of features with deep learning approaches leads to a strong learning ability that improves the prediction performance on the test set. Therefore, deep learning approaches have gained popularity in segmenting ischemic stroke disease regions on CT images. For feature extraction, deep learning uses network architectures, such as convolutional neural networks (CNNs) (Ağralı et al.; Akosman, Öktem, Moral, & Kılıç, 2021; Çaylı, Kılıç, Onan, & Wang, 2022; Doğan & Kılıç, 2021; Keskin, Moral, Kılıç, & Onan, 2021; B. Kilic, Dogan, Kilic, & Kahyaoglu, 2022; Mercan & Kılıç, 2020; Sayraci, Agrali, & Kilic, 2023; Şen et al., 2022; Yüzer, Doğan, Kılıç, & Şen, 2022), reinforcement learning (Agrali, Soydemir, Gökçen, & Sahin, 2021), and recurrent neural networks (RNNs) (Aydın, Çaylı, Kılıç, & Onan, 2022; Fetiler, Caylı, Moral, Kılıc, & Onan, 2021; Gölcez, Kiliç, & Şen, 2019; Keskin, Çaylı, Moral, Kılıc, & Onan, 2021; Kılıc, 2021; Volkan Kılıç; Kökten & Kılıç, 2021; Mercan, Doğan, & Kılıç, 2020; Mercan & Kılıç, 2021; Palaz, Doğan, & Kılıç, 2021). Among these architectures, CNN offers remarkable performance on ischemic stroke disease segmentation.

Various CNN approaches have been proposed for ischemic stroke segmentation. Hui *et al.* proposed a partitioning-stacking prediction fusion (PSPF) method based on an improved Attention U-Net (Hui, Zhang, Li, Mei, & Guo, 2020). Liu *et al.* introduced a deep residual attention network (DRANet) that embeds residual blocks into U-Net architecture to segment ischemic stroke disease and white matter hyperintensity lesions in multi-modal MRIs (Liu, Kurgan, Wu, & Wang, 2020). Kumar *et al.* employed a classifier-segmenter network (CSNet), including a classifier followed by a segmentation network, which takes advantage of Fractal-Net and U-Net for ischemic stroke disease (Kumar, 2020). Wu *et al.* utilized an architecture based on a fully-convolutional network (FCN) with 3D convolution for automatically segmenting subcortical structures in different neural formations within the brain (Wu & Tang, 2019). Rajinikanth \etal proposed an approach using the cuckoo search algorithm, Tsallis entropy-monitored multilevel thresholding, and regularized level set technique, to improve segmentation performance (Rajinikanth, Fernandes, Bhushan, & Sunder, 2018). The

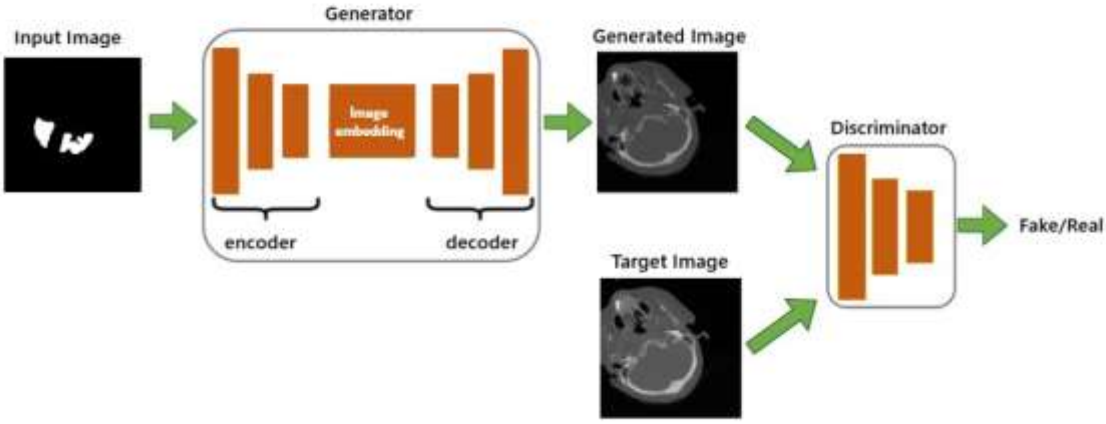
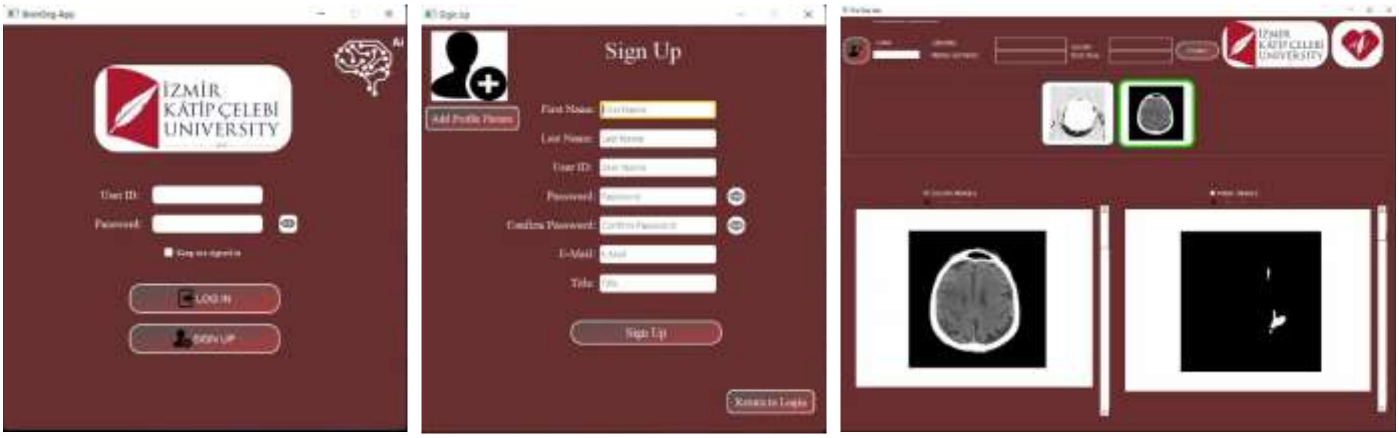


Figure 1: The schematic of Pix2Pix Generative Adversarial Network (GAN) architecture.



(a) (b) (c)

Figure 2: The login screen of the BrainSeg desktop application is shown in (a), and the sign-up screen is illustrated in (b). On the left side of the main screen in (c), brain CT images are displayed, and the predicted mask belonging to ischemic stroke disease is on the right.

partition process utilizes the 3D context that can effectively improve the generalization ability of their proposed method on unseen images for ischemic stroke segmentation**.** The approaches in (Kumar, 2020; Liu et al., 2020) employed relatively small-scale datasets to segment ischemic stroke disease, leading to the poor generalization ability of their models. Moreover, the model in (Hui et al., 2020) is computationally expensive, which causes the stroke lesion segmentation task to be time-consuming. On the other hand, the use of atlas-based segmentation for ischemic stroke in (Wu & Tang, 2019) resulted in being time-consuming and error-prone due to the image registration step.

In this study, the publicly available dataset (Koç et al., 2022) has been utilized for ischemic stroke disease segmentation. However, the dataset, including the brain CT images and the corresponding masks on which the disease region is marked, is relatively small for training CNN architectures. Therefore, several data augmentation approaches, such as Pix2Pix Generative Adversarial Network (GAN), varying brightness, applying Gaussian and blur filters, and adding salt & pepper and Gauss noise, were used to increase the number of images in the dataset. These augmentation approaches reduce the overfitting problem in small-scale datasets and increase the diversity of images, improving the generalization ability of CNN architectures. After dataset augmentation, several CNN architectures were trained, including ResU-Net modified with a dilation convolution to improve the segmentation performance of ischemic stroke disease. Finally, our approach has been integrated into the *BrainSeg* desktop application, which facilitates diagnosis based on the segmentation of the ischemic stroke in brain CT images.

2. Methods

CNN architectures can automatically extract the image features through various layers, such as convolution, pooling, and fully connected. The shallow layers of CNN architectures can capture simple features, while the deep layers process them to learn complex components of the image. Common CNN architectures, including U-Net, ResU-Net, U-Net (VGG-16), U-Net (VGG-19), ResU-Net with a dilation convolution, and Attention U-Net, have been employed for ischemic stroke disease segmentation. CNN-based Pix2Pix GAN architecture was also used to increase the number of images in the dataset.

2.1. Pix2Pix GAN

Pix2Pix GAN, which creates new synthetic data from source images, is a robust architecture for image-to-image translation (Aljohani & Alharbe, 2022). It is particularly useful for data augmentation to increase dataset size and improve segmentation performance. The architecture summarized in *Figure 1* is based on CNN, which consists of generator and discriminator networks. The generator network uses a ground truth including the region of interest as input to generate new realistic images, and typically uses an encoder-decoder structure known as the U-Net architecture, described in the next section. The discriminator produces a single output representing the probability that the generated image is real, and distinguishes between the image generated by the generator network and the real brain image as the target. The output of the discriminator network helps the generator to produce a synthetic image that is very similar to a real image with high probability and classified as fake with low probability.

2.2. U-Net

CNN-based U-Net has a symmetrical structure consisting of an encoder and decoder, leading to a robust architecture for pixel-wise image segmentation even with small-scale dataset (Ronneberger, Fischer, & Brox, 2015). The encoder includes blocks with 3x3 convolutional layers to extract the feature maps of the images at different spatial resolution levels. Each convolution layer follows a rectified linear unit (ReLU) activation function for non-linearity. At the last of each convolution block, a 2x2 max-pooling layer is applied for down-sampling the feature maps. The decoder is responsible for restoring the spatial resolution of the image through up-sampling, 2x2 convolution, and concatenation layers using the corresponding feature maps provide the spatial information. The fact that U-Net combines an encoder and decoder offers a highly-refined segmentation that can capture the spatial information in the input image. Therefore, CNN-based architectures such as VGG-16 and VGG-19 can be used as backbones added to the input of the encoder in U-Net.

2.2.1. VGG-16 as backbone:

VGG-16 consists of five blocks, including 13 convolutional layers with a 3x3 filter (Simonyan & Zisserman, 2014). A ReLu activation function maintains non-linearity at each convolution to guarantee the architecture does not act like a single layer. A 2x2 max-pooling layer is used at the last of each block to reduce the spatial resolution of hidden layers and increase the number of filters. Each convolution in the blocks is equipped with 64, 128, 256, 512, and 512 filters, respectively. The fully connected layers of VGG-16 are removed to take advantage of as a backbone in the segmentation task since they are originally added for classification tasks. Thus, the blocks in VGG-16 can capture low-level segmentation features for segmentation.

2.2.2. VGG-19 as backbone:

VGG-19 architecture has five blocks containing 16 convolutions with a 3x3 filter size to capture small information in the input image (Das, Bhat, & Gogate, 2021). A ReLu activation function is used after each convolution layer, while each block follows a max-pooling. The three fully connected layers are located after the blocks are removed to perform the segmentation

2.3. Attention U-Net

The architecture comprises a traditional U-Net and attention mechanism to dynamically focus on relevant regions of the input image during the segmentation process (Oktay et al., 2018). The attention U-Net consists of a symmetric encoder-decoder structure with skip connections. The encoder part uses multiple convolutional blocks to reduce the spatial dimensions and increase the number of filters, capturing the hierarchical features of the input image. Each convolution layer contains two convolutions, batch normalization, and maximum pooling, with LeakyReLu as activation. Batch normalization is employed to normalize the activation of convolution layers for improving segmentation performance. In the decoder part, the feature maps are up-sampled to their original dimensions through transposed convolutions. The attention mechanism is incorporated into the decoder, using self-attention blocks that adaptively assign weights to the feature maps from the encoder. These weights selectively concatenate the feature maps from the encoder and decoder for pixel-wise prediction.

2.4. ResU-Net

The CNN-based ResU-Net architecture combines the strengths of U-Net, and residual connections (Zhang, Liu, & Wang, 2018). U-Net is known for its satisfactory segmentation performance by extracting features in medical images, while residual connections address the issue of gradient vanishing or exploding gradients, which badly affects the predictive performance in deep layers. In order to improve the flow of gradients and reduce vanishing or exploding gradients, the residual connection aggregates the information from previous layers to the current layer. The ResU-Net architecture consists of an encoder, a bridge, and a decoder where the encoder extracts high-level features from the input images at different spatial resolutions through several convolutional and max-pooling layers. The bridge is located in the middle of the architecture to maintain the connection between the encoder and decoder. The decoder employs convolutions, upsampling, and concatenation layers, which combine the output of convolutions and corresponding features from the encoder to reconstruct the feature maps to the original resolution. The final layer of the decoder is a 1x1 convolution and sigmoid activation to produce a semantic segmentation output.

On the other hand, a dilation convolution has been added to the ResU-Net to improve segmentation performance. Dilation convolution utilizes a dilation rate parameter, which controls the spacing between the values in the kernel. The dilation convolution expands the receptive field in each kernel without increasing the parameters, thereby allowing for larger contextual feature extraction from the feature maps. Dilation convolution is particularly useful in tasks such as semantic segmentation and object detection, where preserving the spatial context of features is essential. Therefore, convolution with a dilation rate of 10 has been used at the last layer of ResU-Net to capture large contextual features of the feature maps.

2.5. Desktop Application: ***BrainSeg***

In this study, a user-friendly desktop application called *BrainSeg* was developed using ResU-Net with a dilation convolution to help specialists detect ischemic stroke disease, as shown in *Figure 2*. *BrainSeg* has a sign-up screen to register a user, while a login screen presents a confident way to the specialists using the application. The screens ensure that the application is logged in with a username and password specified only for specialists. Brain CT images of patients with suspected ischemic stroke disease can be uploaded to the application through the patient selection button on the main screen. It is divided to left and right to locate the images captured from different angles of the brain so that all CT images can be examined via the slider. The segmentation process can be started via the predict button on the main screen after uploading the images. After the process is completed, the ischemic stroke disease mask produced by ResU-Net with a dilation convolution is displayed on the right side of the main screen. Besides, specialists can simultaneously examine the images and corresponding masks in detail through the zoom key. Thus, *BrainSeg* for the segmentation of ischemic stroke makes it easier to detect the disease and can reduce the burden of specialists.

Table 1: The number and percent of the images in the train, validation, and test sets.

Dataset	Train	Validation	Test
Number	3601	1127	900
Percent	64	16	20

3. Experimental Evaluations

The section describes the dataset, the evaluation metrics, and the performance of CNN architectures for ischemic stroke segmentation.

3.1. Dataset

In deep learning, the dataset is essential to make the model robust for previously unseen images. The publicly available dataset (Koç et al., 2022), including 1,130 brain CT images with ischemic stroke in digital imaging and communications in medicine (DICOM) format, was employed to perform segmentation for the disease diagnosis. Data augmentation, which creates modified versions of existing data samples, was performed on the dataset with limited training images to improve the robustness and generalization ability of CNN architectures. The number of images in the dataset was doubled using the Pix2Pix GAN architecture for data augmentation. In addition to this approach, basic image processing approaches, such as varying brightness, applying Gaussian and blur filters, and adding salt & pepper and Gauss noise, were applied to the dataset. After the augmentation, the dataset was enlarged to 5,628 images for the training of CNN architectures. The images in the augmented dataset have been resized from a resolution of 512x512 to 256x256 after cropping them without disturbing the brain region. Next, the images were normalized using the min-max scaler (Abdulkareem et al., 2021). Finally, the dataset has been divided into the train, validation, and test sets for ischemic stroke segmentation, as presented in *Table 1*.

3.2. Evaluation Metrics

Metrics are quantitative measures used to evaluate the performance of CNN architectures through the output image and corresponding ground truth. IoU and DSC are common evaluation metrics to interpret segmentation performance. The DSC, which denotes the similarity between the output image and ground truth, is mathematically explained as follows:

$$DSC = \frac{2 \times TP}{2 \times TP + FN + FP} \quad (1)$$

where true positive (TP) indicates the overlap between the output image and the ground truth, while false positive (FP) represents regions included in the output image but not in the ground truth. True negative (TN) denotes the regions outside the union of the output image and ground truth. False negative (FN) stands for the regions included within the ground truth but not in the output image. The overlap ratio between the output image and ground truth is quantified by the IoU metric, which is calculated by

$$IoU = \frac{TP}{TP + FN + FP} \tag{2}$$

The DSC and IoU metrics provide values in the range of zero to one, with a larger value indicating greater similarity in the segmented region.

4. Results and Discussion

The CNN-based architectures, including U-Net, ResU-Net, U-Net (backbone VGG-16), U-Net (backbone VGG-19), and ResU-Net with a dilation convolution and attention U-Net, were trained and tested on the dataset as mentioned in the method section. The experiments for the CNN architectures were performed in a Python environment using TensorFlow with the parameters Adam optimizer, learning rate=0.0005, he-normal kernel initializer, batch size=32, and the sum of dice and focal losses as the loss function (Dina, Siddique, & Manivannan, 2023). The CNN architectures showed higher performance with these parameters based on the experiments. In addition, batch normalization was used instead of dropout in the CNN architectures to further improve the robustness of the model.

The results of the CNN architectures for the ischemic stroke disease segmentation with respect to DSC and IoU are listed in *Table 2*. Based on the evaluation results, ResU-Net with dilation convolution outperforms other architectures in terms of DSC and IoU scores, achieving 98.45 % and 96.45 %, respectively. The superior performance of ResU-Net with a dilation convolution can be attributed to its use of dilation convolution, which allows the extraction of larger contextual features from the images.

Table 2: The empirical results of the ischemic stroke disease segmentation.

Method	IoU (%)	DSC (%)
U-Net	86.16	92.41
U-Net (VGG-19)	88.44	93.80
ResU-Net	88.94	94.10
U-Net (VGG-16)	91.25	95.41
Attention U-Net	94.77	97.30
ResU-Net with a dilation convolution	**96.95**	**98.45**

Table 3: The comparison of our approach with the state-of-the-art architectures for ischemic stroke disease segmentation.

Method	IoU (%)	DSC (%)
PSPF (Hui et al., 2020)	-	75.40
DRANet (Liu et al., 2020)	-	76.39
CSNet (Kumar, 2020)	-	82.14
FCN (Wu & Tang, 2019)	-	91.86
Tsallis Entropy (Rajinikanth et al., 2018)	-	95.18
Our approach	**96.95**	**98.45**

The fact that Attention U-Net can automatically focus on ischemic stroke regions in brain images without additional supervision lead to showing the second-highest score. The U-Net with VGG-16 architecture achieved the third highest result due to its shallower depth compared to the U-Net (VGG-19). Next, U-Net (VGG-19) followed ResU-Net since the residual connections in ResU-Net deal with the problem of vanishing or exploding gradients observed in deep layers. Finally, U-Net shows the poorest results for ischemic stroke segmentation due to the gradient vanishing or exploding gradient problems.

In addition, the modified ResU-Net with a dilation convolution architecture was compared with the latest studies on the segmentation of ischemic stroke disease with respect to the DSC and IOU values in *Table 3*. The model in (Hui et al., 2020) is unsuitable for embedding in a desktop application that can assist specialists since the architecture requires more computation power, causing more time consumption. The fact that the approaches in (Kumar, 2020; Liu et al., 2020) use relatively small-scale datasets for ischemic stroke disease segmentation; causes the poor generalization ability of the model. The method in (Wu & Tang, 2019) is time-consuming and error-prone due to the image registration approach in the atlas-based ischemic stroke disease segmentation.

Our approach has also been embedded into the user-friendly *BrainSeg* desktop application, which can easily detect ischemic stroke after segmenting the disease region on brain CT images. Thus, specialists who segment the ischemic stroke disease with CT images on *BrainSeg* can pick whether the disease is present. Besides, the desktop application speeds up the diagnosis time of ischemic stroke disease and relieves the burden of specialists.

5. Conclusion

In this study, CNN architectures were compared using the evaluation metrics to segment ischemic stroke disease on brain images and deployed into a user-friendly desktop application called *BrainSeg*. A public dataset with labeled ischemic stroke masks was used to train CNN architectures, including U-Net, ResU-Net, U-Net VGG-16, U-Net VGG-19, Attention U-Net, and ResU-Net with dilation convolution. The modified ResU-Net with a dilation convolution achieved the highest segmentation performance with a 98.45 % DSC and a 96.95 % IoU score on the test set. Compared to the state-of-the-art methods, the experiments showed that the modified architecture had an advantage in detecting ischemic stroke disease. Thus, ResU-Net with a dilation convolution has been deployed into our *BrainSeg* application, which has great potential to assist specialists in diagnosing ischemic stroke disease on CT images.

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References

Abdulkareem, K. H., Mohammed, M. A., Salim, A., Arif, M., Geman, O., Gupta, D., & Khanna, A. (2021). Realizing an effective COVID-19 diagnosis system based on machine learning and IOT in smart hospital environment. *IEEE Internet of things journal, 8*(21), 15919-15928.

Agrali, M., Soydemir, M. U., Gökçen, A., & Sahin, S. (2021). Deep Reinforcement Learning Based Controller Design for Model of The Vertical Take off and Landing System. *Avrupa Bilim ve Teknoloji Dergisi*, 26, 358-363.

Ağralı, M., Kilic, V., Onan, A., Koç, E. M., Koç, A. M., Büyüktoka, R. E., . . . Adıbelli, Z. (2023). DeepChestNet: Artificial intelligence approach for COVID-19 detection on computed tomography images. International Journal of Imaging Systems and Technology, 1-13.

Akosman, Ş. A., Öktem, M., Moral, Ö. T., & Kılıç, V. (2021). *Deep Learning-based Semantic Segmentation for Crack Detection on Marbles.* Paper presented at the 2021 29th Signal Processing and Communications Applications Conference (SIU).

Aljohani, A., & Alharbe, N. (2022). Generating Synthetic Images for Healthcare with Novel Deep Pix2Pix GAN. *Electronics, 11*(21), 3470.

Aydın, S., Çaylı, Ö., Kılıç, V., & Onan, A. (2022). Sequence-to-sequence video captioning with residual connected gated recurrent units. *Avrupa Bilim ve Teknoloji Dergisi*, 35, 380-386.

Castiglioni, I., Rundo, L., Codari, M., Di Leo, G., Salvatore, C., Interlenghi, M., . . . Sardanelli, F. (2021). AI applications to medical images: From machine learning to deep learning. *Physica Medica, 83*, 9-24.

Çaylı, Ö., Kılıç, V., Onan, A., & Wang, W. (2022). *Auxiliary Classifier based Residual RNN for Image Captioning.* Paper presented at the 2022 30th European Signal Processing Conference (EUSIPCO).

Das, S., Bhat, A. P., & Gogate, P. R. (2021). Degradation of dyes using hydrodynamic cavitation: Process overview and cost estimation. *Journal of Water Process Engineering, 42*, 102126.

Dina, A. S., Siddique, A., & Manivannan, D. (2023). A deep learning approach for intrusion detection in Internet of Things using focal loss function. *Internet of Things*, 100699.

Doğan, V., Isık, T., Kılıç, V., & Horzum, N. (2022). A field-deployable water quality monitoring with machine learning-based smartphone colorimetry. *Analytical Methods, 14*(35), 3458-3466.

Doğan, V., & Kılıç, V. (2021). Akıllı Telefon Kullanarak Yapay Zeka Tabanlı Farenjit Tespiti: Artificial Intelligence Based Pharyngitis Detection Using Smartphone. *Sağlık Bilimlerinde Yapay Zeka Dergisi ISSN, 1*(2), 14-19.

Doğan, V., Yüzer, E., Kılıç, V., & Şen, M. (2021). Non-enzymatic colorimetric detection of hydrogen peroxide using a μPAD coupled with a machine learning-based smartphone app. *Analyst, 146*(23), 7336-7344.

Fetiler, B., Caylı, Ö., Moral, Ö. T., Kılıc, V., & Onan, A. (2021). Video captioning based on multi-layer gated recurrent unit for smartphones. *Avrupa Bilim ve Teknoloji Dergisi*, 32, 221-226.

Gölcez, T., Kilic, V., & Şen, M. (2021). A portable smartphone-based platform with an offline image-processing tool for the rapid paper-based colorimetric detection of glucose in artificial saliva. *Analytical Sciences, 37*(4), 561-567.

Gölcez, T., Kiliç, V., & Şen, M. (2019). *Integration of a Smartphone Application with a ¼PAD for Rapid Colorimetric Detection of Glucose.* Paper presented at the 2019 Medical Technologies Congress (TIPTEKNO).

Hui, H., Zhang, X., Li, F., Mei, X., & Guo, Y. (2020). A partitioning-stacking prediction fusion network based on an improved attention U-Net for stroke lesion segmentation. *IEEE Access, 8*, 47419-47432.

Karthik, R., Menaka, R., Johnson, A., & Anand, S. (2020). Neuroimaging and deep learning for brain stroke detection-A review of recent advancements and future prospects. *Computer Methods Programs in Biomedicine, 197*, 105728.

Keskin, R., Çaylı, Ö., Moral, Ö. T., Kılıc, V., & Onan, A. (2021). A benchmark for feature-injection architectures in image captioning. *Avrupa Bilim ve Teknoloji Dergisi*, 31, 461-468.

Keskin, R., Moral, Ö. T., Kılıç, V., & Onan, A. (2021). *Multi-gru based automated image captioning for smartphones.* Paper presented at the 2021 29th Signal Processing and Communications Applications Conference (SIU).

Khezrpour, S., Seyedarabi, H., Razavi, S. N., & Farhoudi, M. (2022). Automatic segmentation of the brain stroke lesions from MR flair scans using improved U-net framework. *Biomedical Signal Processing Control, 78*, 103978.

Kilic, B., Dogan, V., Kilic, V., & Kahyaoglu, L. N. (2022). Colorimetric food spoilage monitoring with carbon dot and UV light reinforced fish gelatin films using a smartphone application. *International Journal of Biological Macromolecules, 209*, 1562-1572.

Kilic, V., & Şen, M. (2019). *Smartphone-based Colorimetric Analysis for the Detection of H 2 O 2 Using a ¼PAD.* Paper presented at the 2019 Medical Technologies Congress (TIPTEKNO).

Kılıc, V. J. (2021). Deep gated recurrent unit for smartphone-based image captioning. *Sakarya University Journal of Computer Information Sciences, 4*(2), 181-191.

Kılıç, V. Yapay Zeka Tabanlı Akıllı Telefon Uygulaması ile Kan Şekeri Tahmini. *Avrupa Bilim ve Teknoloji Dergisi*, 26, 289-294.

Kılıç, V., Mercan, Ö. B., Tetik, M., Kap, Ö., & Horzum, N. (2022). Non-enzymatic colorimetric glucose detection based on Au/Ag nanoparticles using smartphone and machine learning. *Analytical Sciences, 38*(2), 347-358.

Kirshner, H., & Schrag, M. (2021). Management of intracerebral hemorrhage: update and future therapies. *Current Neurology Neuroscience Reports, 21*, 1-5.

Koç, U., Sezer, E. A., Özkaya, Y. A., Yarbay, Y., Taydaş, O., Ayyıldız, V. A., . . . Beşler, M. S. (2022). Artificial Intelligence in Healthcare Competition (Teknofest-2021): Stroke Data Set. *The Eurasian journal of medicine, 54*(3), 248.

Kökten, A., & Kılıç, V. (2021). Detection of COVID-19 Cases with Fuzzy Classifiers Using Chest Computed Tomography. *Avrupa Bilim ve Teknoloji Dergisi*, 26, 68-72.

Kumar, A., et al. (2020). CSNet: A new DeepNet framework for ischemic stroke lesion segmentation. *Computer Methods and Programs in Biomedicine, 193*.

Liu, L., Kurgan, L., Wu, F.-X., & Wang, J. J. (2020). Attention convolutional neural network for accurate segmentation and quantification of lesions in ischemic stroke disease. *Medical Image Analysis, 65*, 101791.

Mercan, Ö. B., Doğan, V., & Kılıç, V. (2020). *Time Series Analysis based Machine Learning Classification for Blood Sugar Levels.* Paper presented at the 2020 Medical Technologies Congress (TIPTEKNO).

Mercan, Ö. B., & Kılıç, V. (2020). *Deep Learning based Colorimetric Classification of Glucose with Au-Ag nanoparticles using Smartphone.* Paper presented at the 2020 Medical Technologies Congress (TIPTEKNO).

Mercan, Ö. B., & Kılıç, V. (2021). *Fuzzy classifier based colorimetric quantification using a smartphone.* Paper presented at the Intelligent and Fuzzy Techniques: Smart and Innovative Solutions: Proceedings of the INFUS 2020 Conference, Istanbul, Turkey, July 21-23, 2020.

Oktay, O., Schlemper, J., Folgoc, L. L., Lee, M., Heinrich, M., Misawa, K., . . . Kainz, B. J. (2018). Attention u-net: Learning where to look for the pancreas. *arXiv preprint arXiv*.

Palaz, Z., Doğan, V., & Kılıç, V. J. (2021). Smartphone-based Multi-parametric Glucose Prediction using Recurrent Neural Networks. *Avrupa Bilim ve Teknoloji Dergisi,* 32, 1168-1174.

Rajinikanth, V., Fernandes, S. L., Bhushan, B., & Sunder, N. R. (2018). Segmentation and analysis of brain tumor using Tsallis entropy and regularised level set. *In Proceedings of 2nd International Conference on Micro-Electronics, Electromagnetics and Telecommunications: ICMEET 2016, (pp. 313-321)*.

Ronneberger, O., Fischer, P., & Brox, T. (2015). *U-net: Convolutional networks for biomedical image segmentation.* Paper presented at the Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18.

Sayraci, B., Agrali, M., & Kilic, V. J. (2023). Artificial Intelligence Based Instance-Aware Semantic Lobe Segmentation on Chest Computed Tomography Images. *Avrupa Bilim ve Teknoloji Dergisi*, 46, 109-115.

Simonyan, K., & Zisserman, A. J. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:*.

Şen, M., Yüzer, E., Doğan, V., Avcı, İ., Ensarioğlu, K., Aykaç, A., . . . Kılıç, V. J. (2022). Colorimetric detection of H2O2 with Fe3O4@ Chi nanozyme modified µPADs using artificial intelligence. *Microchimica Acta, 189*(10), 373.

Tursynova, A., Omarov, B., Sakhipov, A., & Tukenova, N. J. (2022). Brain Stroke Lesion Segmentation Using Computed Tomography Images based on Modified U-Net Model with ResNet Blocks. *International Journal of Online Biomedical Engineering, 18*(13).

Wu, J., & Tang, X. (2019). Brain segmentation based on multi-atlas guided 3D fully convolutional network ensembles. *arXiv preprint arXiv, 1901.01381*.

Yüzer, E., Doğan, V., Kılıç, V., & Şen, M. J. (2022). Smartphone embedded deep learning approach for highly accurate and automated colorimetric lactate analysis in sweat. *Sensors Actuators B: Chemical, 371*, 132489.

Zhang, Z., Liu, Q., & Wang, Y. J. (2018). Road extraction by deep residual u-net. *IEEE Geoscience Remote Sensing Letters, 15*(5), 749-753.