Avrupa Bilim ve Teknoloji Dergisi
Sayı 41, S. 175-182, Kasım 2022

Araştırma Makalesi

www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
No. 41, pp. 175-182, November 2022

Research Article

Artificial Intelligence-based Cerebrovascular Disease Detection on Brain Computed Tomography Images

Ali Fatih Karataş[1*], Vakkas Doğan, Volkan Kılıç

[1] İzmir Katip Çelebi University, Faculty of Engineering and Architecture, Departmant of Electrical and Electronics, İzmir, Turkey, (ORCID: 0000-0003-1872-7550, 0000-0001-5934-4156, 0000-0002-3164-1981), alifatih449@gmail.com, vkksdgn2@gmail.com, volkan.kilic@ikcu.edu.tr

(First received 17 September 2022 and in final form 13 October 2022)

(**DOI:** 10.31590/ejosat.1176648)

ATIF/REFERENCE: Karataş, A. F., Doğan, V., & Kılıç, V., (2022). Artifical Intelligence-based Cerebrovascular Disease Detection on Brain Computed Tomography Images. *European Journal of Science and Technology*, (41), 175-182.

Abstract

Cerebrovascular disease (CVD) causes paralysis and even mortality in humans due to blockage or bleeding of brain vessels. The early diagnosis of the CVD type by the specialist can avoid these casualties with a correct course of treatment. However, it is not always possible to recruit enough specialists in hospitals or emergency services. Therefore, in this study, an artificial intelligence (AI)-based clinical decision support system for CVD detection from brain computed tomography (CT) images is proposed to improve the diagnostic results and relieve the burden of specialists. The deep learning model, a subset of AI, was implemented through a two-step process in which CVD is first detected and then classified as ischemic or hemorrhagic. Moreover, the developed system is integrated into our custom-designed desktop application that offers a user-friendly interface for CVD diagnosis. Experimental results prove that our system has great potential to improve early diagnosis and treatment for specialists, which contributes to the recovery rate of patients.

Keywords: Artificial Intelligence, Deep Learning, Cerebrovascular Disease, Convolutional Neural Network, Image Processing.

Beyin Bilgisayarlı Tomografi Görüntülerinde Yapay Zeka Tabanlı Beyin Damar Hastalıkları Tespiti

Öz

Serebrovasküler hastalık (SVH), beyin damarlarının tıkanması veya kanaması nedeniyle insanlarda felce ve hatta ölüme neden olmaktadır. SVH tipinin uzman tarafından erken teşhisiyle olumsuz etkiler doğru bir tedavi süreci ile engellenebilir. Ancak, hastanelerde veya acil servislerde yeterli sayıda uzmanın görevlendirilmesi her zaman mümkün olmamaktadır. Bu nedenle, bu çalışmada, tanı sürecini hızlandırmak ve uzmanların yükünü hafifletmek için beyin bilgisayarlı tomografi görüntülerinden SVH tespiti için yapay zeka tabanlı bir klinik karar destek sistemi önerilmiştir. Yapay zekanın bir alt kümesi olan derin ögrenme modeli, SVH'nin önce tespit edildiği ve ardından iskemik veya hemorajik olarak sınıflandırıldığı iki aşamalı bir süreçle uygulanmıştır. Ayrıca geliştirilen sistem, SVH teşhisi için kullanıcı dostu bir arayüz sunan özel olarak tasarlanmış¸ masaüstü uygulamamıza entegre edilmiştir. Deneysel sonuçlar, sistemimizin uzmanlar için erken teşhis ve tedaviyi geliştirme konusunda büyük bir potansiyele sahip olduğunu ve hastaların iyileşme oranına katkıda bulunacağını göstermektedir.

Anahtar Kelimeler: Yapay Zeka, Derin Öğrenme, Serebrovasküler Hastalık, Evrişimsel Sinir Ağları, Görüntü İşleme.

[1*] Corresponding Author: alifatih449@gmail.com

1. Introduction

Cerebrovascular disease (CVD) has attracted an increasing amount of attention in the field of medicine due to its mortality and morbidity rates. The Ministry of Health of the Republic of Turkey reports that the number of CVD-related deaths in Turkey is between 35-40 thousand and has been increasing over the years (Erkoyun, Sözmen, Bennett, Unal, & Boshuizen, 2016). CVD ranks second among the top ten diseases that cause death in Turkey (Balbay et al., 2018). Although promising treatments have been developed recently, they need to be further developed before they can be applied to a significant number of patients (Diaz, Belen, Tenorio-Javier, & Juangco, 2022). The main challenge is the early detection of CVD-related risk factors so that these risk factors can be modified to prevent CVD.

Specialists use medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Diffusion-Weighted Magnetic Resonance Imaging (DW- MRI) to categorize brain stroke types into ischemic and hemorrhagic (Jeon et al., 2017). Among these techniques, MRI uses magnetic fields and radio frequency waves to obtain images of structures and organs inside the body (Katti, Ara, & Shireen, 2011). CT is mostly preferred in emergencies due to its rapid acquisition. However, it has lower quality than MRI in terms of contrast (Zhao, Carass, Lee, He, & Prince, 2017). DW-MRI, on the other hand, is an imaging technique that identifies the stroke lesion type within minutes as it is based on the diffusion of water molecules (Dayani, Fatehi, Rostamzadeh, & Rostamzadeh, 2017). Among them, CT is the most preferred technique by specialists, especially for the detection of ischemic stroke. However, CVD diagnosis using CT images is time-consuming and sensitive to human inference. Furthermore, the quality of diagnosis depends on the expertise of specialists, and detection of the stroke zone on CT images by human eyes can lead to misdiagnosis due to lack of awareness or overwork of specialists. Therefore, an automatic system, which can detect and segment the stroke region on a CT image, is needed to assist the specialists during the diagnosis. To address this issue, artificial intelligence (AI) based approaches like deep learning methods have been proposed to classify whether images are healthy or not (Rehman, Iqbal, Xing, & Ahmed, 2021).

AI is defined that a computer can imitate the human mind like object recognition, learning with experience, communiation via languages, giving decisions, and problem solving (Çaylı, Makav, Kılıç, & Onan, 2020). Recent advances in computer processing lead more AI methodologies for big data processing. In that context, deep learning, a branch AI that is capable of extracting features automatically for the classification, regression, segmentation and prediction, has been employed in many applications, including image processing (Gölcez, Kiliç, & Şen, 2021; Volkan Kılıç, Mercan, Tetik, Kap, & Horzum, 2022), video processing (Aydın, Çaylı, Kılıç, & Onan, 2022), speech recognition (Volkan Kılıç, Barnard, Wang, & Kittler, 2013), medical image analysis (Doğan & Kılıç, 2021; Kökten & Kılıç, 2021; Şen et al., 2022), computer vision (Volkan Kılıç, 2021; Mercan & Kılıç, 2020), face recognition (Keskin, Moral, Kılıç, & Onan, 2021), advanced vehicle driving assist (Betül, Çaylı, Kılıç, & Onan, 2022), audio analysis (Keskin, Çaylı, Moral, Kılıç, & Onan, 2021), object detection (Liu et al., 2020) and natural language processing (Fetiler, Çaylı, Moral, Kılıç, & Onan, 2021). In addition, deep learning architectures include CNNs (Yüzer, Doğan, Kılıç, & Şen, 2022), Recurrent Neural Networks (Mercan, Doğan, & Kılıç, 2020; Palaz, Doğan, & Kılıç, 2021), transformers (Sun et al., 2022), and autoencoders (Sewak, Sahay, & Rathore, 2020). Among these architectures, CNNs have a high performance in the classification of images.

Several studies were reported for disease of brain classification (Chin et al., 2017; Hsieh et al., 2019; Lewick, Kumar, Hong, & Wu, 2020; Livne et al., 2019; Talo, Yildirim, Baloglu, Aydin, & Acharya, 2019). China et al. used the Otsu method for data pre-processing to extract cranium from CT images, and the affine transformations were used for data augmentation. Then, the dataset was trained with CNN models to detect ischemic stroke on CT images (Chin et al., 2017). Hsieh et al. classified cerebral small vessel lesions based on risk level and visualized them in 3D with brain MRI (Hsieh et al., 2019). In addition, a 7-layer CNN was used for classification to segment the cranium part in MRI. Talo et al. performed multi-class (bleeding, normal, chronic, and acute infarction) disease detection on brain CT images (Talo et al., 2019). The pre-trained CNN models, such as AlexNet (Alom et al., 2018), VGG16 (Dodge & Karam, 2016), ResNet18, ResNet34, and ResNet50 (Tai, Yang, & Liu, 2017) were employed, and the highest performance was obtained from ResNet50 (Talo et al., 2019). Livne et al. detected CVD with U-net in brain MRI. The model also segmented images to mark diseased parts (Livne et al., 2019). Lewick et al. classified the types of bleeding in brain CT images as intraparenchymal, intraventricular, subarachnoid, subdural, and epidural with ResNet50 (Lewick et al., 2020).

Here, sequential classification was employed to detect CVD first and then determine types (ischemic and hemorrhagic). Six popular CNN models (AlexNet, Xception (Chollet, 2017), VGG16, VGG19 (Johnson, Alahi, & Fei-Fei, 2016), ResNet50, and Inception-v3 (Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, 2016)) were trained for the performance comparison. Two sequential CNN models (ResNet50 and Inception-v3) were chosen for their performance. ResNet50 was employed to diagnose the image as CVD and normal, while Inception-v3 was used to detect the types of CVD (ischemic and hemorrhagic). The proposed two-stage structure is illustrated in Figure 1. Next, the ResNet50 and Inception-v3 models were integrated into a user-friendly and simple desktop application, *DeepBrain*, to detect CVD and its types in the brain.

The rest of this paper is organized as follows: Section 2 introduces the proposed system with CNN models. Experimental evaluations are presented in Section 3, and then, the closing remarks are given in Section 4.

2. Proposed System

In this section, the proposed system is introduced for CVD detection. First, pre-processing steps are presented for CVD detection in CNN. Next, our custom-designed application called *DeepBrain* is introduced.

2.1. Pre-processing

Pre-processing is the stage of preparing data for the CNN models. Raw data usually consists of many outliers such as out-of-range values, inconsistencies, duplications, noises, and redundancies (Doğan, Isik, Kilic, & Horzum, 2022; Kilic, Dogan, Kilic, & Kahyaoglu, 2022). The performance of the CNN models may be degraded as insufficient due to the low quality raw data. Therefore, raw data must be passed through various pre-processing steps to increase its quality. Common pre-processing methods are data augmentation, cleaning, reduction, and noise filtering (Maharana, Mondal, & Nemade, 2022).

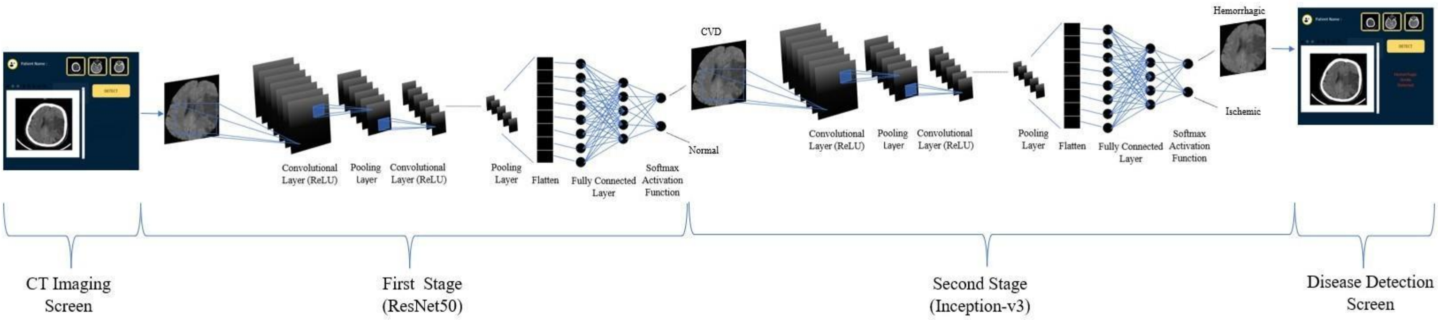


Figure 1. The proposed sequential CVD detection system.

The quality of raw datasets is improved with image processing methods, including image enhancement, transformation, classification, and analysis (Ullah, Farooq, Lee, & An, 2020). Here, the cranium was extracted using the simple threshold, masking, and opening methods. Firstly, the region of interest (ROI) in the image was determined and cropped, as shown in Figure 2(b), to eliminate redundant parts within the images. Then, the simple threshold method was used to convert the image to binary format (Figure 2(c)) before the opening and masking processes. A two-stage opening process was used to remove the cranium fragments in Figure 2(c), as the opening process removes the fine ridges in the images. First, the erosion process was employed in Figure 2(d), and the marked areas were eroded. Later, the eroded areas were enlarged by dilation, and the particles in the marked areas were eliminated from the image (Figure 2(e)). Figure 2(b) and Figure 2(e) are superimposed to obtain Figure 2(f) with common cranium parts. Masking is a method used to extract the desired part from the images. In order to apply the masking process to the original image, the inverse of Figure 2(f) was converted to the mask image in Figure 2(g). Then, Figure 2(b) was masked with in Figure 2(g), resulting in Figure 2(h). Next, images are cropped to eliminate redundant pixels. In addition, images have been resized to 400x400 as the neural networks receive inputs of the same size (Figure 2(i)). ROI was determined by image processing methods after the extraction of the cranium.

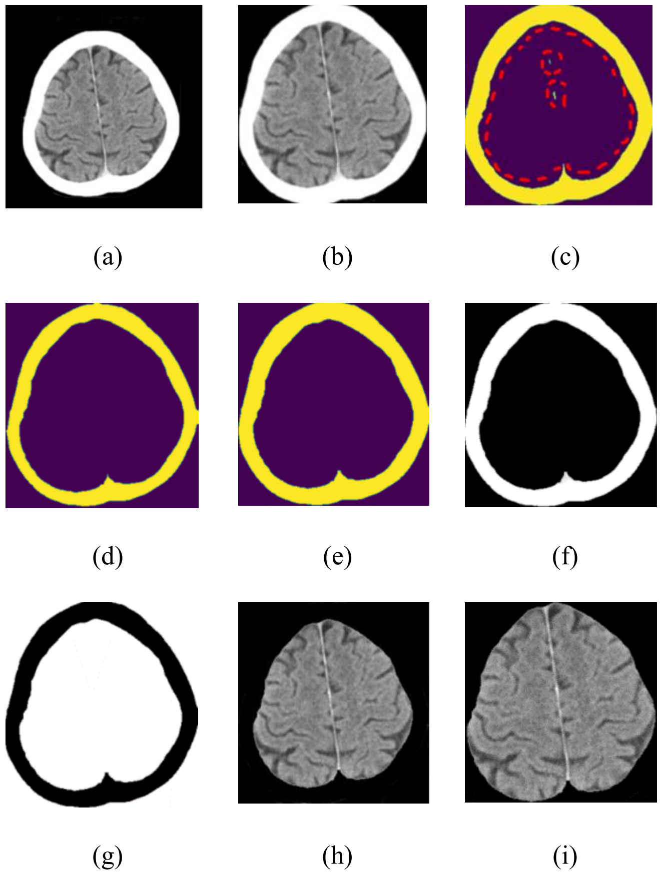


Figure 2. The pre-processing steps of the brain images are illustrated. The original brain image is given in (a), and (b) shows the cropped image. Next, threshold, erosion, and dilation are applied in (c), (d), and (e), respectively. The mask image is given in (g). The final image and its resized version are displayed in (h) and (i), respectively.

2.2. Convolutional Neural Network (CNN)

CNN consists of a multi-layer structure in which images are processed separately in each layer, and the outputs of one layer are the inputs of the next layer (Jo & Jadidi, 2020). As shown in Figure 3, layers in deep learning have different tasks. In the convolution layer, images are scaled down according to the filter size. The pooling layer is used to reduce the size of this output. Pooling is a procedure that summarizes features within the region covered by a specific filter. This operation prevents the network from being memorized at the expense of losing some information. In a fully connected layer, each input is connected to all neurons of the previous layer, and the class score is optimized with a matrix structure. After a feature vector of the ReLU layer is created, each value in the feature vector is passed through a nonlinear layer such as ReLU. In this layer, the thresholding operation is performed independently for each layer to find the approximate solutions of representation feature vectors. Dropout is used in CNN so that the network does not memorize data or learn too much. This layer is used to prevent the network from overfitting, which means memorizing the training data of the model. The basic logic applied in this layer is to remove some nodes of the network. In that sense, the performance of the network is increased, ensuring that weak and unnecessary information is forgotten. The normalization layer is used to speed up the training of CNN, and this layer is where the inputs are normalized. The Softmax activation function is the last step used in the CNN in the classification process and assigns a probability value to the result obtained from the CNN (Gu et al., 2018).

Training of six CNN models were performed independently for both two stages, and in terms of validation and test accuracy, ResNet50 and Inception-v3 outperform their counterparts. Importance of the dataset in training is described in Section 3.1.

2.3. Desktop Application: *DeepBrain*

A desktop application called *DeepBrain* is developed for sensitive and reliable CVD detection in the brain with a deep learning approach. The proposed system detects CVD and its types through the application built with Python standard Graphical User Interface package.

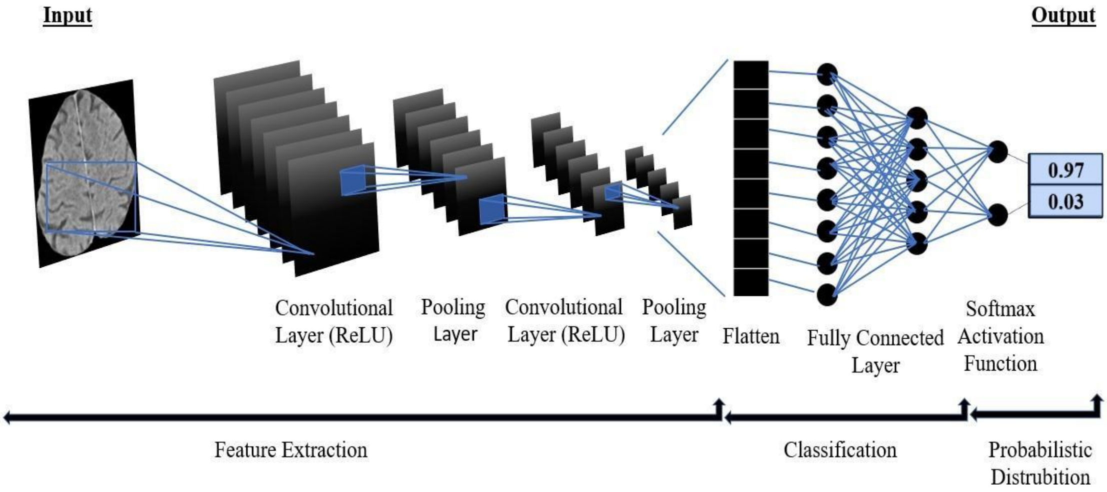


Figure 3. The general structure of CNN.

Table 1. Datasets

Dataset	Normal	CVD	
		Ischemic	Hemorrhagic
Unaugmented	4417	2690	15000
Augmented	30000	15000	15000

Image processing techniques (Section 176) are integrated into the application to make CT images suitable for classification. Then, the models for classifying the images were saved as Hierarchical Data Format 5 File and integrated into the application.

The main screen of the application is shown in Figure 4(a). When the button in the upper left corner of the screen is clicked, the folders containing the patient CT images are displayed in Figure 4(b). The folder to be examined is selected, and the image in Figure 4(c) is displayed on the screen. All CT images in the folder can be viewed by scroll bar movement. In addition, the application provides the ability to enlarge, reduce, save and mark images. After selecting the CT image, the “DETECT” button can be clicked to perform the detection process. The outputs of the system, according to the finding in CT, are shown as an undetected disease, ischemic stroke, and hemorrhagic stroke in Figure 4(d-e-f), respectively.

3. Experimental Evaluations

In this section, the collected dataset, experimental settings, evaluation metrics, and performance comparison of the CNN models are presented.

3.1. Dataset

The dataset plays a significant role to achieve a robust model in deep learning-based systems (Doğan, Yüzer, Kılıç, & Şen, 2021). This study was conducted with the publicly available dataset (Koç et al., 2022). The dataset consists of ischemic, hemorrhagic CVD types and normal class (healthy) brain CT images. It contains a total of 17564 brain CT images, of which 4417, 2690, and 10496 are normal, ischemic, and hemorrhagic, respectively.

In deep learning, the size of the dataset is an essential factor in the performance of the CNN models. Therefore, data augmentation is used in cases where the dataset has insufficient images and also to avoid overfitting. Basic data augmentation operations such as brightness variation, rotation, and translation are applied to the datasets (Perez & Wang, 2017; Taylor & Nitschke, 2018). Images in the dataset were increased using rotation from 5 to 40 degrees, zooming from 3% to 14%, and cropping from 2% to 5%. As a result, the total number of images in the dataset reached 60000 brain CT images as normal, ischemic, and hemorrhagic, as shown in Table 1.

3.2. Results and Discussion

Here, the experiments were performed on Keras, a Python framework, to train the CNN models for the CVD and its types. The workstation used for training the models has an Intel Core i7-7700HQ 2.80 GHz processor, 32 GB of DDR4 RAM, and 11 GB GDDR6 NVIDIA Geforce RTX 2080 Ti graphics card. Each dataset has been split into train and test subsets by 80 % and 20 %, respectively. The selection of hyper-parameters such as epochs, learning rate, batch size, and optimizer, which vary according to the problem and dataset, is effective in the performance of CNN models. In that sense, the hyper-parameters of the models were chosen as follows: the epochs of 30, the learning rate of 0.001, the batch size of 64, and the optimizer of Adam.

The ResNet50 and Inception-v3 models showed the highest performance in terms of Validation accuracy with 0.9972 and 0.9951 compared to other models in the first and second stages, respectively. Beside validation accuracy (Eq. (1)), precision (Eq. (2)), recall (Eq. (3)), and F1-score (Eq. (4))values were also used in the comparison (Table 2).

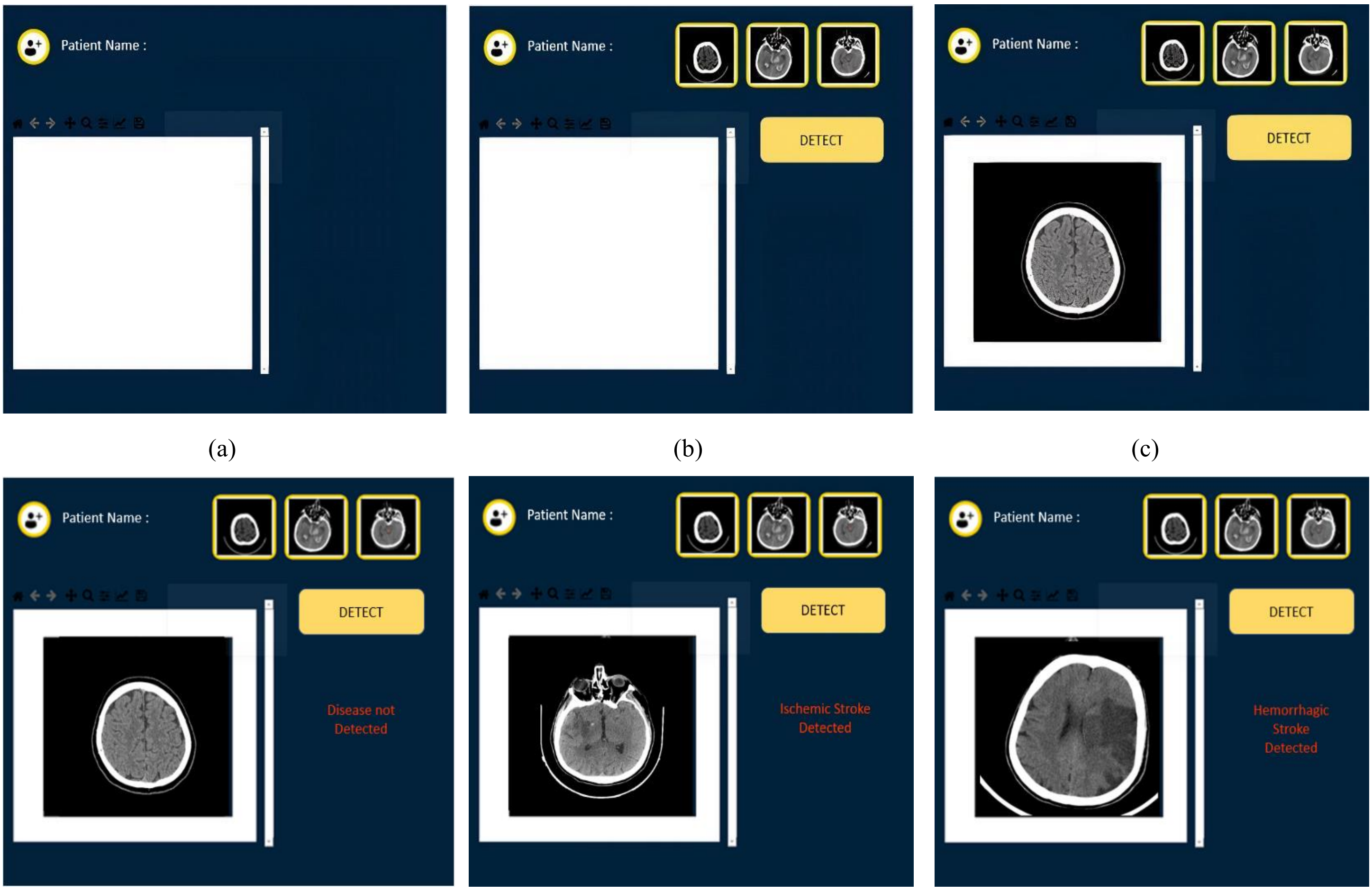
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

$$F1 - score = 2x\frac{Precision \ x \ Recall}{Precision + Recall} \qquad (4)$$

where TP (True-Positive) indicates the correctly classified as positive, TN (True-Negative) points the correct classification as negative, FP (False-Positive) is the number classified as positive when required to be negative, FN (False-Negative) is the number



(a) (b) (c)

(d) (e) (f)

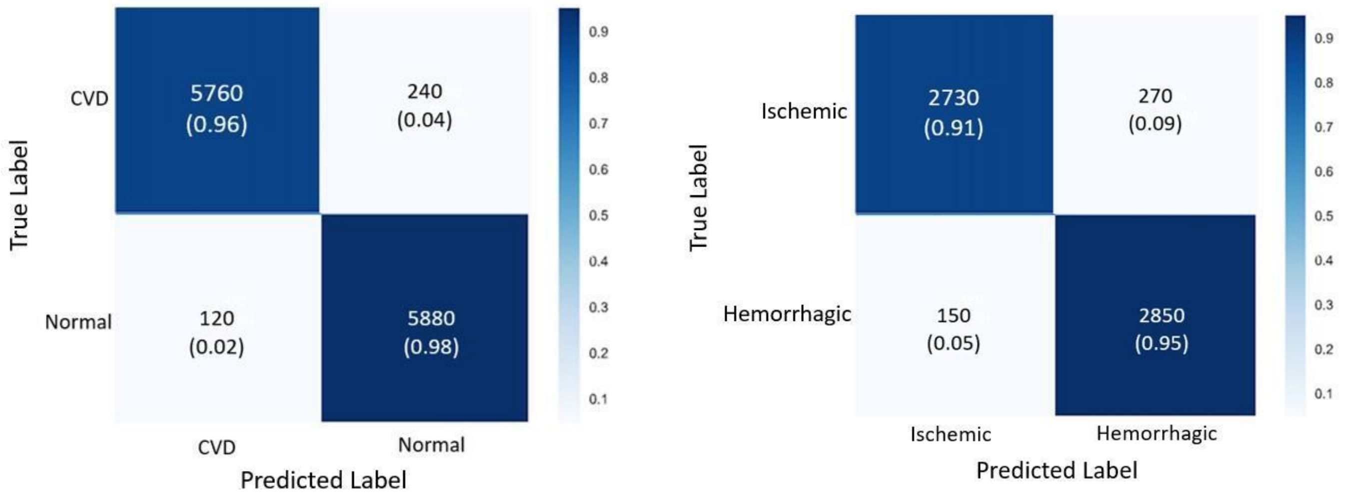
Figure 4. The home screen of the DeepBrain application is given in (a) while the patient folder can be displayed in (b). CT image is shown in (c) and the disease not detected state is given in (d). Ischemic and hemorrhagic strokes are detected in (e) and (f), respectively.

defines correct classification as positive which supposed to be negative. Precision is calculated by dividing the number of correctly classified records by the total number of predicted positives. Precision is a metric that indicates how many positives the classification model predicts are true positives. The recall is also called the True Positive Rate (TPR). It indicates number of the true positives that classified correctly. F1-score is a metric consisting of the harmonic averaging of precision and recall metrics. It is used as an evaluation metric in many classification processes as it considers both precision and recall (Mercan, Kılıç, & Şen, 2021).

The accuracy of the proposed deep learning-based system was tested with 6000 normal, 3000 ischemic, and 3000 hemorrhagic CT images. The results are shown in Figure 5 with the confusion matrices of the ResNet50 and Inception-v3 models. While the ResNet50 model (Figure 5(a)), which is the first classifier, predicted 5760 CVD of true (96%) and 240 CVD of false (4%), it also predicted 5880 normal of true (98%) and 120 normal CT images of false (2%). On the other hand, the second classifier, Inception-v3, was tested with 3000 ischemic and 3000 hemorrhagic images, resulting in 2730 ischemic (91%) and 2850 hemorrhagic (95%) images correctly (Figure 5(b)). The test results prove the advantage of the proposed system in terms of accuracy. In that context, the ResNet50 and Inception-v3 models were integrated into *DeepBrain* for CVD type determination in the brain.

Table 2. Evaluation of the ResNet50 and Inception-v3 for CVD in terms of accuracy, recall, precision and F1-score.

Stages	Models	Accuracy	Recall	Precision	F1-Score
First	**AlexNet**	0.7337	0.7436	0.7213	0.7320
	VGG19	0.7346	0.7512	0.7235	0.7344
	VGG16	0.9370	0.9447	0.9185	0.9194
	Xception	0.9635	0.9681	0.9467	0.9475
	Inception-v3	0.9654	0.9698	0.9654	0.9695
	ResNet50	**0.9972**	**0.9821**	**0.9783**	**0.9788**
Second	**AlexNet**	0.6609	0.6891	0.6699	0.6759
	VGG19	0.6670	0.6792	0.6695	0.6766
	VGG16	0.6981	0.7169	0.7069	0.7053
	Xception	0.8764	0.9021	0.8946	0.8953
	ResNet50	0.9087	0.9217	0.9123	0.9149
	Inception-v3	**0.9951**	**0.9354**	**0.9316**	**0.9343**



(a) (b)

Figure 5.Confusion matrices of ResNet50 in (a) and Inception-v3 in (b) for different CVD types of the test dataset.

Table 3. Comparison between the proposed system and state-of-the-art approaches.

	Disease	Train Accuracy
(Chin et al., 2017)	Ischemic Stroke	0.9766
(Hsieh et al., 2019)	Cerebral Small Vessel	0.9857
(Talo et al., 2019)	Multi-Class Brain	0.9523
(Lewick et al., 2020)	Hemorrhagic	0.9800
Proposed System	**CVD (Normal / CVD)**	**0.9972**
	CVD Type (Ischemic / Hemorrhagic)	**0.9951**

The performance of the proposed system has been compared with state-of-the-art approaches in Table 3. In (Chin et al., 2017), 0.9766 accuracy value was obtained during the training to detect an ischemic stroke. The train accuracy value of the model created for detecting cerebral small vessel disease was 0.9857 (Hsieh et al., 2019). The ResNet50 model predicted a training accuracy value of 0.9523 in (Talo et al., 2019) to classify multi-class brain disease. In (Lewick et al., 2020), the study was conducted to determine the hemorrhagic types, and the accuracy value was obtained as 0.98 per class. Unlike the others, the proposed system divides diagnostic mechanisms into CVD detection and ischemic-hemorrhagic classification. The proposed system provides 0.9972 training accuracy for the first stage (CVD- normal) while it offers 0.9951 for determining the second stage (CVD types) which proves the outstanding performance of the system.

The *DeepBrain* were demonstrated step by step with screenshots in Figure 4, where the uploaded image was analyzed for CVD detection. In the background of the application, the image is entered into the first classifier model to detect whether there are disease findings or not. If there are no findings signs of disease, the message “Disease not detected” is displayed on the screen. When CVD is detected, the image enters the second classifier model to determine the type of disease. The result is displayed as ischemic or hemorrhagic stroke based on the CVD type. The application is developed to be used by doctors in health institutions. The results show that the proposed system can be used effectively in the detection of CVD and its types.

4. Conclusion

This study proposes to detect CVD and its types on brain CT images using CNN models. Our proposed system performs a two-stage classification process that detects CVD as ischemic and hemorrhagic. The highest classification performance was obtained in ResNet50 (first classifier) and Inception-v3 (second classifier) with 99.72% and 99.51%, respectively. Then, this system was integrated with our custom-designed desktop application called *DeepBrain*. The application provides zooming, cutting, recording, and marking operations on medical images. Experimental results show the advantage of the proposed system in the detection of CVD and its types which offers great potential to be used in medical centers.

References

Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., . . . Asari, V. K. (2018). The history began from alexnet: A comprehensive survey on deep learning approaches. *arXiv preprint arXiv:.01164*

Aydın, S., Çaylı, Ö., Kılıç, V., & Onan, A. (2022). Sequence-to-Sequence Video Captioning with Residual Connected Gated Recurrent Units. *J Avrupa Bilim ve Teknoloji Dergisi*(35), 380-386.

Balbay, Y., Gagnon-Arpin, I., Malhan, S., Öksüz, M. E., Sutherland, G., Dobrescu, A., . . . Habib, M. (2018). Modeling the burden of cardiovascular disease in Turkey. *Anatolian Journal of Cardiology 20*(4), 235.

Betül, U., Çaylı, Ö., Kılıç, V., & Onan, A. (2022). Resnet based Deep Gated Recurrent Unit for Image Captioning on Smartphone. *J Avrupa Bilim ve Teknoloji Dergisi*(35), 610-615.

Çaylı, Ö., Makav, B., Kılıç, V., & Onan, A. (2020). *Mobile Application Based Automatic Caption Generation for Visually Impaired.* Paper presented at the International Conference on Intelligent and Fuzzy Systems.

Chin, C.-L., Lin, B.-J., Wu, G.-R., Weng, T.-C., Yang, C.-S., Su, R.-C., & Pan, Y.-J. (2017). *An automated early ischemic stroke detection system using CNN deep learning algorithm.*

Paper presented at the 2017 IEEE 8th International conference on awareness science and technology (iCAST).

Chollet, F. (2017). *Xception: Deep learning with depthwise separable convolutions.* Paper presented at the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Dayani, M. A., Fatehi, D., Rostamzadeh, O., & Rostamzadeh, A. (2017). Evaluation the sensitivity of diffusion and perfusion weighted imaging in therapeutic timing of stroke. *Research Journal of Pharmacy Technology, 10*(6), 1951-1956.

Diaz, A. B. F., Belen, A. A., Tenorio-Javier, A. M. J., & Juangco, D. N. A. (2022). Cerebrovascular Disease in Asia: Causative Factors. In *Hypertension and Cardiovascular Disease in Asia* (pp. 271-284): Springer.

Dodge, S., & Karam, L. (2016). *Understanding how image quality affects deep neural networks.* Paper presented at the 2016 eighth international conference on quality of multimedia experience (QoMEX).

Doğan, V., Isik, T., Kilic, 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. *J Sağlık Bilimlerinde Yapay Zeka Dergisi, 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.

Erkoyun, E., Sözmen, K., Bennett, K., Unal, B., & Boshuizen, H. (2016). Predicting the health impact of lowering salt consumption in Turkey using the DYNAMO health impact assessment tool. *J Public Health, 140*, 228-234.

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

Gölcez, T., Kiliç, 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.

Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., . . . Cai, J. (2018). Recent advances in convolutional neural networks. *Pattern recognition 77*, 354-377.

Hsieh, Y.-Z., Luo, Y.-C., Pan, C., Su, M.-C., Chen, C.-J., & Hsieh, K. L.-C. (2019). Cerebral small vessel disease biomarkers detection on MRI-sensor-based image and deep learning. *Sensors 19*(11), 2573.

Jeon, C. H., Park, J. S., Lee, J. H., Kim, H., Kim, S. C., Park, K. H., . . . Kim, Y.-M. (2017). Comparison of brain computed tomography and diffusion-weighted magnetic resonance imaging to predict early neurologic outcome before target temperature management comatose cardiac arrest survivors. *Resuscitation 118*, 21-26.

Jo, J., & Jadidi, Z. (2020). A high precision crack classification system using multi-layered image processing and deep belief learning. *Structure Infrastructure Engineering, 16*(2), 297-305.

Johnson, J., Alahi, A., & Fei-Fei, L. (2016). *Perceptual losses for real-time style transfer and super-resolution.* Paper presented at the European conference on computer vision.

Katti, G., Ara, S. A., & Shireen, A. (2011). Magnetic resonance imaging (MRI)–A review. *International journal of dental clinics 3*(1), 65-70.

Keskin, R., Çaylı, Ö., Moral, Ö. T., Kılıç, V., & Onan, A. (2021). A benchmark for feature-injection architectures in image captioning. *J 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).

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.

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

Kılıç, V., Barnard, M., Wang, W., & Kittler, J. (2013). *Adaptive particle filtering approach to audio-visual tracking.* Paper presented at the 21st European Signal Processing Conference (EUSIPCO 2013).

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.

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.*

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

Lewick, T., Kumar, M., Hong, R., & Wu, W. (2020). *Intracranial hemorrhage detection in CT scans using deep learning.* Paper presented at the 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService).

Liu, L., Ouyang, W., Wang, X., Fieguth, P., Chen, J., Liu, X., & Pietikäinen, M. (2020). Deep learning for generic object detection: A survey. *International journal of computer vision 128*(2), 261-318.

Livne, M., Rieger, J., Aydin, O. U., Taha, A. A., Akay, E. M., Kossen, T., . . . Frey, D. (2019). A U-Net deep learning framework for high performance vessel segmentation in patients with cerebrovascular disease. *Frontiers in neuroscience 13*, 97.

Maharana, K., Mondal, S., & Nemade, B. (2022). A Review: Data Pre-Processing and Data Augmentation Techniques. *Global Transitions Proceedings.*

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). *Fuzzy classifier based colorimetric quantification using a smartphone.* Paper presented at the International Conference on Intelligent and Fuzzy Systems.

Mercan, Ö. B., Kılıç, V., & Şen, M. (2021). Machine learning-based colorimetric determination of glucose in artificial saliva with different reagents using a smartphone coupled µPAD. *Sensors Actuators B: Chemical 329*, 129037.

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

Perez, L., & Wang, J. (2017). The effectiveness of data augmentation in image classification using deep learning. *arXiv preprint arXiv:.04621*

Rehman, A., Iqbal, M. A., Xing, H., & Ahmed, I. (2021). COVID-19 detection empowered with machine learning and deep learning techniques: A systematic review. *Applied Sciences 11*(8), 3414.

Şen, M., Yüzer, E., Doğan, V., Avcı, İ., Ensarioğlu, K., Aykaç, A., . . . Kılıç, V. (2022). Colorimetric detection of H2O2 with Fe3O4@ Chi nanozyme modified µPADs using artificial intelligence. *Microchimica Acta 189*(10), 1-11.

Sewak, M., Sahay, S. K., & Rathore, H. (2020). An overview of deep learning architecture of deep neural networks and autoencoders. *Journal of Computational Theoretical Nanoscience 17*(1), 182-188.

Sun, X., Qian, H., Xiong, Y., Zhu, Y., Huang, Z., & Yang, F. (2022). Deep learning-enabled mobile application for efficient and robust herb image recognition. *Scientific Reports 12*(1), 1-18.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). *Rethinking the inception architecture for computer vision.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

Tai, Y., Yang, J., & Liu, X. (2017). *Image super-resolution via deep recursive residual network.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

Talo, M., Yildirim, O., Baloglu, U. B., Aydin, G., & Acharya, U. R. (2019). Convolutional neural networks for multi-class brain disease detection using MRI images. *Computerized Medical Imaging Graphics 78*, 101673.

Taylor, L., & Nitschke, G. (2018). *Improving deep learning with generic data augmentation.* Paper presented at the 2018 IEEE Symposium Series on Computational Intelligence (SSCI).

Ullah, Z., Farooq, M. U., Lee, S.-H., & An, D. (2020). A hybrid image enhancement based brain MRI images classification technique. *Medical hypotheses 143*, 109922.

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

Zhao, C., Carass, A., Lee, J., He, Y., & Prince, J. L. (2017). *Whole brain segmentation and labeling from CT using synthetic MR images.* Paper presented at the International Workshop on Machine Learning in Medical Imaging.