Automatic stroke classification: Domain knowledge injection augmented transfer learning approach

Otomatik inme sınıflaması: İmkansız piksellerin eliminasyonuyla etkinleştirilmiş transfer öğrenme yaklaşımı

Ilker Ozgur Koska[1], Cagan Koska[2], Antonio Fernandes[3]

[1] Division of Radiology, İzmir Behçet Uz Training and Research Hospital

[2] Department of Electrical Electronical Engineering, Faculty of Engineering, Yaşar University

[3] Sliced Group

Abstract

Aim: To build an artificial intelligence model to classify stroke into ischemic or hemorrhagic classes using the labeled stroke computer tomography (CT) slices that were shared in the 2021 Teknofest artificial intelligence in health competition.

Methods: We developed a set of methods that can inject domain knowledge into the models to provide a more refined search space for the model for better performance. We used pre-trained MobileNet and EfficientNet architectures and fine-tuned them for our 2-class output model. We discarded impossible pixel values and pixel spatial locations to provide a space that was conditioned into only possible spatial locations and signal values using our knowledge of brain anatomy, stroke pathology, and imaging.

Results: With the dataset which we just used [0-1] normalization and adjusted the input dimension into 224*224, accuracy values of 0.74 with adapted MobileNetV2 and 0.72 with adapted EfficentNetB0 were obtained in the group without further pre-processing. In the data transformation group where bone structures were removed and pixel values were restricted by eliminating impossible values, an accuracy level of 0.91 with MobileNetV2 and 0.88 with EfficientNetB0 at test time were achieved.

Conclusion: In conclusion, CT-based slice prediction of mechanism of stroke as ischemic or hemorrhagic was achieved with high accuracy by integrating human knowledge into the pre-trained off-the-shelf models which was promising to shorten the time of the triage of stroke patients which can potentially improve stroke patient outcomes.

Keywords: Artificial intelligence; stroke; machine learning; deep learning

Öz

Amaç: Derin öğrenme yöntemleri ve özellikle evrişimsel sinir ağları (CNN) tıbbi görüntü sınıflamasında otomatizasyon açısından geliştirilen uygulamalarda altın standart niteliğindedir. İnme görüntülemesinde zaman oldukça kritik olup hızlı müdahale ile morbidite ve mortalite azaltılabilmektedir. Bu çalışmada amacımız hızlı inme triajı ve uygun tedavi seçimi sağlayacak iskemik inme ile hemorajik inmeyi birbirinden ayırt edebilen otomatize yöntem geliştirmektir.

Yöntemler: Teknofest sağlıkta yapay zekâ yarışması tarafından sağlanan kimliksizleştirilmiş ve anonimleştirilmiş 2000 adet iskemik inme, 2000 adet hemorajik inme içeren bilgisayarlı tomografi (BT) kesitleri kullanılarak, MobileNet ve EfficientNet CNN mimarileri transfer öğrenme metodolojisi ile, özel bir imkansız piksel değeri ve uzamsal lokalizasyonları dışlama stratejisi kullanılarak arama uzayı daraltılmış ve otomatik inme sınıflaması sağlanmıştır.

Bulgular: [0-1] normalizasyon ve 224*224' e girişin ayarlanması dışında ön işleme yapılmayan grupta adapte MobileNetV2 ile 0.74 ve adapte EfficentNetB0 ile 0.72 doğruluk değerleri elde edildi. Öte yandan kemik yapıların çıkarıldığı ve piksel değerlerin imkânsız değerler elimine edilerek kısıtlandığı veri dönüşümü uygulanan grupta MobileNetV2 ile 0.91 ve EfficientNetB0 ile 0.88 doğruluk düzeyine ulaşıldı.

Sonuç: Derin öğrenme yöntemleri kullanılarak inme teşhisi, radyoloji uzmanı olmayan inme görüntülemeye aşina olmayan ancak inme triaj ve sağaltımında aktif rol oynayan sağlık personelleri için özellikle yararlı olabilir. Bu şekilde tedaviden fayda görecek hastanın seçimi ve tedavi kararının verilme hızı artırılabilir. Sonuç olarak iskemik-hemorajik inme sınıflandırmada yüksek doğruluk oranlarına ulaşan çalışmamız, otomatik inme tespitine katkı sağlayabilir ve hekimlerin hızlı ve uygun tedavi kararları vermelerine yardımcı olabilir.

Anahtar Sözcükler: Derin öğrenme; inme; makine öğrenimi; yapay zekâ

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Corresponding author/*Yazışma yazarı*

İlker Özgür Koska
İzmir Behçet Uz Eğitim Araştırma Hastanesi, Radyoloji Bölümü, İzmir, Türkiye.
E-mail: ozgurkoska@yahoo.com

ORCID
İlker Özgür Koska: 0000-0003-0971-3827
Çağan Koska: 0000-0003-0484-5046
Antonio Fernandes: 0000-0002-0446-4422

INTRODUCTION

Deep learning methods form the basis of artificial intelligence methods in image classification and segmentation problems. AlexNet, VGG16/19, GoogleNet (Inception), and ResNet artificial neural networks achieved higher success than humans on the ImageNet dataset in the International Large Scale Computer Vision (ILSCV) competition (1-5). Medical imaging has also benefitted from these developments and has become an important application area. In this respect, stroke is a very attractive application area, both because it has high mortality and morbidity rates and because it can benefit greatly from automated applications that may help initiate appropriate treatment promptly. Indeed, a significant number of startups developing artificial intelligence applications in radiology have developed stroke-related applications and are trying to improve them further (6). When it comes to stroke treatment, every minute that passes can cause another piece of brain tissue to be irreversibly damaged. Therefore, the first step in deciding on treatment is to understand whether it is an ischemic or hemorrhagic stroke and start thrombolytic therapy early in ischemic lesions. For this purpose, in patients presenting with suspicion of stroke, non-contrast computer tomography (CT) imaging is performed quickly to try to rule out bleeding. (Figure 1)

One of the most important catalysts in the development of artificial intelligence projects in radiology worldwide is the anonymization of large numbers of medical images and making them available for public use through platforms such as Kaggle. The main driving force behind the products that can be developed regarding stroke is the labeled brain hemorrhage data set publicly presented in the 2018 Kaggle competition (7). Radiological Society of North America (RSNA) stroke dataset, CQ500, and University College of London Hospitals (UCLH) stroke datasets are important public datasets in this field (7,8,9).

In order to eliminate this labeled radiological data scarcity in our country, Teknofest, has created a platform where the best strategies for solutions are sought as a project pool with the artificial intelligence competition in health, the first of which was held in 2021. Based on the success of this platform, it was decided to repeat it every year, and in 2022, data was provided for models to classify the causes of acute abdomen, and in 2023, data was provided for cancer and breast density classification in mammograms. Our aim in this study was to develop an artificial intelligence model to classify stroke using the labeled hemorrhagic and ischemic stroke CT slices shared in the 2021 Teknofest artificial intelligence in health competition (10).

MATERIAL AND METHODS

Patients and dataset

The dataset shared by Teknofest contained 2000 ischemia and 2000 hemorrhage slices from different patients and at different anatomic levels (11). After the data embargo period which ended in 2022, the dataset could be freely used by the participitants for academic research. Therefore ethical board approval was not required for this study. The slices included both posterior fossa and supratentorial levels and were randomly distributed both anatomically and etiologically, including intraventricular, subdural, epidural, subarachnoid, intraparenchymal hemorrhage, and embolic, large vessel and border zone infarcts. Since deep learning systems require many data points, it was necessary to develop strategies to overcome data limitations. One of these strategies is to apply a transfer learning strategy. In transfer learning, networks trained using many natural images can be applied to a medical imaging problem. The data set frequently used for this purpose is ImageNet (5). Indeed, ImageNet has played an important catalyst role for developments in this field, both by providing a comparison environment in computer vision applications and by providing labeled data to those who want to develop models containing over 10 million labeled natural images. Thus, teaching the special features of the target domain to the models that have already learned image primitives such as edges, corners, and circles from natural images becomes much easier than teaching all the information from scratch.

Preprocessing

Images were resized into 224x224 for MobileNet and EfficientNet pre-trained networks (12,13). While normal gray matter shows values of 37-41 Hounsfield units (HU) and white matter shows values of 29-33 HU, bleeding can show densities of 30-90 HU, and

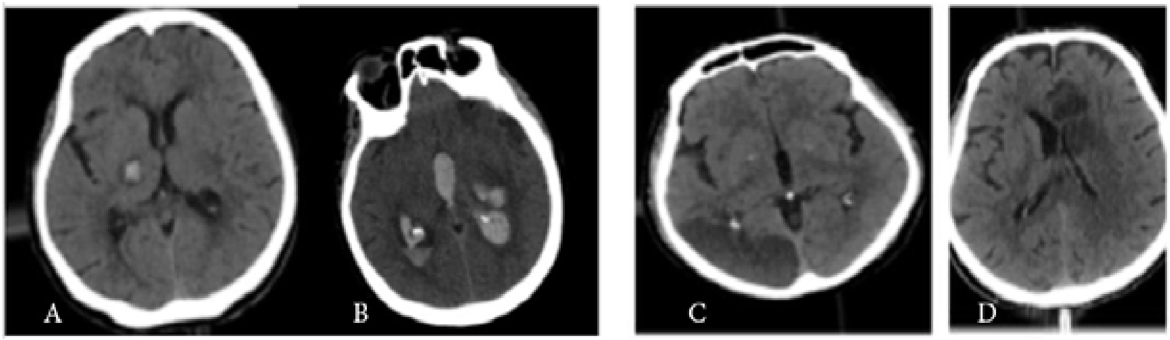

Figure 1: Hemorrhagic and ischemic stroke CT images. The sections are randomly distributed in the posterior fossa and supratentorial intra- and extra-axial hemorrhage and ischemia spectrum and localizations. A) Thalamic parenchymal hemorrhage B) Intraventricular hemorrhage C) Posterior circulation ischemic stroke D) Anterior circulation ischemic stroke

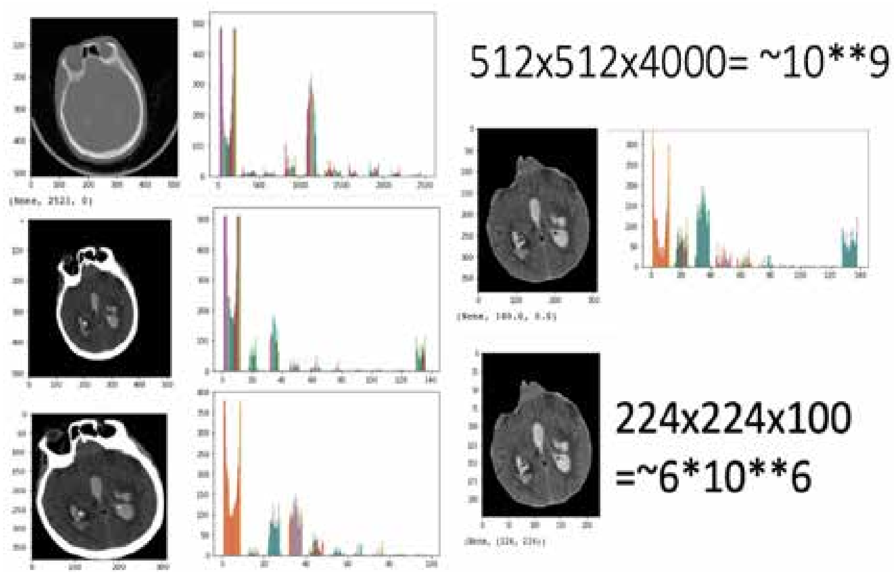

Figure 2: Various structures on CT can mimic bleeding or ischemia with their density features. While those that mimic ischemia with low density are cisterns containing cerebrospinal fluid, ventricles, developmental cysts and sequelae spaces, those that mimic bleeding with high density are bones and calcifications.

ischemia can show densities ranging from 0 HU to 30 HU. Along with bleeding, various conditions such as basal ganglia, epiphysis, falx, and vascular calcifications can be observed as hyperdense on the tomography. (Figure 2)

On the other hand, cerebrospinal fluid, lesions that reflect previous sequela lesions, areas of encephalomalacia, and cystic brain lesions are in the low-density band close to water density. Therefore, while it may not be easy to solve the problem with simple thresholding, eliminating impossible density values and spatial positions from the image can significantly narrow the search space of the model and enable it to reach the global minimum point more easily and quickly. For this reason, the images were subjected to a 5-step preprocessing process. These operations were carried out in the order as follows. The black space around the skull was removed and the remaining image was resized to 224x224. Then, RescaleIntercept and RescaleSlope values were found from the image metadata, and numerical values were converted to HU values according to the equation "Real HU = Pixel value * Slope + Intercept". Thus, HU values that are important for classification are kept limited.

Then, the skull was removed from the image using the Otsu threshold method and morphological op-

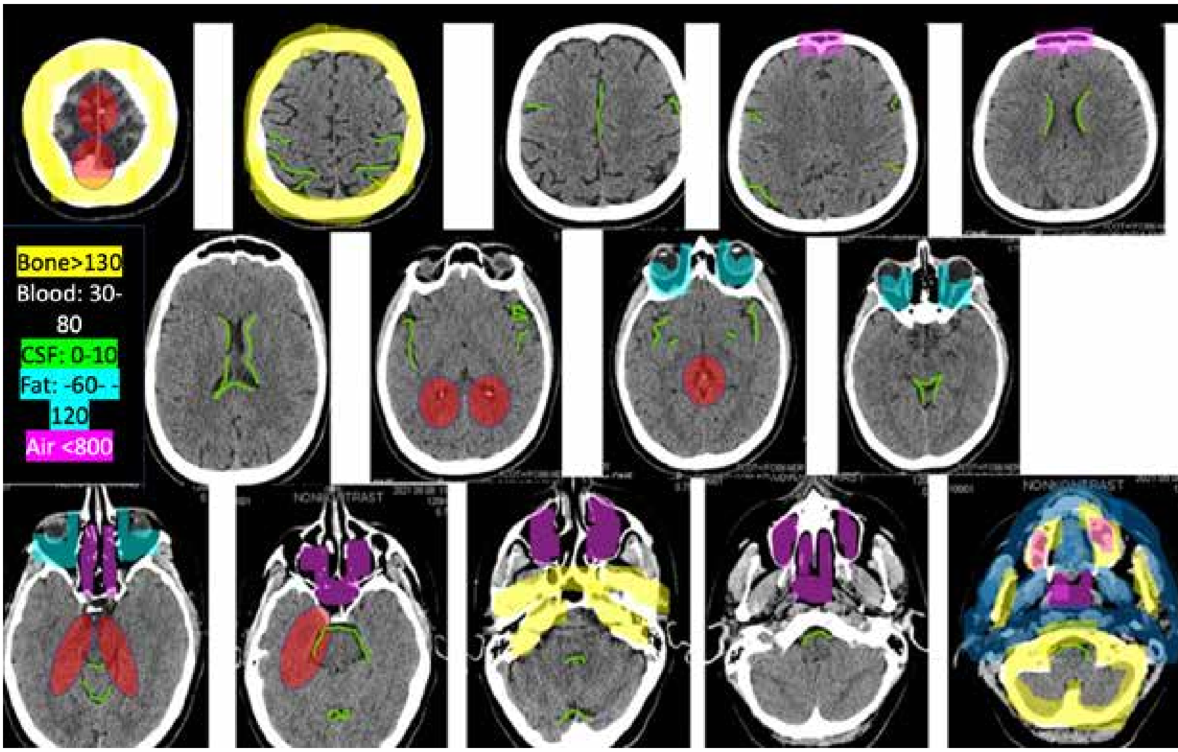

Figure 3: Intracranial field images remaining with diluted information after preprocessing. Histograms can reveal how the search space is diluted by table cleaning, windowing to the appropriate range, discarding the surrounding spaces, discarding the bone, and density normalization, respectively.

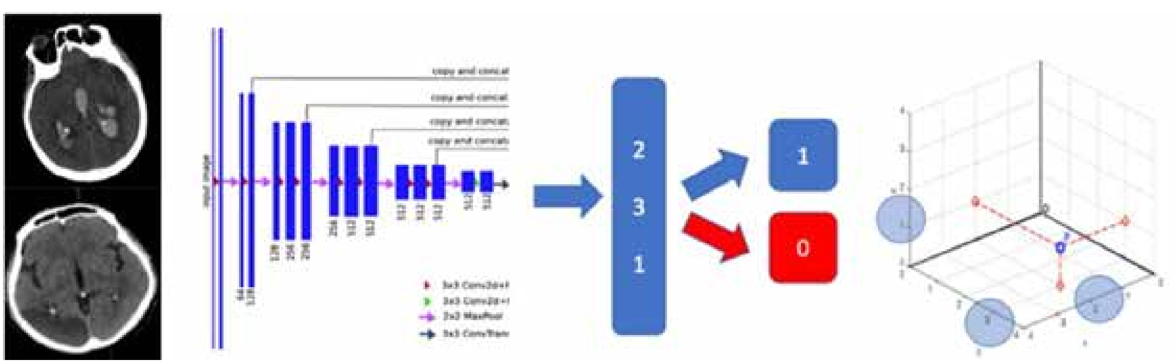

Figure 4: The artificial neural network projects the image to become a point in the feature space. It then searches for the interface separating these points.

erations. Density values were limited to the range of 0-150 with the np.clip function in the numpy library of the standard Python programming language. Finally, normalization was applied, and the pixel values were reduced to the range 0-1. (Figure 3)

In this way, all information in the image that could be noise for the classifier was removed and only the necessary signal was left. This led to a kind of refinement such that, unnecessary pixel localizations and values, which constitute more than 90% of the image, were eliminated and the model was enabled to converge more easily.

In classification with artificial neural networks, the image and the features obtained from the image are compressed, unnecessary ones are eliminated, and each example is reflected in the feature space. Thus,

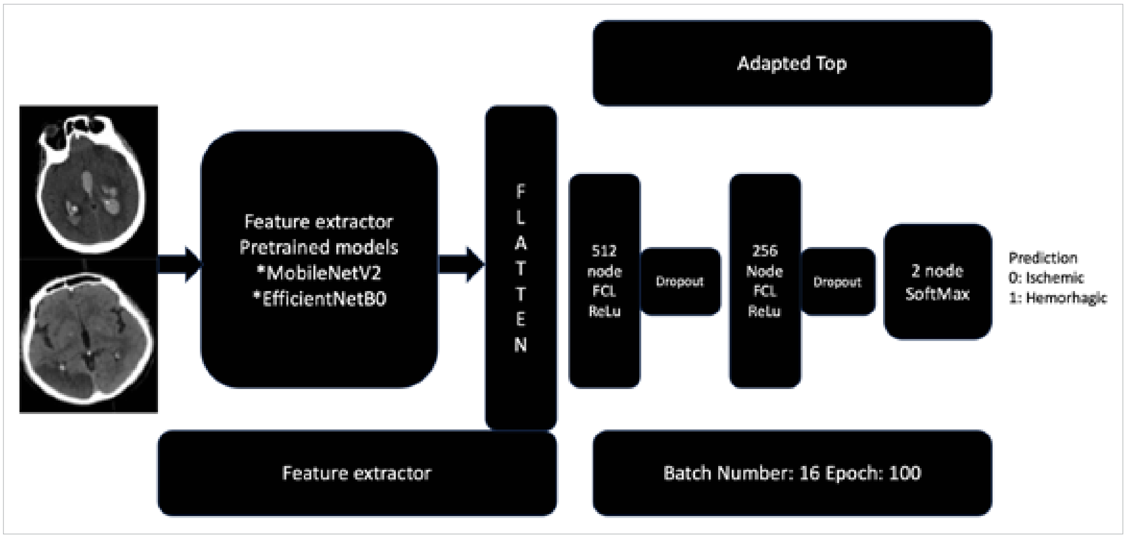

Figure 5: MobilenetV2 and EfficientNetB0, initialized with pre-trained weights and adapted to our problem, were used as classifiers.

each image becomes a point in a feature space whose number of coordinates is equal to the number of features. The purpose of the classifier is to determine the boundary hyperplane that correctly separates the points in different classes (Figure 4).

In cases where access to the required number of data is limited, such as medical image classification, additional strategies are required to reach the necessary number of samples. Data augmentation can be used for this purpose. In the dictionary used for augmentation purposes in our experiments, parameters such as {rotation:10 degrees, random_magnification= 0.1, random_horizontal_shift = 0.2, random_vertical_shift = 0.1, horizontal_mirror_view = Yes} were used. Thus, it has become possible to obtain a much larger number of images by producing various versions of an image that are slightly rotated, shifted, or enlarged. 150 slices from the hemorrhagic and 150 slices from the ischemic classes were reserved for validation and the remaining 3700 slices were used for training. Additionally, 150 ischemia and 150 hemorrhage sections provided in the final stage of the competition were used as an independent test set.

Model building

The spread of cloud-based services, the development of automatic machine learning methods, the design of easier-to-use libraries, and easier access to data have paved the way for artificial intelligence studies and brought spring again after a long artificial intelligence winter period. On the other hand, Sigmoid and Tanh activation functions, previously used in intermediate layers, were causing gradient vanishing in deep networks. However, this problem has been largely solved with rectified linear units (ReLU) and similar activation functions. The use of residual units implemented with the ResNet architecture has also enabled the gradient not to vanish and to be propagated back more easily. In ResNet, residual blocks are connected with skip connections. This allows the compressed information to be copied and move more smoothly between layers (4). The cost of this is that the number of parameters increases greatly. Solving this problem is an active area for artificial intelligence studies. For this purpose, Mobilenet V2 architecture has been developed in recent years. This architecture, built on inverted bottleneck units, makes it possible to achieve similar performance without increasing the number of parameters too much. It is possible to think of inverted bottleneck units as ResNet blocks in reverse order. In this architecture, channels are first expanded, then compressed, and their number is reduced to establish skip connections between them. Thus, higher efficiency can be achieved with fewer parameters (12). The next development in this regard was the addition of scaling on all three channels to the inverted bottlenecks. Thus, the EfficientNet family was born (13). MobilenetV2 and EfficientNet are modern convolutional artificial neural

Table 1: Performance metrics of the models

Models		Validation Accuracy	Testing Accuracy	Testing ROC_AUC
Without Domain Knowledge	MobileNetV2	0.78	0.74	0.86
	EfficientNetB0	0.77	0.72	0.85
With Domain Knowledge	MobileNetV2	0.93	0.91	0.94
	EfficientNetB0	0.90	0.88	0.92

networks that can perform effective image classification with a smaller number of parameters.

In our study, we took the pre-trained versions of the MobileNetV2 and EfficientNetB0 models and applied additional training in the form of fine-tuning with the data set we had. For this purpose, we separated the feature extractor part of these models from the classifier part, vectorized the resulting feature maps, and added a 2-layer fully connected layer (FCN) containing 512 and 256 nodes. Finally, we connected the final 2-class classifier with the Softmax layer. To prevent overfitting, we added the DropOut operator, which selects nodes with a 30% probability between layers. (Figure 5)

We applied 100 epochs of training by giving 16 image batch sizes that were on the fly synthesized from the data set using the data augmentation techniques.

Statistical analyses

Python scripting language with a scikit-learn package was used for statistical analysis. Tensorflow and Keras libraries with Python were used for model building and analysis.

RESULTS

In the data set that we used in our study, a total of 4300 CT slices, 2150 of which were ischemic (50%: 2150/4300) and 2150 hemorrhagic (50%: 21500/4300) were used. The distribution of both classes was equal. On the other hand, since the patients were deidentified and anonymized, which is a mandatory step to make the data set available to the public, it was not possible to make comparisons about their age and gender distributions. However, considering that this image set was prepared to automatically detect the distinction between ischemic/hemorrhagic stroke and that it was presented as an award-winning competition and hoped to attract the attention of many researchers and find a solution to the problem, we can think that it was prepared balanced between the two groups. With the dataset which we just used [0-1] normalization and adjusted the input dimension into 224*224, accuracy values of 0.74 with adapted MobileNetV2 and 0.72 with adapted EfficentNetB0 in test time and 0.78 and 0.77 in the training set respectively were obtained in the group without preprocessing. On the other hand, in the data transformation group where bone structures were removed and pixel values were restricted by eliminating impossible values, an accuracy level of 0.91 with MobileNetV2 and 0.88 with EfficientNetB0 in test time and 0.93 and 0.90 in the validation set respectively were achieved (Table 1). This approach is an example of injecting domain knowledge into the model by narrowing the search space of the model, and its application to the problem of ischemic/hemorrhagic automatic stroke classification in the literature is the first to our knowledge. It has been a concrete example of the usefulness of domain knowledge in developing more effective models. Because the model can work more effectively by directing its search to the target without wasting time with impossible pixel locations and values.

DISCUSSION AND CONCLUSION

In this study, a model that can automatically classify stroke from anonymous axial CT images containing 2150 ischemic and 2150 hemorrhagic stroke diagnoses was developed. An accuracy value of 0.91 was achieved with MobileNetV2, which was prepared by eliminating impossible pixels and localizations.

Transfer learning approach was used in training the dataset prepared for stroke detection. MobileNetV2 and EfficientNet-B0 CNN architectures, pre-trained with the ImageNet dataset, were used for transfer learning (12,13).

Nazari-Farsani et al. achieved 73% accuracy in stroke detection with a data set consisting of Diffusion weighted imaging (DWI) and ADC images of 192 samples, including 106 strokes and 86 healthy cases (14).

In a study evaluating the success of the CNN model in detecting stroke using a dataset containing non-contrast CT images of ischemic stroke, hemorrhagic stroke, and normal images, an accuracy of 90% was obtained (15). However, only 45 CT images were available in this study. Additionally, for the test set, each class consisted of only 5 images. For these reasons, it can be said that the research findings are far from being generalizable.

Pereira et al. achieved the most successful results in stroke detection with CNN and non-contrast CT. These researchers evaluated the accuracy of the CNN model they developed on a cross-sectional basis using a data set of 300 slices (100 ischemic stroke, 100 hemorrhagic stroke, 100 normal) and obtained approximately 99% accuracy (16). In this study, which used the methodology closest to ours, a cross-section-based classification approach was used, and the small number of cross-sections used makes it difficult to generalize the results. Indeed, while 4300 slices were used for 2 classes in our study, 300 slices were used for 3 classes in this study. Considering that as the number of classes increases, the number of samples to be used must also increase, it is more reasonable to think that the 99% value reflects overfitting. To reduce overfitting, the authors did not mention an additional strategy. In our study, the measures taken to prevent overfitting were the greater number of samples, the application of data augmentation methods, and the use of a more homogeneous data set by purifying the signal from noise and feeding it to the model. Indeed, in the models we developed without taking precautions to adapt the signal into the desired range, the accuracy we achieved remained at 0.74, similar to Nazarani et al., even though the number of data we used was much higher. With the added methodology of narrowing the search space of the model using domain knowledge, the accuracy reached 0.91.

China et al. reached over 90% accuracy for ischemic stroke detection on non-contrast CT and Marbun et al. reached 90% classification accuracy for multi-class stroke prediction. (17,18)

In a study using GoogleNet to detect hemorrhagic stroke in the basal ganglia, 80% specificity, area under the curve (AUC=1) and 100% sensitivity were obtained (19). Arabbhsian et al. achieved 80% specificity, 73% sensitivity and AUC = 0.846 in their model for the triage of head CT scans for the detection of intracranial hemorrhage. With this model, the pathology detection time was reduced from 512 to 19 minutes (20).

In the study using the largest cohort for stroke detection, Oman and colleagues addressed the problem of middle cerebral artery (MCA) stroke detection using computed tomographic angiography (CTA) source images. Takahashi and colleagues used support vector machines (SVM) to identify the dot sign on noncontrast CT as a candidate for thromboembolism. They reached 93% and 82% accuracy, respectively (21,22). These studies also addressed the automatic classification of the stroke problem, and although the data sets and methodology they used were quite different from our study, they were able to obtain similar or less accurate values.

The limitations of our study were that due to its preprocessed data set and retrospective nature, the effect of patient demographics on the results cannot be evaluated optimally. However, it is a desirable feature for automatic classifiers to be able to make correct decisions regardless of demographics and acquisition conditions. Another important limitation was that slice-wise classification was employed due to the characteristics of the data set we have, and therefore there were limitations in generalizing the results obtained to the patient level.

Today, thrombolysis in the early stages and in appropriate patients is the gold standard in stroke treatment, and pre-hospital thrombolysis is on the agenda, which increases the importance of automatic stroke diagnosis (23). Stroke diagnosis using deep learning methods may be particularly useful for healthcare personnel who are not radiologists and are not familiar with stroke imaging but play an active role in stroke diagnosis and treatment. In this way, the selection of the patient who will benefit from the treatment and the speed of treatment decision making can be increased. In conclusion, this study, which achieved high accuracy rates in ischemic-hemorrhagic stroke classification, may contribute to automatic stroke detection and help physicians make rapid and appropriate treatment decisions.

Conflict-of-interest and financial disclosure

The authors declare that they have no conflict of interest to disclose. The authors also declare that they did not receive any financial support for the study.

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