Kamila BIAŁEK, Jacek JAKUBOWSKI, Rafał BIAŁEK

Military University of Technology, Department of Electronics

doi:10.15199/48.2025.03.06

The application of convolutional neural networks in age recognition based on handwriting samples

***Abstract**.. This paper presents an attempt to use a convolutional neural network to recognize the age group of people based on handwriting images recorded on a graphics tablet. A binary classification was performed between three age groups: young adults, middle-aged adults, and older adults.*

Streszczenie.** Artykuł przedstawia próbę wykorzystania konwolucyjnej sieci neuronowej do rozpoznawania przynależności do grupy wiekowej osób na podstawie obrazów pisma ręcznego zarejestrowanych za pomocą tabletu graficznego. Przeprowadzono klasyfikację binarną między trzema grupami wiekowymi: młodszymi dorosłymi, dorosłymi w średnim wieku i starszymi dorosłymi. (**Zastosowanie konwolucyjnych sieci neuronowych w rozpoznawaniu wieku na podstawie próbek pisma odręcznego)

Keywords: convolutional neural networks, neural networks, age recognition, handwriting
Słowa kluczowe: konwolucyjne sieci neuronowe, sieci neuronowe, rozpoznawanie wieku, pismo odręczne

Introduction

Handwriting is one of the basic human skills that is used in daily life. This process involves precise, sequential hand movements with simultaneous eye-hand coordination, which requires appropriate manual skills. Although the development of technology has caused handwriting to be used less frequently, it is still one of the basic behavioral biometrics. Graphism, or a set of graphic features of handwriting, commonly called handwriting style, is very individual and depends on many factors, including artistic abilities, right- or left-handedness, the way the pen is held, gender, age or simply the sense of aesthetics of the person writing. Age has a particularly significant impact on graphism because it is associated with mental and physical changes. From the moment one begins to learn to write until old age, both the handwriting style and the way it is created change. Aging can have a significant impact on handwriting in particular. The aging process is associated with neurodegenerative changes, including anatomical, physiological, and chemical changes occurring in the brain [1]. These changes specifically concern brain areas associated with high-level cognitive functions required to perform complex everyday activities [2]. Identification studies aimed at identifying the age-related group affiliation of the writer of a handwriting are widely used [3]. In forensic investigations, they help narrow the scope of the investigation to a specific age group, which translates into better efficiency in identifying and verifying the writer. In document examination, they support the process of distinguishing between attempted forgery and changes in handwriting resulting from aging of the writer [4,5]. Also in the case of diagnostic studies on the effect of symptoms of neurodegenerative diseases on handwriting, it is important to distinguish between changes in handwriting associated with normal aging processes and those resulting from the occurrence of the disease. Examples of diseases that can affect graphomotor skills include Parkinson's disease, Alzheimer's disease, dementia, or depression [6]. These diseases most often affect the elderly, which is why research in this field seems to be of particular importance. In the presented work, the authors attempted to use convolutional neural networks to recognize the age group of study participants based on handwriting images recorded with a graphic tablet.

Transformation of handwriting with age

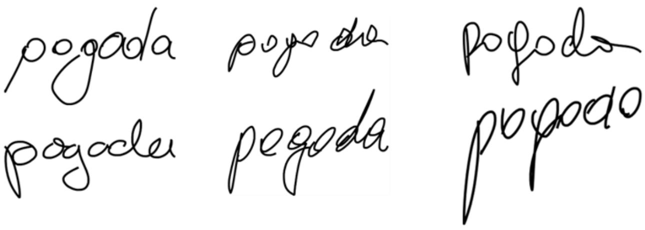
The process of shaping handwriting begins early and lasts for a dozen or so years. The first differences in handwriting appear after about 2 years of primary school and result from the differentiation of children's psychological characteristics such as temperament, self-confidence, intellect, and sense of aesthetics. The quality of vision and the musculoskeletal structure of the arm, forearm, hand, and fingers also influence the appearance of the first individual features of handwriting. As the writing progresses, certain group features begin to appear and become established. In particular, around the age of 13, clear quantitative and qualitative differences can be observed between the handwriting of women and men. Between the ages of 16 and 25, there is a phase of further improvement of writing skills. Abbreviations and simplifications begin to appear in writing, forced by the need to write faster and faster, and the automation of drawing an increasing number of letter groups occurs. In the period from the completion of school to old age, handwriting stabilizes and the way of writing becomes a permanent habit. This applies primarily to graphic features such as the construction of characters, the way they are connected, and the layout of the writing on the surface. However, this does not mean that the writing becomes unchangeable. The lack of systematic use of writing or a change in the nature of work from physical to mental and vice versa may have an impact on writing. Also, deterioration of health, through vision problems, disability, or the appearance of a neurodegenerative disease during this period will cause significant changes in handwriting [7]. The writing of older people gradually shows features that indicate a decrease in the psychophysical fitness of the performers. Studies have shown that older people write slower [8]. An increase in the size of the writing [8] and the distance between characters [5] is also typical for them. With age, the pressure of the writing medium on the surface decreases [4,5]. The freedom and fluidity of the line course decrease [4,5].

Related works

Handwriting analysis for age recognition is an active area of research. There are many publications in the literature with studies that aim to identify and describe age-related differences in handwriting. For example, the authors of [9] were the first to analyze the writing practices of healthy older adults. Previous work focused on analyzing the handwriting of children and adolescents. The authors described the characteristics of handwriting and writing behaviors of older adults based on the diary kept by 30 people over 65 years of age. The authors noted that older adults most often use handwriting to take notes and solve crossword puzzles. The participants did not write often in their daily lives, and the individual entries were short. Most of the collected samples were self-generated text, not copied or transcribed text. In [8], using statistical analysis, the authors conducted research based on kinematic measures of the handwriting process collected using a graphics tablet. 80 people aged 31 to 76 years and older were examined, divided into 4 age categories. The results confirmed that the time of writing and the font size increase with age. The authors of [4], who, based on the signatures of 42 healthy individuals aged 60 to 91, conducted a statistical analysis of some kinematic features such as writing time, font size, and pen pressure, reached similar conclusions. The main conclusions of the authors include the observation that the duration of vertical strokes and the writing disfluency increase with age, while the amplitude and speed of writing vertical strokes decreased with age. Pen pressure on the surface also decreases with age. Interestingly, the authors noticed that the influence of age on the kinematics of writing is stronger in men than in women. In [10], the team of authors developed a two-level clustering approach for online handwriting characterization style. At the first level, raw spatial-dynamic information was extracted, while at the second level, the style of word variability was extracted and transformed into a database of prototypical words. At the first level, linear discriminant analysis (LDA) detected features that distinguish different age groups. The authors used the publicly available IRONOFF database, supplemented by a database collected by the authors. The IRONOFF database contains handwriting samples from 880 people aged 11 and 86, recorded on a tablet in English and French. The study revealed three different types of elderly people. One specific to the elderly, where writing involved multiple lifts of the pen, long time on the surface, and low speed and acceleration. The other two groups shared features with other age groups. It was only after 2020 that studies began to appear in this area, aiming to classify people into different age groups based on handwriting samples, used a different approach. In [11] the problem of classification of four age groups was solved using Canny and Sobel edge images and k-means clustering. The proposed method was applied to the author's database containing 400 handwriting samples belonging to people aged 11-24 years, and the classification accuracy was 66.25%. The authors also used the proposed solution for the IAM and KHATT databases. The IAM database contains samples of sentences written in English from 168 people divided into two age groups (25-34 years and 35-56 years). The KHATT database contains Arabic handwriting data generated by 270 people divided into two age groups (16-25 and 26-56 years). The classification accuracies obtained by the authors of [11] are equal to IAM 63.6% and KHATT 64.4%, respectively. In [12], the KHATT database and the FSHS database containing 2000 Arabic handwriting samples divided into 2 age groups (16-24 and 25-55 years) were used to perform the classification using the SVM and KNN classifiers. They developed a feature set that included numerical parameters defining, among others, tilt irregularity, and pen pressure irregularity, text line irregularity. The classification accuracies obtained were the following: SVM-FSHS 71%, SVM-KHATT 65.2%, KNN-FSHS 63.5%, KNN-KHATT 67%. The authors of [13] also performed classification (SVM, random forest) between two age groups based on the feature set developed by the SFFS algorithm, using the author's database in Japanese. The key thing is that these studies distinguished between two extreme age classes. The first class represented adults (19-59 years) and the second class represented children (12-13 years old). Recognition results were 87.4% using SVM and 91.5% using random forest. The authors [14, 15, 16], who used the potential of convolutional neural networks in recognizing age group membership based on handwriting samples. The motivation to use this tool in the above problem is the fact that CNNs are based directly on whole images, without the need to process them in search of a feature vector, which is why they seem to be a suitable tool for analyzing handwriting images created as a result of writing. The authors [14], used the transfer learning technique and used pre-trained ResNet and GoogleNet networks to extract features, which were then fed to the input of a classic SVM classifier. In these studies, data from the above-mentioned FSHS database were used. The classification accuracies obtained by this method are 69.7% for ResNet and 61.1% for GoogleNet. In the works [11, 12, 14], the classification results are not very high and are in the range of 61% - 71%. However, they were obtained for classification between two similar age groups, where the differences in handwriting may not be adequately visible. None of the described databases contained handwriting samples from people over 56 years of age. In [13], the authors managed to obtain a result of the accuracy of assigning handwriting to the group of children or adults equal to more than 90%. This high result probably results from the characteristic features of children's handwriting, which is still in the process of development. An interesting study is an attempt at 11-class classification conducted in [15], where a database containing a total of 51,179 handwriting samples was used. The author's data processing method, which combines Fourier transformation, wavelet transformations, and the VGG-16 convolutional neural network, gave a result of accuracy of class assignment equal to 82.38%. It is worth noting that this impressive database contained samples written in as many as six languages. In [16], the authors made recognition of belonging to one of three age groups: young adults (18-32 years), middle-aged people (37-57 years) and older adults (62-90 years). Each time, a binary classification was performed. The author's database contained a series of 10 signatures (name and surname) collected from 156 people. The DBNet network was used for automatic signature detection on the recorded image, while a modified ResNet-50 network was used for processing and classification. The authors developed a specialized, multi-view network structure capable of simultaneously processing a set of k-samples of handwriting extracted from one participant. Thus, in the classification of younger adults vs. middle-aged adults, the accuracy was 79%, in the classification of middle-aged adults vs. older adults 74% and in the classification of younger adults vs. older adults 77%. In the context of this work, the results contained in [16] are most important, because they will serve as a comparison to the results obtained by the author.

Material

The handwriting image data for the analysis came from the author's database. The study involved 49 people (17 women and 32 men). All the people taking part in the study were right-handed, their native language was Polish, and they had at least secondary education (they were students and academic and administrative staff of the Faculty of Electronics of the Military University of Technology in Warsaw). None of the participants reported skeletal disorders or vision problems that significantly affected handwriting. In addition, none of the participants took medications affecting the central nervous system. The Intous Pro Paper Edition PTH-860 graphics tablet from WACOM was used to record the handwriting. The tablet allows for recording the coordinates of the pen's location on the tablet surface as well as the pressure force and the angles of the pen's tilt during writing. During the study, the patients were asked to write down the sentence: "The weather is nice today" (in the national language of the patients, it was "Dzisiaj jest ładna pogoda") five times, one after the other within the same recording. The size and layout of the paper writing on the sheet were arbitrary and depended only on the preferences of the writer. The recorded samples were then processed into single-word images in a format appropriate to the selected network structure. This resulted in a total of 960 single-word writing images, which were then used as training data in the CNN structure training process. Examples of images recorded for three sample age groups are presented in Figure 1.



a) b) c)

Fig. 1. Examples of handwriting samples from people: a) under 30 years of age, b) about 50 years of age, c) over 80 years of age.

Three age groups were selected from all the examined people: young adults (YA), middle-aged adults (MA), and older adults (OA). Due to the fact that there are no clear premises suggesting age limits for which age-related changes in handwriting will be visible or not, the individual age ranges were selected through experiments and based on the literature. According to research [17], the greatest decline in motor functions related to age occurs after age of 70. Due to this and the older small number of data, the group was defined as people over 65 years of age. In the case of younger people, the age range between 26 and 33 was chosen. The upper limit is similar to that used in [16], where the younger people were defined as people between 18 and 32 years of age. The lower limit, on the other hand, results from the fact that handwriting stabilizes after the age of 25, as indicated in [7]. In the case of middle-aged people, the age range between 46 and 60 was chosen. The characteristics of the individual age groups are presented in Table 1.

Table 1. Basic characteristics of the age groups

group	age	number of people	mean age	standard deviation of age
YA	26 - 33	12	28,9	2,5
MA	46 - 60	13	54,9	4,0
OA	65 - 84	15	73,1	6,1

Method

Convolutional neural networks are deep networks commonly used in image processing because they automatically generate a set of features based on an image fed directly to the network input. The structure of convolutional networks consists of two parts, one of which is a series of convolutional layers that generate a feature vector at the end, and the other is a classifier with a full connection of neurons. The basis of convolutional networks is the convolution operation during which the filter mask moves across the entire image with a specified step, generating subsequent pixel values of the resultant image, taking into account the value of the filter mask. The convolution operation is performed multiple times, using filters with different weight values. The characteristic way of processing means that increasingly deeper layers recognize increasingly detailed features of the image. However, building your own sufficiently developed network structure and using it to solve classification tasks requires the use of a sufficiently large database of patterns. In the absence of such a database, the transfer learning technique is used, which consists in using a network pre-trained to solve a completely different task and only retraining this structure with a new set of data. Due to the different nature of the problem to be solved, the last layers of the network should be modified accordingly, so that the number of outputs corresponds to the number of classes in the classification problem being solved. Currently, there are publicly available libraries that contain ready-made network structures trained on very large databases. Examples include the following. AlexNet, GoogleNet, or ResNet. However, despite the use of transfer learning, some databases are still too small for the convolutional network to be able to generalize knowledge based on them, and using too small a training set in the case of a large-capacity network will lead to overfitting. However, in practice, the number of data is often limited and collecting a larger set is not easy, and sometimes even impossible. In such a case, the so-called data augmentation is performed, which consists in increasing the training set by appropriate transformations of the input data. Due to the processing method, many augmentation techniques can be distinguished. In the traditional approach, geometric transformations (image shift, scaling, rotation, or reflection) or colour transformations (changing brightness, contrast, or saturation) are used. In this work, a different approach is taken, increasing the amount and variety of data by introducing different images from a given person without performing any operations, and then developing a final decision based on the system's response to each image from a given person.

Results

In this work, the AlexNet network with 5 convolutional layers and 3 fully connected layers was used, which was originally created to distinguish objects belonging to 1000 different classes. In order to adapt the network to the task of recognizing the age group, its last three layers were removed, i.e. the fully connected, softmax, and classification layers, and replaced with new ones, which, together with the remaining layers, were trained in the network training process. The new fully connected layer contains two neurons, so it distinguishes two age categories. Binary classification was carried out in three variants: YA vs. MA, MA vs. OA and YA vs. OA. To reliably evaluate the classification process, the commonly used cross-validation technique was used. Due to the fact that a person received as many as 20 images of words, the final classification decision for a given person was made by majority voting from the 20 individual decisions developed for each person. The classification result was expressed by accuracy, calculated as the ratio of all correct classifications to all classified cases.

The results obtained for age group recognition accuracy are presented in Table 2. Figure 2 presents the confusion matrices.

Table 2. Age group recognition accuracy results

	Accuracy [%]
YA vs. OA	92,6 %
YA vs. MA	76,0 %
MA vs. OA	78,6 %

In the case of binary classification YA vs. MA and MA vs. OA, accuracy results similar to those of the authors [16] were obtained. For the binary classification YA vs. MA, an accuracy result of 76.0% was obtained, while the authors of [16] obtained 79%. The binary classification MA versus OA gave a result of 78.6%, while in [16] the authors obtained 74%. In the case of the classification YA vs. OA, an accuracy result of 92.6% was obtained, which is much better than in [16], where for similar age ranges of the analyzed groups (YA 18-32, OA 62-90) a recognition accuracy of 77% was obtained.

recognized class		actual class YA	actual class OA
	YA	11	1
	OA	1	14

a)

recognized class		actual class YA	actual class MA
	YA	11	4
	MA	1	8

b)

recognized class		actual class MA	actual class OA
	MA	8	1
	OA	5	14

c)

Fig. 2. Confusion matrices of binary classification: a) YA vs. OA, b) YA vs. MA, c) MA vs. OA

Conclusions

The article presents the possibility of using convolutional neural networks and an original approach to data processing in order to increase their number in the problem of recognizing a person's age group based on handwriting samples. The use of the transfer learning technique and the pre-trained AlexNet network is presented. Binary classification was performed between three groups in all combinations, i.e., younger adults vs. older adults, younger adults, vs. middle-aged adults and middle-age adults vs. older adults. The results were compared to those obtained in similar studies, obtaining similar values of age group recognition accuracy for two cases. In the case of the classification of younger adults vs. older adults, a significantly higher result of 92.6% was obtained. Despite a significantly smaller database, the results obtained are very promising and show the potential of the applied methodology. In further studies, the authors plan to extend the research by collecting a larger database and checking the performance of other available convolutional network structures.

***Authors**: mgr inż. Kamila Białek, Wojskowa Akademia Techniczna, Instytut Systemów Elektronicznych, ul. Gen. Sylwestra Kaliskiego 2, 00-908 Warszawa, E-mail: kamila.jadczak@wat.edu.pl; dr hab. inż. Jacek Jakubowski, Wojskowa Akademia Techniczna, Instytut Systemów Elektronicznych, ul. Gen. Sylwestra Kaliskiego 2, 00-908 Warszawa, E-mail: jacek.jakubowski@wat.edu.pl; dr inż. Rafał Białek, Wojskowa Akademia Techniczna, Instytut Systemów Elektronicznych, ul. Gen. Sylwestra Kaliskiego 2, 00-908 Warszawa, E-mail: rafal.bialek@wat.edu.pl.*

REFERENCES

[1] Treitz, F. H., Heyder, K., & Daum, I. (2007). Differential course of executive control changes during normal aging. Aging, Neuropsychology, and Cognition, 14(4), 370-393
[2] Lin, H., Chan, R. C., Zheng, L., Yang, T., & Wang, Y. (2007). Executive functioning in healthy elderly Chinese people. Archives of Clinical Neuropsychology, 22(4), 501-511
[3] Alaei, F., & Alaei, A. (2023). Review of age and gender detection methods based on handwriting analysis. Neural Computing and Applications, 35(33), 23909-23925
[4] Caligiuri, M. P., Kim, C., & Landy, K. M. (2014). Kinematics of signature writing in healthy aging. Journal of forensic sciences, 59(4), 1020-1024
[5] Wang, J. (2017). A Comparison of the Identifying Features of Imitated Handwriting and Elderly Handwriting. Journal of Forensic Science and Medicine, 3(1), 38-41
[6] Shukla, A. W., Ounpraseuth, S., Okun, M. S., Gray, V., Schwankhaus, J., & Metzer, W. S. (2012). Micrographia and related deficits in Parkinson's disease: a cross-sectional study. BMJ open, 2(3), e000628
[7] Koziczak, A. (1997). Metody pomiarowe w badaniach pismoznawczych. Wydawnictwo Instytutu Ekspertyz Sądowych
[8] Rosenblum, S., Engel-Yeger, B., & Fogel, Y. (2013). Age-related changes in executive control and their relationships with activity performance in handwriting. Human movement science, 32(2), 363-376
[9] Van Drempt, N., McCluskey, A., & Lannin, N. A. (2011). Handwriting in healthy people aged 65 years and over. Australian Occupational Therapy Journal, 58(4), 276-286
[10] Rosales, J. C., Marzinotto, G., El-Yacoubi, M. A., & Garcia-Salicetti, S. (2016). Age characterization from online handwriting. In Pervasive Computing Paradigms for Mental Health: 5th International Conference, MindCare 2015, Milan, Italy, September 24-25, 2015, Revised Selected Papers 5 (pp. 176-185). Springer International Publishing
[11] Basavaraja, V., Shivakumara, P., Guru, D. S., Pal, U., Lu, T., & Blumenstein, M. (2019, September). Age estimation using disconnectedness features in handwriting. In 2019 International Conference on Document Analysis and Recognition (ICDAR) (pp. 1131-1136). IEEE
[12] Najla, A. Q., Khayyat, M., & Suen, C. Y. (2023). Age detection from handwriting using different feature classification models. Pattern Recognition Letters, 167, 60-66
[13] Shin, J., Maniruzzaman, M., Uchida, Y., Hasan, M. A. M., Megumi, A., Suzuki, A., & Yasumura, A. (2022). Important features selection and classification of adult and child from handwriting using machine learning methods. Applied Sciences, 12(10), 5256
[14] Najla, A. Q., & Suen, C. Y. (2022). Transfer Learning to Detect Age From Handwriting. Adv. Artif. Intell. Mach. Learn., 2(2)
[15] Huang, Z., Shivakumara, P., Kaljahi, M. A., Kumar, A., Pal, U., Lu, T., & Blumenstein, M. (2023). Writer age estimation through handwriting. Multimedia Tools and Applications, 82(11), 16033-16055
[16] Asci, F., Scardapane, S., Zampogna, A., D'Onofrio, V., Testa, L., Patera, M., ... & Suppa, A. (2022). Handwriting Declines with Human Aging: A Machine Learning Study. Frontiers in Aging Neuroscience, 14, 889930
[17] Rodríguez-Aranda, C. (2003). Reduced writing and reading speed and age-related changes in verbal fluency tasks. The Clinical Neuropsychologist, 17(2), 203-215