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The application of convolutional neural networks in the diagnosis of Parkinson's disease on the basis of handwriting samples

***Abstract**. . The article presents an attempt to use a convolutional neural network to recognize Parkinson's disease on the basis of handwriting images recorded using a graphics tablet. Based on studies with participation of healthy subjects and patients with Parkinson's disease, the overall accuracy of 85.4% of the sick-healthy binary classification was achieved.*

Streszczenie.** Artykuł przedstawia próbę wykorzystania konwolucyjnej sieci neuronowej do rozpoznawania choroby Parkinsona na podstawie obrazów pisma zarejestrowanych za pomocą tabletu graficznego. Na podstawie badań z udziałem osób zdrowych i pacjentów z chorobą Parkinsona uzyskano całkowitą dokładność klasyfikacji binarnej chory-zdrowy na poziomie 85.4 % (**Zastosowanie konwolucyjnych sieci neuronowych w rozpoznawaniu choroby Parkinsona na podstawie próbek pisma.)

Keywords: convolutional neural networks, neural networks, Parkinson's disease, diagnostics, handwriting
Słowa kluczowe: konwolucyjne sieci neuronowe, sieci neuronowe, choroba Parkinsona, diagnostyka, pismo odręczne

Introduction

Parkinson's disease is currently the second most common neurodegenerative disease after Alzheimer's disease. Currently, more than 10 million people suffer from it in the world [1]. The main symptoms of this disease include tremor, limb stiffness, slowness of movement called bradykinesia and instability of body posture [2]. The appearance of any of the above symptoms can affect graphomotorics, i.e. the ability to write by hand. This process requires manual dexterity and correct visual perception, as it consists of precise, sequential hand movements with simultaneous hand-eye coordination [3]. For example, slowness of movement may manifest itself in the fact that a sick person needs a longer time than a healthy person to perform a writing task. Tremor, i.e. rhythmic, oscillating involuntary movements of the limbs can cause the handwriting to be irregular, blurred or ragged. In addition, one of the most characteristic features of Parkinson's disease is the phenomenon of micrography, which consists in a gradual reduction in font size as you write [4]. Therefore, changes in writing and problems with writing may be the first noticeable signs of Parkinson's disease and at the same time become the basis for automating the process of diagnosing the disease at an early stage of its development using technical tools for registering handwriting and processing of the acquired data. Of course, the occurrence of changes in writing and their severity will depend on the type and stage of the disease, however, differences may be noticeable in some cases already during visual analysis (Fig. 1).

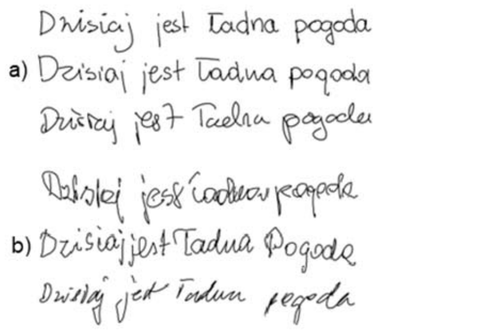

Fig.1. Exemplary samples written by healthy subjects (a) and subjects with Parkinson's disease (b)

In addition, it should be remembered that the way of writing is very individual and depends on many other factors not necessarily related to the disease, such as artistic skills, right-left-handedness, the way of holding a pen, age or simply the sense of aesthetics of the person writing.

Related works

Analysis of handwriting in terms of diagnostic capabilities over neurodegenerative diseases, including Parkinson's disease, is has been an active area of many research centres. Initially, the focus was only on the occurrence of the phenomenon of micrography, measuring the size of the font written on paper with a ruler [4-5]. The advent of electronic recording devices such as graphics tablets or electronic pens has opened up new possibilities for computer analysis of handwriting, due to the fact that, in addition to the trajectory of movement, these devices record additional information such as the pressure force or position of the pen in space [6]. There are many publications in the literature, the authors of which tried to determine on the basis of digital data as many parameters as possible that may indicate the occurrence of Parkinson's disease. The described parameters can be divided into two groups: static and dynamic. Static features include font size, height and width of individual strokes or length of the trajectory [7-15]. Dynamic features requiring time information include, for example, speed [9-17] or acceleration [12-17]. Pressure analysis has also been performed in some studies [12-17]. The acquisition of a number of characteristics made it possible to recognize the various symptoms of Parkinson's disease [8-11]. However, their coexistence, which takes place in most cases did not allow a reliable classification of sick people. Only the determination of a very large number of parameters and the use of an appropriate discriminatory algorithm made it possible to find a satisfactory classification result [12-15]. It is also worth mentioning that in most of the works the proposed parameters concerned single strokes, and as a model of writing took a sequence of single letters forming loops [11, 16] or words or sentences in which there were easily definable characters [7-10, 12-15]. The above considerations, however, present the so-called classic approach to recognizing the disease on the basis of handwriting samples, otherwise known as feature engineering, which consists in indicating vectors of numerical values characteristic of the population directly from the results of pre-processing experimental data and then using one of the machine learning methods, e.g. SVM classifier [12-15]. The recognition accuracy obtained in this way is about 80% and depends on the extraction and selection methods used and the classification methods. Thanks to modern neural network solutions, a different approach is possible, based not on feature vectors, but directly on whole images, in search of static visual information. The first papers on this subject have already been written [18-20], but they are based on the previously created database of handwriting (PaHaW) [21], on which classic methods have also proven themselves [12-15]. This database contains handwriting samples recorded while performing 8 different tasks They were among others spiral drawing, single letters, whole sentence. In contemporary literature, however, there is no use of convolutional neural networks to analyse handwriting for neurodegenerative diseases on new handwriting samples presenting only simple words or sentences, without taking into account additional tasks such as spiral drawing, which is not a typical handwriting.

Material

The material for the following tests was obtained as part of clinical trials conducted by a medical team at the Department of Neurology at the Medical University of Warsaw. A total of 48 people were examined, 24 of whom had Parkinson's disease (PD) at various stages of its development. All PD patients were pharmacologically prepared for examination in such a way that their condition corresponded to the early stage of the disease, where the symptoms of the disease are not yet sufficiently visible to clearly diagnose the disease. The characteristics of the study groups are presented in Table 1.

Table 1. Basic characteristics of the research group (PD) and the healthy control group (HC)

volunteers	male	female	total	age range
PD	8	16	24	28-84
HC	19	5	24	25-74

The Intous Pro Paper Edition PTH-860 graphics tablet from WACOM was used to register the handwriting samples. In addition to registering the position of the stylus on the tablet, it also allows you to read the pressure force and the position of the stylus in space (deviation from vertical, azimuth). Patients were asked to write five complete sentences "Today is nice weather" one below the other. The recorded handwriting samples were then processed into images of individual words. As a result, a total of 960 handwriting images of individual words were obtained, which were then used as training data in the process of training the structure of the CNN network.

Convolutional neural networks (CNN)

Neural convolutional networks are an important element of deep learning commonly used in image processing [22]. The idea of their operation arose many years ago, but their practical implementation into common has occurred relatively recently[]. In fact, they are a combination of an unsupervised process of automatic generation of image diagnostic features through the use of many hidden convolutional layers with a final classifier, usually in the form of a softnet solution. Figure 2 shows the structure of a convolutional neural network.

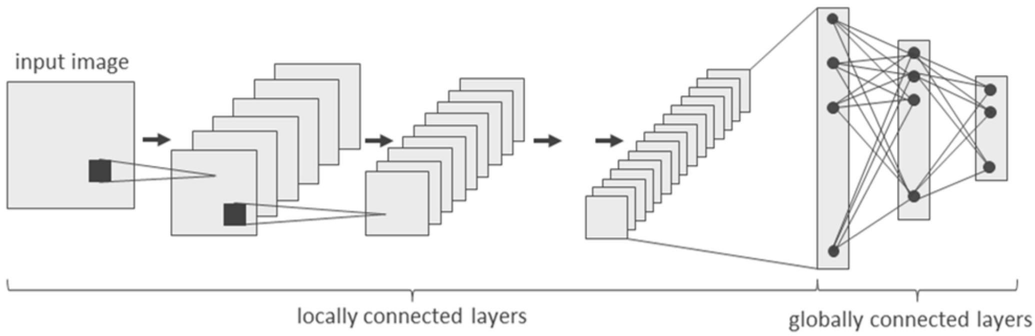

Fig.1. CNN network structure

In the structure of CNN, two parts can be distinguished:
- a series of successive layers with a local connection of neurons, the operation of which is based on a convolution operation providing diagnostic features,
- the end part of the network with a full neuronal connection, constituting the appropriate classifier [24].

Unfortunately, the construction of its own extensive structure of the CNN network, and training it to solve classification tasks, usually requires the use of a sufficiently large database of patterns. In the absence of such a database, an alternative approach called transfer learning is possible. It consists in using a trained network to solve a completely different task as a basic structure and additional training this structure using a new database of learners. First of all, a network trained on a large database of learning images should be download. Its first layers detect so-called low-level features such as edges, colors or characteristic clusters of pixels, while the final layers generate features adequate to the task for which the network was prepared. In the next step, the final layers should be removed and replaced with an untrained network structure, but adapted to the current, newly solved task. In the case of the diagnosis of Parkinson's disease, the structure had to be built so that it could distinguish two categories: "sick" and "healthy". With such a modification, the network, can be trained using the new database. Available network structures trained on a large database are, for example, AlexNet, GoogleNet, VGG-16, Inception3. However, their structures differ in the number of layers or the degree of development of the structure, and thus the number of weights whose values the network must calculate in the learning process. Therefore, the application of some of them will require a very long learning time, even in the transfer learning approach. Therefore, the AlexNet [25] network was used in this work, which has only 8 layers: 5 convolutional layers and 3 layers of full connection. Originally, this network was created to distinguish objects belonging to 1000 different classes in images, but the present considerations require distinguishing only two classes. Another issue that should be addressed using the transfer learning technique is the appropriate preparation of input data to the network requirements. ALexNet uses 227x227x3 colour images.

Results

In order to customize the AlexNet network, the last three layers, i.e. the fully connected, SoftMax and classifying layers, were removed and replaced with new ones, which, along with the remaining layers, were trained in the process of training the network. In order to reliably assess the process of classification of sick and healthy people, a commonly used cross-validation method was used. This method involves randomly dividing the entire dataset into N subsets of equal size, and then using a single set as validation data and the remaining subsets as training data. Then the process is repeated N times, changing each time the validation and learning sets. The classification results obtained by means of validation subsets are then averaged [24].

As a result of registration, handwriting samples were collected representing 5 sentences consisting of 4 words. In order to obtain as many images as possible, it was decided to create images of single words from the resulting file. Thus in total, 20 different images come from one patient. After examining a group of 48 people, the initial database consists of 960 images presenting single words. Examples of samples images created in this way from one sentence are shown in Figure 3.

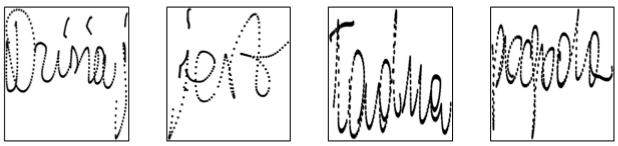

Fig.3. Sample word images

Using the 6-fold cross-validation technique, in each round, images from a randomly selected 40 people (20 from each class) were added to the learning data set, for a total of 800 images. Paintings from the remaining 8 people (160 paintings) became a validation set.

The use of more than one image from a person to train the network is a special case of augmentation, that is, increasing the number and diversity of learning data , in order to improve the operation of the network. Most often, this is done by performing a series of operations on a single image to create new images, different from the original one. In this work, the number of data was increased by entering different images coming from a person, without performing any operations.

The final classification decision for a person was made by majority vote from a decision worked out for each of the 20 images assigned to that person. Recognition results are expressed by Accuracy, Specificity, Sensitivity and Precision. Accuracy, sensitivity, specificity and precision are defined as:

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

(2) $$Sensitivity=\frac{TP}{TP+FN}$$

(3) $$Specificity=\frac{TN}{TN+FP}$$

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

where TP (True Positive) and FP (False Positive) represent the number of correctly classified people with Parkinson's disease and the number of actually healthy people diagnosed with the disease, respectively. Similarly, TN (True Negative) and FN (False Negative) represent respectively the total number of correctly classified healthy people and Parkinson's patients misclassified as healthy.

Finally, the accuracy of the diagnosis was achieved Acc at the level of 85.4%. Out of a pool of 48 people, it means only 7 incorrect classifications. The following values were obtained for the remaining quality measures of the classifier: Specificity 83.3%, Sensitivity 87.5%, Precision 84.4%. Figure 4 shows the obtained confusion matrix for the diagnosis of Parkinson's disease when the convolutional neural network was used.

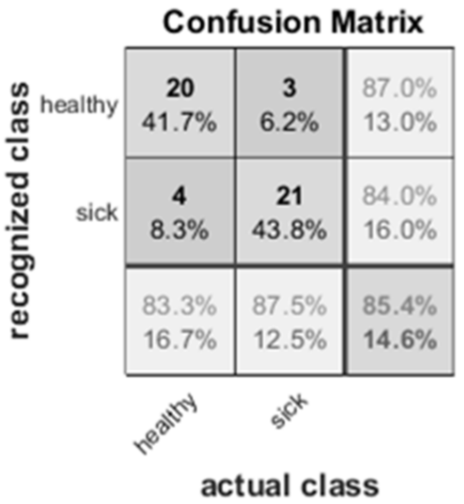

Fig.4. Confusion matrix

Conclusions

The article presents the possibility of using convolutional neural networks in the problem of recognizing Parkinson's disease based on handwriting images. The use of transfer learning technique on the basis of the most popular AlexNet network was presented. Based on the images obtained as a result of own recordings, the accuracy of recognition 85.4% was obtained. Due to the specificity of the study, the obtained results can be compared with the results in [18, 19], where CNN networks were used to recognize the disease in handwriting images. Both studies analysed handwriting samples from the PaHaW database [21] and used AlexNet. The authors [18] obtained Accuracy of 83%, Precision of 89%, Sensitivity of 84%, Specificity of 82%. However, this result were obtained by training 8 independent networks, each of which learned on images presenting other writing tasks, including spiral drawings, single letters and whole sentences. The final classification decision was made on the basis of one common vector of features formed by these networks. The authors of the work [18] also considered cases for single tasks and obtained Accuracy of only 68% score for single words. In [19], the authors obtained the Accuracy of 89.29% in the disease diagnosis on a single word, but this effect was obtained after deep interference in the network structure and the use of additional popular databases containing various images such as MNIST and ImageNet. The Accuracy result of 85.4% obtained by the authors of this paper is therefore definitely better than the result presented in [18] and slightly worse than the result in [19].

In further research, the authors plan to check how the presentation of data in the image will affect the accuracy of recognition and how the choice of network structure will affect the results.

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