IRSTI 50.53.17, 76.01.11 DOI: https://doi.org/10.26577/JMMCS.2021.v112.i4.09

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CONVOLUTIONAL DEEP LEARNING NEURAL NETWORK FOR STROKE IMAGE RECOGNITION: REVIEW

Abstract. Deep learning is one of the developing area of artificial intelligence research. It includes artificial neural network-based machine learning approaches. One method that has been widely used and researched in recent years is convolution neural networks (CNN). Convolutional neural networks have different research issues and medicine is one of the main ones. Today, the predominant global problem is acute cerebral blood flow disorder - stroke. The most important diagnostic tests for stroke are computerized tomography (CT) imaging and magnetic resonance imaging (MRI). However, late recognition and diagnosis by a specialist can affect the lives of many patients. For such cases, the role and help of convolutional neural networks are extraordinary. In-depth clustering neural networks apply non-linear transformations and abstractions of high-level models in large databases. Year after year, advances in the field of deep learning architecture, namely crate neural networks for the recognition of stroke, are making an important contribution to medicine's evolution. In this paper, a review of the achievements of deep learning neural networks in the recognition of stroke from brain images is considered. This review chronologically presents the main neural network block diagram and open databases providing MRI and CT images. In addition, a comparative analysis of convolutional neural networks are used in this study of stroke detection is exhibited, in addition achieved indicators of the methodologies used.
Key words:: artificial intelligence, deep learning, stroke, convolutional neural network, MRI, CT.

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Инсультті тануға арналған конволюциялық нейрондық терең оқыту желісі: шолу

Аңдатпа. Терең оқыту-жасанды интеллектті зерттеудің дамып келе жатқан салаларының бірі. Ол жасанды нейрондық желілерге негізделген машиналық оқыту әдістерін қамтиды. Соңғы жылдары кеңінен қолданылатын және зерттелетін әдістердің бірі – конволюциялық нейрондық желілер (CNN). Конволюциялық нейрондық желілер әртүрлі зерттеу міндеттеріне ие, ал медицина саласы – басты міндеттердің бірі болып табылады. Бүгінгі таңда бас миының қанмен қамтамасыз етілуінің күрт бұзылуы – инсульт, басым жаһандық проблема болып саналады. Инсульттің ең маңызды диагностикалық зерттеулері – компьютерлік томография (КТ) және магниттік-резонанстық томография (МРТ). Алайда, маманның уақтылы диагноз қойып, көмектесе алмай қалуы көптеген пациенттердің өміріне әсер етуі мүмкін. Мұндай жағдайларда конволюциялық нейрондық желілердің рөлі мен көмегі зор. Терең оқытудың конволюциялык нейрондық желілері үлкен мәліметтер базасында жоғары деңгейлі модельдердің сызықты емес түрлендірулері мен абстракцияларын қолданады. Жылдан жылға терең білім беру архитектурасындағы жетістіктер, атап айтқанда инсультты тануға, конволюциялық нейрондық желілер медицинаның дамуына айтарлықтай үлес қосады. Бұл мақалада инсультты мидың суреттерінен анықтауға нейрондық терең оқыту желілеринің жетістіктері туралы шолу берілген. Берілген шолуда нейрондық желінің негізгі схемасы хронологиялық түрде ұсынылған және МРТ мен КТ суреттерін ашық түрде қолданысқа беретін мәліметтер базасы келтірілген. Сонымен қатар, инсультты анықтауда конволюциялық нейрондық желілерді қолдануға салыстырмалы талдау, сондай-ақ қолданылатын әдіснамалардың жетістік көрсеткіштері ұсынылған.
Түйін сөздер: жасанды интеллект, терең оқыту, конволюциялық нейрондық желі, инсульт, МРТ, КТ.

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Сверточная нейронная сеть глубокого обучения для распознавания изображений инсульта: Обзор

Аннотация.Глубокое обучение является одним из развивающихся области исследования искусственного интеллекта. Она включает в себя методы машинного обучения, которые основаны на искусственных нейронных сетях. Одним из методов, который широко применяется и исследуется в последние годы, это - сверточные нейронные сети (CNN). Они имеют разный спектр задач исследований, и медицина одна из главных. На сегодняшний день, превалирующей глобальной проблемой считается острое нарушение кровоснабжения головного мозга - инсульт. Наиболее важными диагностическими исследованиями при инсульте считаются компьютерная томография (КТ), а также магнитно-резонансная томография (МРТ). Однако, несвоевременное распознавание и диагностирование со стороны специалиста могут повлиять на жизни многих пациентов. Для подобных случаев, роль и помощь сверточных нейронных сетей велика. Сверточные нейронные сети глубокого обучения использует нелинейные реформирования и абстракции моделей высокого уровня в больших базах данных. Год за годом, достижения в области архитектуры глубокого обучения, а именно сверточных нейронных сетей, для распознавания инсульта вносят значительный вклад в развитие медицины. В этой статье представлен обзор достижения нейронных сетей глубокого обучения в распознавания инсульта по изображениям мозга. В следующем обзоре хронологически представлено, основная блок-схема нейронной сети и открытые базы данных, предоставляющие изображения МРТ и КТ. Кроме того, представлен сравнительный анализ использования сверточных нейронных сетей при выявлении инсульта, а также достигнутые показатели используемой методологий.
Ключевые слова: искусственный интеллект, глубокое обучение, сверточная нейронная сеть, инсульт, МРТ, КТ.

1 Introduction

Data mining and deep learning have recently become the most popular topics among the scientific community, with surprising results in robotics, image recognition and artificial intelligence (AI). For many years, vast amounts of data have been collected for statistical purposes. Statistical curves can be used to forecast future behavior by describing the past and present. For decades, however, only traditional methods and algorithms have been employed, and refining these algorithms can result in successful self-learning [1]. Based on existing numbers, diverse criteria, and advanced statistical methodologies, better decision-making can be achieved. As a result, one of the most important applications of this optimization is in medicine, where vast datasets of symptoms, causes, and medical judgments can be utilized to anticipate the best approaches for quick mapping and treatment of stroke [2].

Stroke, also known as impaired cerebral circulation, is a central nervous system injury that is one of the major causes of death in developed countries. The average global lifetime risk of stroke grew from 22.8 percent in 1990 to 24.9 percent in 2016, according to The Global Burden of Disease 2016 Lifetime Risk of Stroke Collaborators, a relative rise of 8.9 after accounting for the competing risk of death from any cause other than stroke [3]. According to a research from the Centers for Disease Control and Prevention, stroke has risen from third position in 2007 to fifth position in 2017 due to mortality in the United States[4-6]. Nevertheless, there is the possibility of recovery in the injured area if treatment is given immediately. In the past, neuroimaging was performed mainly to exclude haemorrhagic, tumour diseases and infectious etiology from the ischaemic cause of stroke, and the role of diagnostic and therapeutic efficacy of neuroimaging and interventional neuroradiology in the acute treatment of stroke has been limited. With recent advances, neuroimaging is now an important part of stroke treatment. Information from CT scans can be useful to show the differences and similarities between the objects that make it up. The medical examiner performs visual segmentation during the examination in order to highlight specific areas capable of displaying pathological changes. However, the changes that appear on MRI and CT scans are usually subtle and in some cases imperceptible to simple visual analysis [7]. These digital images contain approximately 4,000 different shades of grey, whereas the human visual system can distinguish approximately 64 shades of grey in the same light condition. Thus, computational analysis can reveal a large number of features that are not easily detectable to the human observer. In this context, it is crucial to develop computational tools to help the physician to make a diagnosis in order to prevent, detect and monitor this neurological disease. These tools are based on research of medical images, as they can provide a lot of information about a patient's health. Such computational analysis often reduces the subjectivity of diagnosis while providing higher accuracy of invasive treatments [8]. The reported research suggests that an automated diagnostic system trained to use large amounts of patients' physiological signal and image data, based on artificial integration of advanced signal processing and deep learning in an automated fashion, can help neurologists, neurosurgeons, radiologists and other medical professionals make better clinical decisions. So far, convolutional neural networks, one of the deep learning techniques, have given good practical results in medical imaging research. In view of this, it is an urgent task to study convolutional neural network artificial intelligence for stroke diagnosis from medical-images.

The purpose of this paper is to provide an overview of deep learning convolutional neural networks and image processing approaches for detecting strokes in MRI and CT images.

2 Material and methods

Deep learning was initially coined in 2006 as a new discipline of machine learning research. It was first described in a similar way to hierarchical learning in [9], and it usually encompassed a wide range of pattern recognition-related disciplines of study. Deep learning takes into account a few crucial elements, including non-linear processing in layers or stages, as well as supervised or unsupervised learning. [10].The input algorithm in nonlinear multilayer processing of the active layer is the preceding layer. Between the layers, a hierarchy is formed to sort the value of the data that is regarded helpful. A similar time, supervised or unsupervised learning is linked to the class target label, with its presence indicating a supervised system and its absence indicating an unsupervised system.

2.1 Convolutional neural networks

Artificial neural networks have risen to prominence in the processing of unstructured data in recent years, including pictures, text, audio, and voice. Convolutional neural networks (CNNs) are giving very good results for such unstructured data. Whenever there is a topology associated with the data, convolutional neural networks are doing a good job on features extraction from given set of data. Architecturally, CNNs are inspired by multilayer perceptron neural network (MLP-NN). By setting local connectivity constraints between neurons of neighboring layers, CNNs make use of local spatial correlation. The core element of CNN is the processing of data through a convolution operation. The convolution of any signal with another signal creates a third signal that can reveal more information about the signal than the original signal itself. Convolutional neural networks (CNNs) are based on image convolution and detect features based on filters that are learned by CNNs through training. For example, we do not apply any known filters to detect disease or to remove Gaussian noise, but using a convolutional neural network to train, the algorithm learns the image processing filters itself, which may be very different from conventional image processing filters. For supervised learning, the filters are learned so that the overall cost function is reduced as much as possible. Typically, the first layer of convolution learns to detect the presence of stroke, while the second layer can learn to detect more complex forms that can be formed by the formation of different types of stroke, such as ischaemic, haemorrhagic, and so on. The third layer and beyond learns much more complex objects based on those created in the previous layer. One of the fundamental things about convolutional neural networks is the sparse connectivity that arises from the weight of sharing, which decreases the number of parameters to learn by a significant amount. The same filter can learn to detect the same edge in any given part of the image because of equivariance property, which is an excellent convolution property useful for object detection.

2.2 Convolutional neural network components

A convolutional neural network's typical components are listed below:

The image's pixel intensity will be stored in the input layer.. For the red, green, and blue (RGB) color channels, an input picture with width 64, height 64, and depth 3 would have an input size of 64x64x3.

The convolution layer takes the pictures from the preceding layers and convolves them with a specified number of filters to generate output object mappings. The supplied number of filters equals the number of output object mappings. TensorFlow's or PyTorch's CNNs have largely employed 2D filters up until now, however 3D convolution filters have just been added.

Theactivation functions for CNN are usually ReLUs. After traveling through the ReLU activation layers, the output measurement is the same as the input value. The ReLU layer gives the network non-linearity while also providing unsaturated gradients for the positive network inputs.

In terms of height and breadth, the merging layer will lower the dimensionality of the 2D activation cards. The depth or number of activation maps is unaffected and remains constant.

Traditional neurons in fully linked layers get distinct sets of weights from preceding layers; unlike convolution processes, there is no weight sharing between them. Through independent weights, each neuron in this layer will be linked to all neurons in the previous layer or all coordinate outputs in the output maps. Class output neurons are fed inputs from finite fully connected layers for classification.

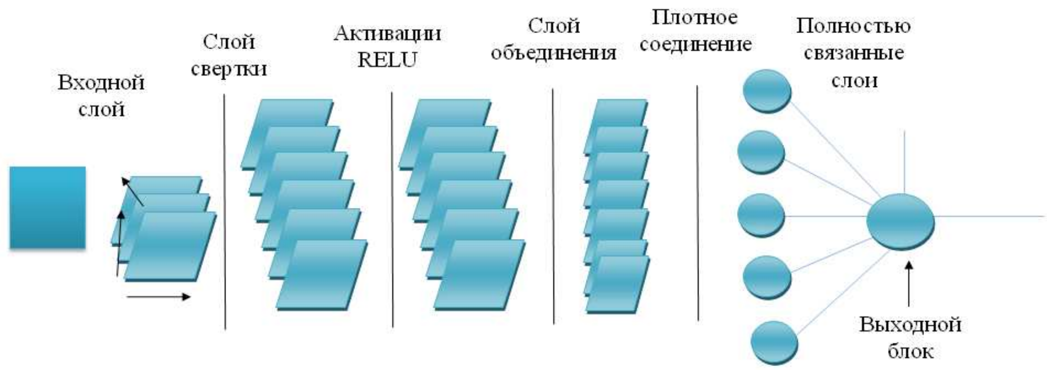

Figure 1 – Basic block diagram of a convolutional neural network

Figure 1 shows a basic convolutional neural network that uses one convolutional layer, one ReLU layer and one association layer, followed by a fully connected layer and finally an output classification layer. The network tries to distinguish images of the brain with a stroke from images of a healthy brain. The output device can be thought of as a sigmoid activation function because it is a binary image classification problem. Typically, for most CNN architectures, multiple layer-ReLU convolutional layer combinations are stacked one after the other before the completely unified layers.

2.3 Data sets Algorithms that use deep learning of convolutional neural networks are promising, but they require large training data sets to optimize the performance of large productions. For research and software development in stroke detection, vast datasets have been created and are publicly available, here are some of them:

- ISLES - data collection on patients with stroke and related expert segmentations.
- ATLAS Open Data provides open access to proton-proton collision data on the tank for educational purposes. Developed in collaboration with students and educators, ATLAS Open Data resources are suitable for high school and college students as well as researchers.
- BraTS, which uses multi-institutional preoperative MRI scanning and focuses on the segmentation of internally heterogeneous (in appearance, shape and histology) brain tumours, namely gliomas.
- BioGPS is a free, extensible and customizable gene annotation portal, a complete resource for studying gene and protein function, with datasets.
- The International Stroke Database is designed to provide the international stroke research community with access to clinical and research data to accelerate the development and application of advanced neuroinformatics in clinical settings to improve patient management and ultimately patient outcomes.

3 Results and discussion

Convolutional neural networks have proven to be a leader in image recognition and segmentation for large datasets among deep learning methods. Year by year, researchers in the field of brain lesions, namely stroke, get good results in identifying convolutional neural networks were used to study the illness in compatibility with various machine learning algorithms. Table 1 below shows the results of researchers in the field of stroke using convolutional neural networks over the last 4 years and their results.

Table 1. Comparative analysis of the use of convolutional neural networks for stroke detection

Link to article	Year of research	Neural network	Image type	Dice or Accuracy
[11]	2020	DCNN	MRI	0.86
[12]	2020	CNN	CT	0.88
[13]	2020	DCNN	MPT	74%
[14]	2020	3DRCNN	MRI	0.64
[15]	2020	CNN	CT	79%
[16]	2020	CNN	2DMRI	95.33%
[17]	2019	CNN (LeNet, SegNet)	MRI	96%, 85%
[18]	2019	3DCNN	KT	93%
[19]	2018	CNN	CT	90%
[20]	2018	CNN	CT	88%
[21]	2017	CNN	CT	0,89
[22]	2017	3DCNN	CT	0.996
[23]	2017	CNN	MRI	0.83

Convolutional neural networks applied to 3D and 2D MRI and CT images in combination with different algorithms and machine learning techniques have been found to give the best results.

4 Conclusion

This article reviewed the application of convolutional deep learning neural networks for the recognition of brain stroke from MRI and CT images. Neuroimaging has favorably aided in the diagnosis of brain disease and has also advanced the world of research in medicine. Due to the development of artificial intelligence, the collaborative use of deep learning techniques, namely CNN has shown good results in many works of brain scientists. Convolutional neural networks are a new era in the diagnosis of disease varieties, so it will be a good aid in detecting brain stroke for the specialist, enabling timely treatment and prolonging the patient's life.

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