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DEVISING AN APPROACH TO PERSONALITY IDENTIFICATION BASED ON HANDWRITTEN TEXT USING A VISION TRANSFORMER

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The object of this study is the approach to personality identification based on handwritten text using machine learning methods. Increasing the accuracy of personality identification and automating feature extraction could make it possible to perform more accurate analysis of handwritten text. A functional model has been built, and an experimental study of the proposed approach was conducted. The results of the study showed that the proposed approach increased the overall accuracy of identification, compared to other studies, as evidenced by the obtained accuracy values with the lowest indicator of 94.84 % for Friendliness and the highest 99.48 % for Conscientiousness. The accuracy indicator also improved compared to other models, as evidenced by the average accuracy value, which increased from 0.65 to 0.94. Such results were obtained through the use of the "Vision Transformer" method, which makes it possible to remove the need for feature extraction as a separate step, and the scale-invariant feature transformation approach made it possible to extract relevant image patches. An experimental validation was conducted using retrieval and classification approaches, which minimizes the variability of the results. The use of the Big Five model and the CVL dataset improves the accessibility of the study for comparison and reproducibility. In practice, handwriting analysis is widely used in forensics, for personnel selection, as well as in other areas of activity. The results increase the reliability of automated handwriting analysis systems in the area of personality identification, which could help graphologists and handwriting experts in their work both to assess personality traits and to determine whether a certain handwritten text belongs to a specific person

Keywords: convolutional neural network, handwriting analysis, functional model, vision transformer

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1. Introduction

Handwriting remains important in many areas of human life, despite the fact that its use in personal communication has decreased due to technological development of humankind.

A person's handwriting has unique features that are related to their personality traits, health, abilities, and character. This creates a theoretical basis for the analysis of handwriting.

Handwriting analysis has three main branches: graphology, handwriting experts, and forensic linguistics [1]. Graphology studies the behavior of a person, which can be recognized from handwriting. The reliability of graphology is characterized by the fact that the measurable variables in handwriting are extremely consistent [1].

Identifying personality during handwriting analysis is a type of behavioral biometric identification, which is well recognized by psychologists, neuroscientists, paleographers, forensic scientists, document analysts, and computer science researchers. Similarly, the existence of a connection between handwriting and various demographic characteristics of text authors, such as gender, left- or right-handedness, and age, has also been confirmed by psychologists and neuroscientists [2].

Handwriting personality analysis is used in many areas of human activity. Areas of activity include forensics, medicine, psychology, personnel selection, self-development or even partner compatibility.

For example, in forensics, graphology and handwriting analysis play an important role in criminal investigations and legal proceedings. In this case, handwriting personality analysis is used to create a psychological portrait of a criminal [3], because handwriting can indicate the emotional state of the criminal at the time of the crime, their level of aggression, impulsivity, etc. Handwriting can also provide important context for understanding the circumstances of the crime [4].

In medicine, graphology is used to detect early signs of neurological diseases, such as Parkinson's or Alzheimer's disease, as well as to monitor the condition of patients with mental disorders.

In psychology, graphology is used to assess personality, diagnose psychological problems, such as depression or anxiety, and understand the emotional state of patients.

Modern technologies significantly expand the capabilities of graphology and handwriting examination. Modern cameras, owing to their high resolution, make it possible to capture the smallest details of handwriting, and specialized software, in particular, created on the basis of machine learning technologies, helps conduct analysis using measurements, comparisons, and visualizations.

Further scientific research in this area could help improve handwriting analysis methods and increase the accuracy of personality identification. In addition to increasing the accuracy of analysis, an important direction of development is also enhancing objectivity, as well as devising standards and recommendations for handwriting examination, including using automated interactive statistical methods [5].

Therefore, research on personality identification based on handwritten text is relevant.

2. Literature review and problem statement

During the analysis of handwriting for personality identification, the difference between written samples and standard writing is investigated and, based on this, the personality of the person providing the writing sample is determined [1]. Research in the field of personality identification includes a wide range of approaches based on different methods. Considering the type of features as a functional context, the methods reported in the literature can be categorized into four main groups: structural, textural, grapheme, and based on machine learning [6].

Analyzing the research in the field of personality identification, it was found that in [7] a 3-level neural network architecture with ANN, SVM, and KNN classification at the 3rd level was proposed, which demonstrated an accuracy of 86.7 %, the Myers-Briggs type indicator was used as personality types, and a private set of 64 subjects was selected as a data set. Objective difficulties associated with the lack of existing data sets, a complex feature extraction system, and a low-efficiency neural network system as a feature aggregator led to the fact that in [8] the approach to a 3-level architecture was improved as follows:

– the base layer includes normalization and segmentation;

– the intermediate layer generates a handwritten text (HM) map using binary code;

– the top layer performs classification using a forward neural network (FFNN).

The results of this approach showed an accuracy of 84.4 %. The Big Five type indicator was used as the personality types, and a private set of 128 subjects was selected as the data set. However, the issues related to overfitting and the need for manual correlation of graphological features with the features of the type indicator remained unresolved. The reason for overfitting can be both a poorly broken data set and an unsuitable model that performs the classification. An option to overcome the relevant difficulties may be the use of specialized methods for classification.

This is the method used in [9], in which the authors developed a classification structure based on SVM and used pattern matching to extract letters, which demonstrated an accuracy of up to 97 %. As personality types, a special set of traits was used to assess the candidate's employability from an HR perspective, and as a dataset, a private set was selected, which included 1890 samples of handwriting images. However, the results indicate a very narrow focus of the study, aimed at determining the level of employability based on a limited set of images.

However, in work [10] with a similar classification method, the authors compared the segmentation of the left, right, upper, and lower fields and used SVM for classification. As a result, an accuracy of 82.73 % was demonstrated; in the work, no personality types were used, and a private set was selected as a dataset, which included 42 subjects.

In [11], a classification based on convolutional neural networks (CNN) with SGD and AdaDelta optimization methods was proposed, and an accuracy of 82.5 % was demonstrated. This was achieved due to the fact that instead of personality types, only graphological features such as fields, line spacing, word spacing, and word inclination were tested. A private set of 128 subjects was chosen as the data set.

In those two works, the issue of the feasibility of using such approaches as CNN and SVM for the feature extraction stage remained unresolved. Despite the fact that they can cope with this task, they require large data sets for training. It should also be noted that those works lack a personality identification component, which makes the relevant studies inappropriate for comparison in our work.

An option for using more appropriate technologies for feature extraction is work [12], in which the authors proposed to perform feature extraction using the Histogram Oriented Gradient (HOG) technique and classify using SVM; an accuracy of 80 % was demonstrated. 5 personality traits were used as personality types, namely Energetic, Extravert, Introvert, Untidiness, and Optimism, and a private set of 50 subjects was selected as the data set. Although the histogram oriented gradient method is widely used in image processing and computer vision for object detection, it has a number of disadvantages, such as sensitivity to noise and artifacts in images. If we consider this approach in the context of text recognition, the disadvantages include insensitivity to minor changes due to its focus on strong gradients. A variant of overcoming the corresponding difficulties can be template matching, which is exactly the approach used in [13].

In [14], the authors used a CNN model and logistic regression, and selected seven features for the classification task, and an accuracy of 65 % was demonstrated. The Big Five personality type indicator was used as the personality type, and a private set of 112 handwriting image samples written by ten subjects was selected as the data set.

In [13], the authors proposed a deep neural network architecture based on CNN with long short-term memory (LSTM) and connectionist temporal classification (CTC); and an accuracy of 97.7 % was demonstrated. In the study, instead of personality types, only graphological features such as margins, line spacing, word spacing, word slant, baseline, pen pressure, and others were tested. The public IAM dataset was chosen as the data set, which included 1539 handwriting samples written by 657 subjects. However, issues related to the mapping of graphological features to certain traits remained unresolved. An option to overcome these difficulties may be the use of a type indicator, which is the approach used in [14–16].

In [15], the authors proposed a new personality trait level definition model (PTLDM), where they use a personality analysis network (PAN) and PersonaNet for classification; an accuracy of 65 % was demonstrated. The Big Five personality type indicator was used as the personality type, and a private set of 125 subjects was selected as the data set. The results show that the presented deep learning models perform worse in classification than other methods. The reason for this may be that deep learning models can be computationally expensive and difficult to train, and the size and quality of the data set affect the performance of the model. In addition, traditional deep learning architectures, such as CNNs, may not be optimally suited for detecting subtle but important features of handwriting. In this context, the study of Vision Transformers, which, owing to the attention mechanism, are able to more effectively model the relationships between different parts of the text, might prove promising. Another option to overcome the difficulties may be to use classification methods such as semi-supervised learning with a generative adversarial network.

This is the approach used in [16]; the authors proposed to extract features using a graph-based written representation approach and perform classification using a semi-supervised generative adversarial network (SGAN), which made it possible to achieve an accuracy of 91.3 %. The Big Five type indicator was used as personality types. And a private set of 173 subjects was chosen as the data set. However, graph-based feature extraction is problematic due to its computational complexity and sensitivity to variations in handwriting style, which leads to inaccurate or unreliable results. In addition, creating a graph structure may cause the loss of some of the information present in the original handwriting, and for specific tasks may require complex tuning of parameters and functions, which makes the search for an alternative relevant. From a classification perspective, the issue of training the model remains a challenge; SGAN has been trained on labeled, unlabeled, and generator-generated data. This may be due to the competitive nature of the training process and the dual nature of the model. Traditional machine learning can be an option to overcome these challenges, where models are generally simpler, trained exclusively on labeled data, and often provide better performance for classification tasks. However, there are also fundamentally new approaches, such as the Vision Transformer, which, although it belongs to deep learning, is significantly different from traditional CNNs. The Vision Transformer has the potential to combine the advantages of deep learning with the efficiency of extracting important handwriting features, making it a promising area for further research.

The application of the Vision Transformer to handwriting analysis could open up new possibilities for feature extraction and classification. Due to its ability to model long-range dependences, the Vision Transformer could potentially detect complex patterns in handwriting that conventional methods cannot detect. The Vision Transformer is able to learn on large data sets and considers images as a sequence of patches. It also uses the attention mechanism to model the relationships between patches, which makes it possible to capturing both local and global features, which can lead to a more accurate definition of personality traits.

Based on the analysis, it can be seen that some of the studies [10, 11, 13] were limited to the extraction of graphological features and did not use indicators of personality types in their studies. This indicates the need for more comprehensive approaches to research using certain indicators of personality types.

Two studies [7, 12] that used the Myers-Briggs Type Indicator and the 5 personality traits (Energetic, Extraverted, Introverted, Conscientiousness, and Optimism) resulted in mediocre accuracy ranging from 80 % to 87 %.

If we consider studies [8, 14–16] that used the Big Five personality type indicator, we can see that this area still has room for improvement. This is evidenced by the fact that the obtained accuracy of personality identification is still below 92 %.

From the point of view of feature extraction, one can see the diversity of the choice of graphological features for conducting research and the ambiguity of comparing these features with indicators of personality types, which is generated as a result of the subjective choice of graphological features.

Thus, the combination of these problems and shortcomings indicates the need for additional research in the field of personality identification based on handwritten text.

All this gives grounds to argue that it is advisable to conduct research into personality identification using a personality type indicator, machine learning methods, and automated feature extraction.

3. The aim and objectives of the study

The purpose of our work is to develop an approach to identify personality based on handwritten text using machine learning methods. Increasing the accuracy of personality identification and automating feature extraction could make it possible to perform more accurate analysis of handwritten text when identifying personality. In turn, this would increase the reliability of automated handwriting analysis systems in the field of personality identification, which could help graphologists and handwriting experts in their work.

To achieve the goal, the following tasks were set:

– to build a functional model of personality identification using such machine learning methods;

– to conduct an experimental study of the proposed approach.

4. The study materials and methods

The object of our study is personality identification based on handwritten text.

The main hypothesis of the study assumes that the use of machine learning methods, such as vision transformers, could allow for effective and accurate personality identification during handwritten text analysis. This would help graphologists and handwriting experts conduct analysis and provide a more accurate and complete assessment through automation.

For a comprehensive approach to personality identification, the choice of a personality type indicator remains important. In this study, the Big Five personality type indicator was used. Study [17] that compared psychological tests for personality assessment has shown that despite the fact that algorithms trained on other tests may have better performance, the Big Five traits are much more informative and have greater variability in performance depending on the algorithm. The Big Five model defines personality according to 5 bipolar scales: Extraversion (sociability versus shyness); Neuroticism (secure or neurotic); Agreeableness (friendliness versus ugliness); Conscientiousness (organization versus carelessness); Openness to experience (insightful versus unimaginative).

The research used a public dataset of handwritten text images as the input data source. The CVL dataset consists of images of cursive handwritten texts in German and English, selected from literary works [18]. The dataset consists of 7 different handwritten texts for each subject and a total of 310 authors participated in the dataset [18]. The research was conducted using a part of this handwritten text dataset with a total of 404 images and 75 subjects.

To work with machine learning models, the dataset is divided into the following parts: training, validation, and testing. This approach has the disadvantage that the accuracy can vary depending on the test set. In order to overcome this problem, a double validation approach was used. This approach involves performing validation using retrieval and classification approaches.

The image retrieval approach is based on calculating distances or similarities between images [19]. Retrieval engines calculate the distance or similarity of a requested image to other images in a dataset. The most similar images (i.e., those with the smallest distances) are returned as retrieval results.

The approach to image classification is based on assigning predefined categories/labels based on their visual content. Classification engines are trained on categorized/labeled datasets to recognize patterns and classify new unlabeled data.

The Vision Transformer (ViT) [20] was used as a machine learning model. This model uses attention as the main learning mechanism. An overview of the model is shown in Fig. 1.

The basis of the vision transformer is the Transformer Encoder, which consists of two main layers: multi-head self-attention and a feed-forward neural network. The Transformer Encoder is responsible for processing input tokens using two main layers to create context-sensitive representations. The multi-head self-attention performs the following functions: captures the relationships between several patches of the input sequence, calculates a weighted sum of patch embeddings to focus on important patches while taking into account both global and local context. The function of the feed-forward neural network is reduced to the formation of nonlinearity and the ability to learn complex relationships between patches. The result of the work of each of these layers is transmitted to the normalization and residual connections sub-layer, which is responsible for stabilizing and accelerating learning by normalizing the inputs for each of the layers and helps to mitigate the problem of vanishing gradient.

The CVL dataset was created and intended for author identification, so in addition to the unique identifier that identifies the author, additional markings need to be created to make it possible to use the dataset to identify personality traits. Handwritten text was analyzed manually and using graphological features, personality traits were determined according to the Big Five model, and an appropriate identifier was assigned to each image in the dataset.

The correlation of graphological features to personality traits was formed as follows:

– openness to experience: baseline – ascending (indicating optimism and ambition), slant – reclined (indicating independence, originality), line spacing – wide (indicating creativity and need for space), word spacing – wide (indicating independent thinking), pen pressure – light (indicating sensitivity), font size – large or variable (indicating creativity);

– conscientiousness: baseline – straight (indicating self-discipline and organization), slant – straight (indicating practicality and control), line spacing – regular (indicating orderliness), word spacing – regular (indicating adherence to norms), pen pressure – regular (indicating balance and control), font size – regular (indicating practicality);

– extraversion: baseline – ascending (indicates enthusiasm and confidence), slant – inclined (indicates openness and sociability), line spacing – normal or wide (indicates outgoing nature), word spacing – normal (indicates ease of communication), pen pressure – Heavy (indicates persistence), font size – large (indicates expressiveness);

– agreeableness: baseline – straight or slightly ascending (indicates sincerity), slant – straight or slightly inclined (indicates empathy), line spacing – normal (indicates cooperation), word spacing – normal or slightly wide (indicates tolerance), pen pressure – light or normal (indicates tenderness), font size – normal or slightly rounded (indicates warmth);

– neuroticism: baseline – descending (indicating pessimism or fatigue), slant – irregular (indicating emotional instability), line spacing – narrow (indicating anxiety or tension), word spacing – irregular (indicating mood swings), pen pressure – variable (indicating emotional fluctuations), font size – small or narrow (suggesting insecurity).

The dataset was divided into five classes according to the new labels. When using images from the dataset, the image is assumed to be broken down into patches, since the vision transformer works with image patches and relies on transformation layers to learn the corresponding functions. Each patch is linearly projected into a vector, to which a positional coding vector is added, containing information about the location of the patch in the image. Then the sequence of these vectors enters the input of the transformer. The attention mechanism allows the model to establish connections between different image patches, taking into account their mutual location and content. After passing through the transformer layers, the output vector is categorized using a fully connected layer. The result of the vision transformer is the probability of the image belonging to a certain class.

Taking into account the features of the indicators of personality types, the object of study and machine learning methods, the following simplifications were adopted in the study:

– one subject can have only one of the five traits that make up a person's personality;

– the meanings of words and sentences are not taken into account, only their graphological features are important.

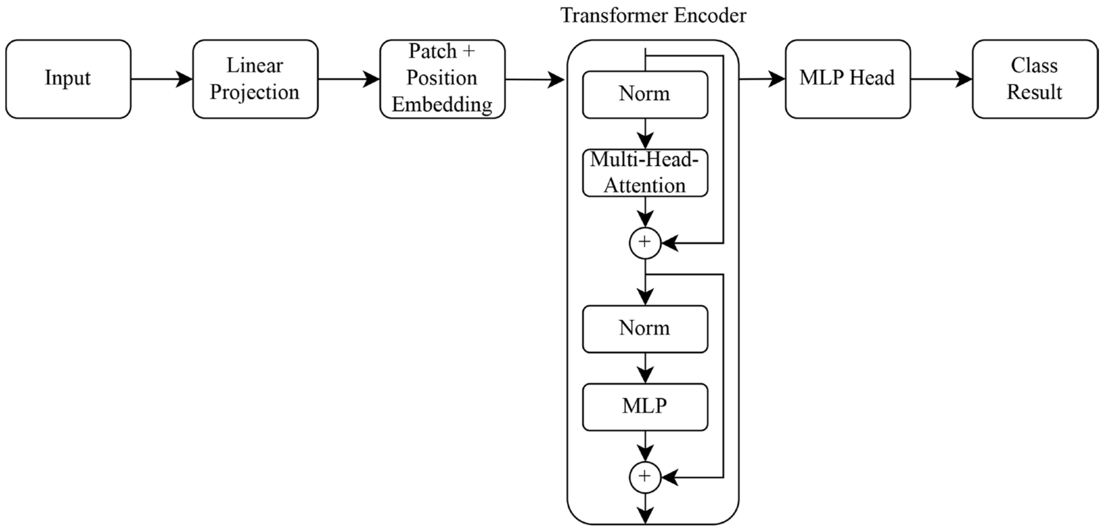

Fig. 1. Vision Transformer model

The experimental part of the study was conducted using the Python programming language, the OpenCV library, and the PyTorch library.

The test bench used for the study had the following characteristics: Intel 12th generation processor, NVIDIA GeForce RTX 3070Ti Laptop, DDR4 32 GB.

The metrics used to evaluate the retrieval performance were as follows: soft top k, hard top k, completeness on k, accuracy on k, average accuracy.

The metrics used to evaluate the classification performance were as follows: accuracy, precision, completeness, F1 score, true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

5. Results of investigating the approach to identifying personality based on handwritten text using machine learning methods

5. 1. Functional model of identifying personality using machine learning methods

The construction of a handwritten text analysis system for identifying personality is based on the fact that during handwriting analysis for identifying personality, the difference between written samples and standard writing is studied and based on this, the personality of the person providing the writing sample is determined.

Having analyzed the approaches and methods of analyzing handwritten text for identifying personality used in the literature, we can conclude that the approach to building a personality identification model using the machine learning method should include the following steps:

1) pre-processing of input data;

2) extraction of graphological features of handwritten text;

3) determination of personality based on the features of written samples of handwritten text.

A high-level model of the approach to identifying personality based on handwritten text using the machine learning method is built on these steps and is shown in Fig. 2.

Based on this high-level model, a functional model of personality identification using machine learning methods was built. This model includes a pre-processing step and combined steps of graphological feature extraction and personality identification.

The input data pre-processing step is an important component of the handwriting-based personality identification approach, as it performs several tasks at once.

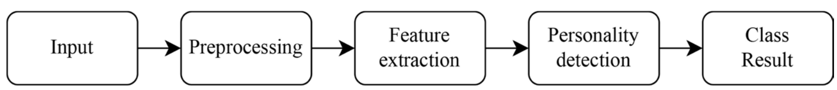

Fig. 2. High-level model of the personality identification approach

Given that the input data is an image, and it can be multi-colored, working with such an image is complicated and also requires additional computational capabilities. To facilitate work with the image, the first step of pre-processing is to convert the image from color to grayscale.

Input images can have various sizes, for example, in the CVL dataset, some images have an average size of 2500×1500. This is very large for machine learning models, because processing such an image will result in a huge number of tokens, and, for example, the computational complexity of self-attention in vision transformers scales quadratically with the number of tokens. In order to avoid the computational complexity of processing such images, one of the preprocessing steps is a patch extraction step. The image is divided into patches of fixed size, the patch size was chosen to be 32×32, because this size is often used for very high resolution images, and it significantly reduces the number of tokens that the model processes.

The images in the CVL dataset have rather large internal fields in which there is no relevant information, so the patch extraction should be done taking this into account. In order to extract the relevant image patches, a preprocessing step was added in which the scale-invariant feature transformation approach was used [21]. This approach converts the image data into scale-invariant coordinates relative to local objects. As a result, a large number of features are formed that densely cover the image in the entire range of scales and locations. The coordinates of these features are used as the central point of the patch with a width of 32 and a height of 32.

During the preprocessing of the input data, it is also important to separate the objects from their background. For this purpose, a preprocessing step was added in which an automatic thresholding algorithm was used for binarization of grayscale images [22]. The optimal threshold is chosen according to a discriminant criterion in such a way as to maximize the interclass variance in gray levels. The image is binarized by setting all pixels with a brightness value below the optimal threshold to 0 (black) and all pixels with a value above the threshold to 1 (white).

The preprocessing model for the handwritten input data is shown in Fig. 3.

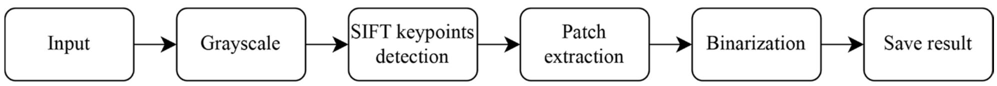

Fig. 3. Input data preprocessing model

The proposed functional model of personality identification using machine learning methods is depicted in Fig. 4.

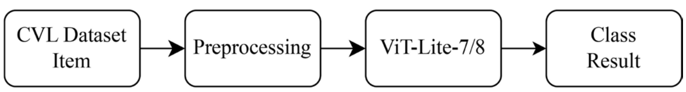

Fig. 4. A proposed functional model of personality identification

After preprocessing, the input data is fed into the vision Transformer. The small-scale learning model from [23] was used. This model is suitable for small data sets and makes it possible to train on small data sets such as CVL and smaller than those conventionally used in computer vision, such as ImageNet. The used model ViT-Lite-7/8 includes 7 Transformer Encoder layers and 8 attention heads, which together with the classifier and 32×32 patches provides over 3.74 million parameters.

5. 2. Results of experimental study on the proposed approach

To verify the proposed approach and conduct the experiment, several models were trained; while the model architecture, parameters, etc. are the same, the key difference is only in the validation and composition of the dataset. The dataset was composed as follows:

1. A dataset that is divided into half, where the first half is used for training and validation, and the second half for testing.

2. A dataset in which 2 samples for training, 1 for validation, and 4 samples for testing are selected from 7 handwritten text samples from each subject.

Fig. 5 shows the composition of the dataset for the classification approach.

Fig. 6 demonstrates the composition of the dataset for the retrieval approach.

Also, during the experiment, a random seed was used; it was applied in all modules of the model. This is necessary for the reproducibility of the result and in order to ensure that the same order of shuffling of the data set is ensured during each run of the experiment.

To avoid overtraining, the optimal number of iterations was chosen with the possibility of early termination of training. Training is terminated early if the value of the average training loss per batch does not decrease within 10 epochs.

The parameters for tuning the model that were selected are given in Table 1.

The parameters selected when setting up the scale-invariant feature transformation are given in Table 2.

During model training, training validation was performed in the form of collecting and monitoring metrics such as loss_val, loss_train, accuracy_val, accuracy_train. They were collected to confirm the correct training process.

0001-1 train	0001-2 val	0001-3 train	0001-4 test	0001-6 test	0001-7 test	0001-8 test	0002-1 train	0002-2 val	0002-3 train	0002-4 test	0002-6 test	0002-7 test	0002-8 test	0003-1 train	0003-2 val	0003-3 train	0003-4 test	0003-6 test	0003-7 test	0003-8 test
0004-1 train	0004-2 val	0004-3 train	0004-4 test	0004-6 test	0004-7 test	0004-8 test	0005-1 train	0005-2 val	0005-3 train	0005-4 test	0005-6 test	0005-7 test	0005-8 test	0006-1 train	0006-2 val	0006-3 train	0006-4 test	0006-6 test	0006-7 test	0006-8 test
0012-1 train	0012-2 val	0012-3 train	0012-4 test	0012-6 test	0012-7 test	0012-8 test	0013-1 train	0013-2 val	0013-3 train	0013-4 test	0013-6 test	0013-7 test	0013-8 test	0014-1 train	0014-2 val	0014-3 train	0014-4 test	0014-6 test	0014-7 test	0014-8 test
0015-1 train	0015-2 val	0015-3 train	0015-4 test	0015-6 test	0015-7 test	0015-8 test	0016-1 train	0016-2 val	0016-3 train	0016-4 test	0016-6 test	0016-7 test	0016-8 test	0017-1 train	0017-2 val	0017-3 train	0017-4 test	0017-6 test	0017-7 test	0017-8 test
0018-1 train	0018-2 val	0018-3 train	0018-4 test	0018-6 test	0018-7 test	0018-8 test	0020-1 train	0020-2 val	0020-3 train	0020-4 test	0020-6 test	0020-7 test	0020-8 test	0021-1 train	0021-2 val	0021-3 train	0021-4 test	0021-6 test	0021-7 test	0021-8 test
0022-1 train	0022-2 val	0022-3 train	0022-4 test	0022-6 test	0022-7 test	0022-8 test	0023-1 train	0023-2 val	0023-3 train	0023-4 test	0023-6 test	0023-7 test	0023-8 test	0024-1 train	0024-2 val	0024-3 train	0024-4 test	0024-6 test	0024-7 test	0024-8 test
0025-1 train	0025-2 val	0025-3 train	0025-4 test	0025-6 test	0025-7 test	0025-8 test	0026-1 train	0026-2 val	0026-3 train	0026-4 test	0026-6 test	0026-7 test	0026-8 test	0027-1 train	0027-2 val	0027-3 train	0027-4 test	0027-6 test	0027-7 test	0027-8 test
0028-1 train	0028-2 val	0028-3 train	0028-4 test	0028-6 test	0028-7 test	0028-8 test	0029-1 train	0029-2 val	0029-3 train	0029-4 test	0029-6 test	0029-7 test	0029-8 test	0041-1 train	0041-2 val	0041-3 train	0041-4 test	0041-6 test	0041-7 test	0041-8 test
0042-1 train	0042-2 val	0042-3 train	0042-4 test	0042-6 test	0042-7 test	0042-8 test	0047-1 train	0047-2 val	0047-3 train	0047-4 test	0047-6 test	0047-7 test	0047-8 test	0050-1 train	0050-2 val	0050-3 train	0050-4 test	0050-6 test	0050-7 test	0050-8 test
0052-1 train	0052-2 val	0052-3 train	0052-4 test	0052-6 test	0053-1 train	0053-2 val	0053-3 train	0053-4 test	0053-6 test	0057-1 train	0057-2 val	0057-3 train	0057-4 test	0057-6 test	0058-1 train	0058-2 val	0058-3 train	0058-4 test	0058-6 test	0059-1 train
0059-2 val	0059-3 train	0059-4 test	0059-6 test	0073-1 train	0073-2 val	0073-3 train	0073-4 test	0073-6 test	0074-1 train	0074-2 val	0074-3 train	0074-4 test	0074-6 test	0075-1 train	0075-2 val	0075-3 train	0075-4 test	0075-6 test	0076-1 train	0076-2 val
0076-3 train	0076-4 test	0076-6 test	0077-1 train	0077-2 val	0077-3 train	0077-4 test	0077-6 test	0078-1 train	0078-2 val	0078-3 train	0078-4 test	0078-6 test	0079-1 train	0079-2 val	0079-3 train	0079-4 test	0079-6 test	0080-1 train	0080-2 val	0080-3 train
0080-4 test	0080-6 test	0081-1 train	0081-2 val	0081-3 train	0081-4 test	0081-6 test	0083-1 train	0083-2 val	0083-3 train	0083-4 test	0083-6 test	0084-1 train	0084-2 val	0084-3 train	0084-4 test	0084-6 test	0095-1 train	0095-2 val	0095-3 train	0095-4 test
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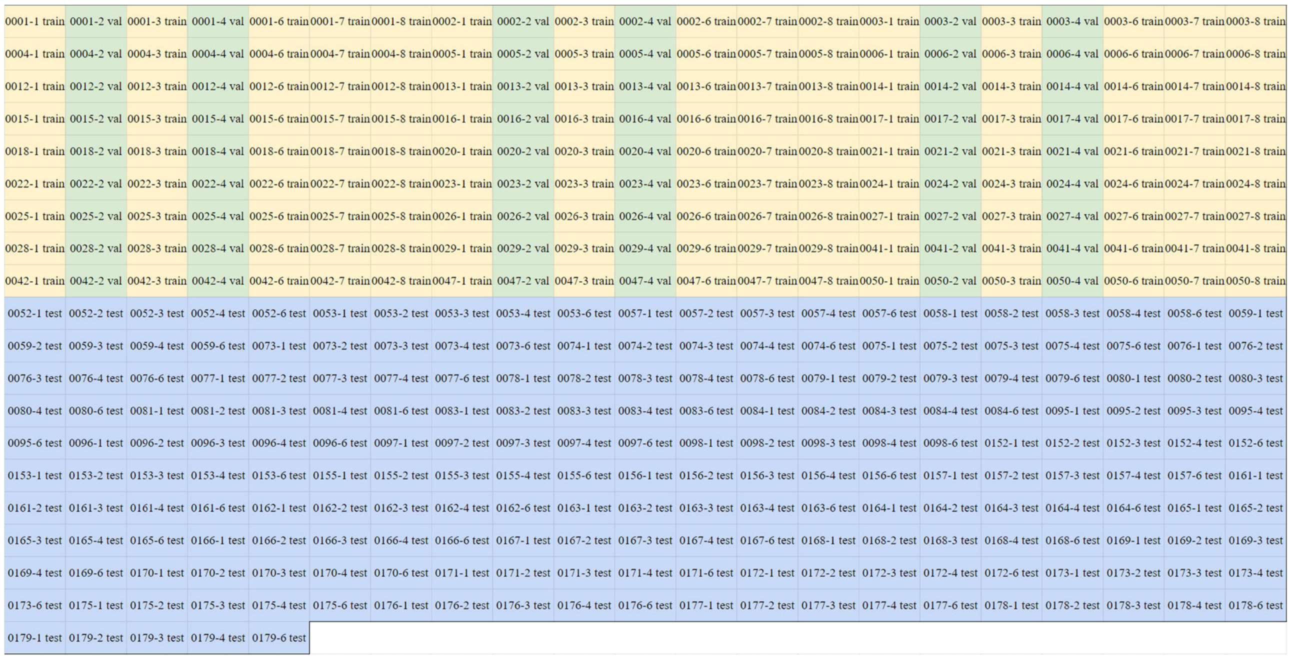
0179-1 train	0179-2 val	0179-3 train	0179-4 test	0179-6 test																

Fig. 5. Dataset composition for the classification approach



0001-1 train	0001-2 val	0001-3 train	0001-4 val	0001-6 train	0001-7 train	0001-8 train	0002-1 train	0002-2 val	0002-3 train	0002-4 val	0002-6 train	0002-7 train	0002-8 train	0003-1 train	0003-2 val	0003-3 train	0003-4 val	0003-6 train	0003-7 train	0003-8 train
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0169-4 test	0169-6 test	0170-1 test	0170-2 test	0170-3 test	0170-4 test	0170-6 test	0171-1 test	0171-2 test	0171-3 test	0171-4 test	0171-6 test	0172-1 test	0172-2 test	0172-3 test	0172-4 test	0172-6 test	0173-1 test	0173-2 test	0173-3 test	0173-4 test
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0179-1 test	0179-2 test	0179-3 test	0179-4 test	0179-6 test																

Fig. 6. Dataset composition for the retrieval approach

Table 1

Model setup options

Parameter	Value	Description
lr	0.0005	Classical learning rate;
num-epochs-warmup	5	Number of epochs to warm up the learning rate
batch-size	128	Batch size
num-workers	4	Number of PyTorch workers
num-epochs-patience	10	Number of epochs after which training will stop if the validation loss no longer improves;
num-epochs	60	Number of epochs

Fig. 7–10 show the plots constructed during model training. The plots in Fig. 7, 8 illustrate the metrics collected during model training for the classification approach; the plots in Fig. 9, 10 display the metrics collected during model training for the retrieval approach.

Table 2

Parameters of scale-invariant feature transformation

Parameter	Value
nfeatures	0
nOctaveLayers	3
contrastThreshold	0.04
edgeThreshold	10
sigma	3.75

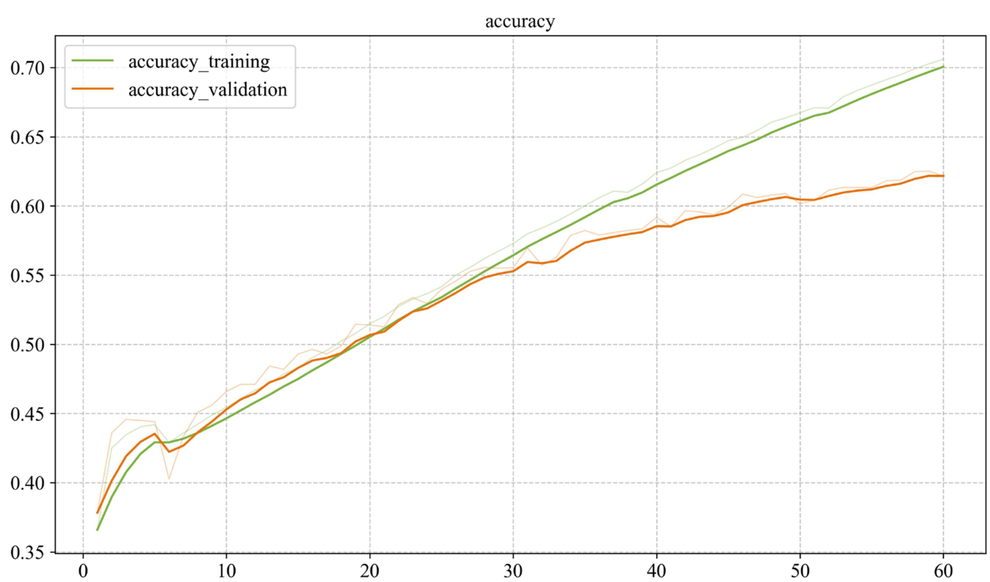

Fig. 7. Accuracy of validation and training of the ViT-based model on the test dataset for the classification approach: X-axis — epoch (number); Y-axis — average training accuracy (proportion)

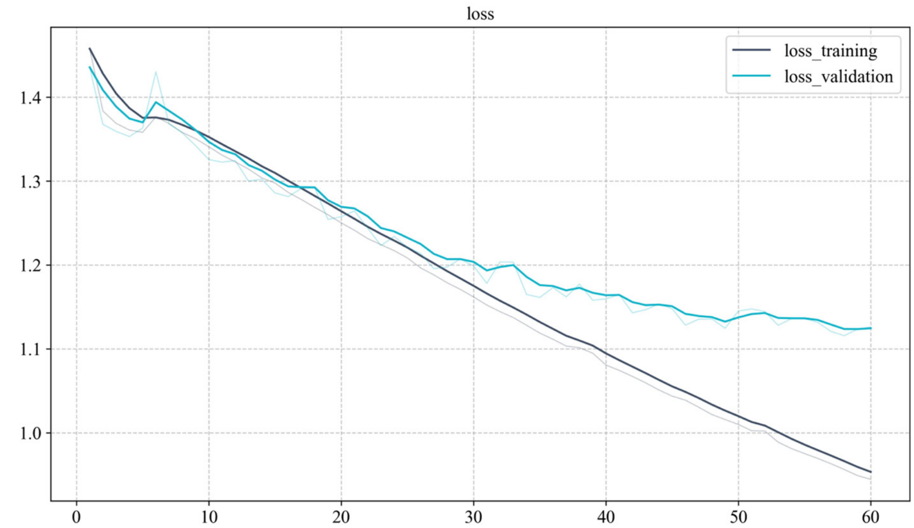

Fig. 8. Validation and training loss of the ViT-based model on the test dataset for the classification approach: X-axis – epoch (number); Y-axis – average training loss per batch (bit)

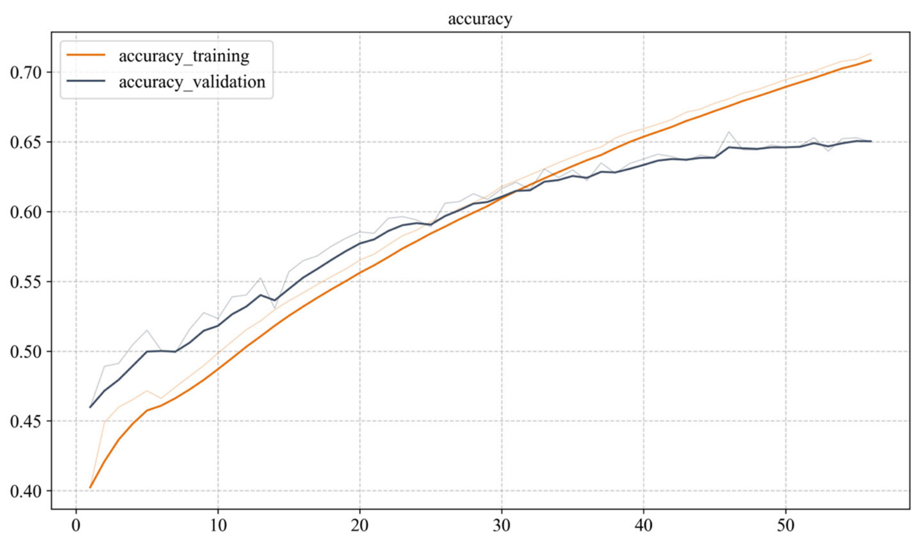

Fig. 9. Accuracy of validation and training of the ViT-based model on the test dataset for the retrieval approach: X-axis – epoch (number); Y-axis – average training accuracy (proportion)

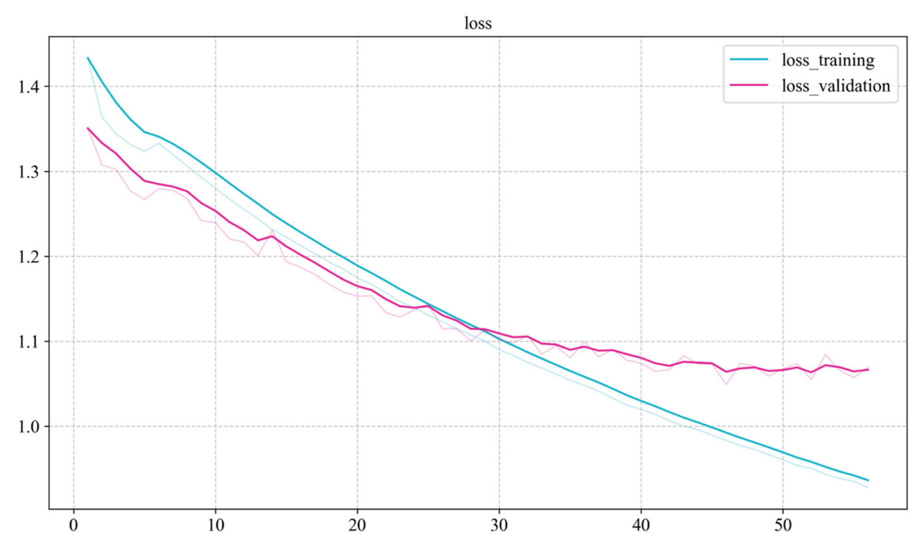

Fig. 10. Validation and training loss of the ViT-based model on the test dataset for the retrieval approach: X-axis – epoch (number); Y-axis – average training loss per batch (bit)

For the main experiment, the model accuracy analysis for the classification approach and the accuracy of finding the corresponding features based on the Euclidean distance of their feature vectors for the retrieval approach were conducted. Additionally, other basic metrics were calculated for both approaches, useful for assessing the success of the handwriting-based personality identification approach using machine learning methods. The metrics obtained as a result of the tests for the classification approach and for the retrieval approach are given in Tables 3, 4.

Table 3

ViT performance evaluation metrics for the classification approach

Metric	Feature	Value
Accuracy	Conscientiousness	99.48 %
	Agreeableness	94.84 %
	Extraversion	96.39 %
	Openness to experience	97.93 %
	Neuroticism	97.93 %
F1 Score	Conscientiousness	0.98
	Agreeableness	0.91
	Extraversion	0.82
	Openness to experience	0.93
	Neuroticism	0.96
Precision	Conscientiousness	1.0
	Agreeableness	0.86
	Extraversion	1.0
	Openness to experience	0.96
	Neuroticism	0.92
Recall	Conscientiousness	0.97
	Agreeableness	0.96
	Extraversion	0.70
	Openness to experience	0.89
	Neuroticism	1.0

Table 4

ViT performance evaluation metrics for the retrieval approach using Euclidean distance

Metric	k	Value
Hard Top K	1	0.84
	2	0.65
Soft Top K	1	0.84
	2	0.91
	3	0.94
	4	0.97
	5	0.98
Precision at K	1	0.84
	2	0.78
	3	0.75
	4	0.73
	5	0.68
Recall at K	1	0.02
	2	0.03
	3	0.05
	4	0.07
	5	0.08
mAP		0.45

Fig. 11 shows a confusion matrix for the classification approach.

The model confusion matrix displays the correctly and incorrectly categorized samples. In Fig. 11, the X-axis is the true label, the Y-axis is the predicted label, and the intersection of the axes shows the number of correct predictions.

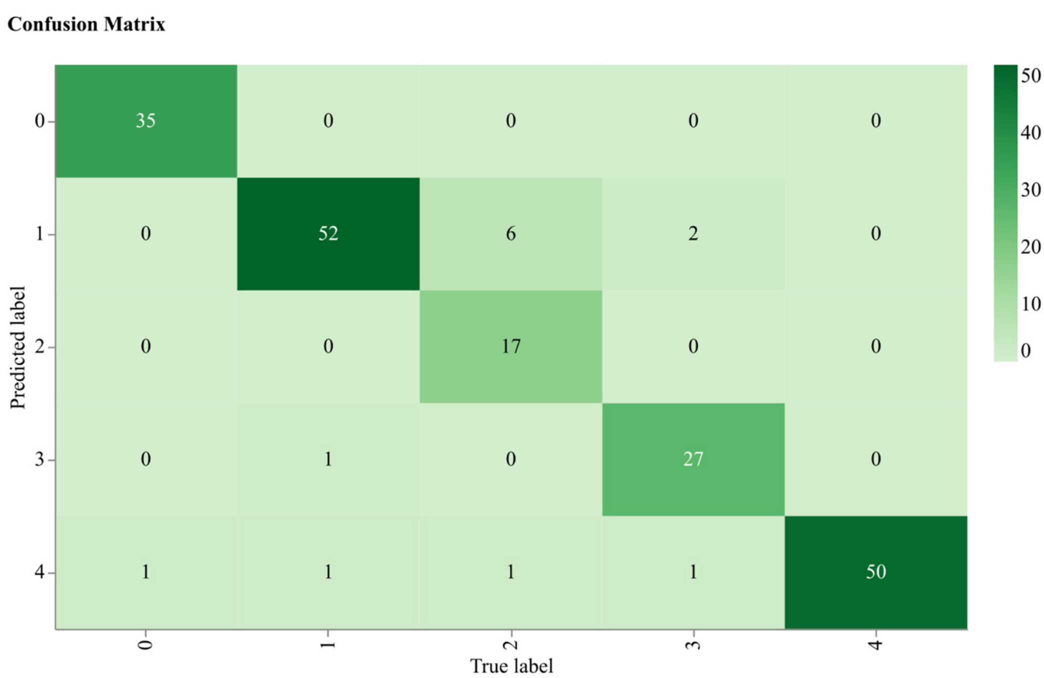

Fig. 11. ViT-based model confusion matrix on the test dataset for the classification approach

6. Discussion of results based on investigating the approach to identifying the personality based on handwritten text

From the functional model, it can be seen that the handwritten text analysis system has the main steps used in the literature and demonstrated in Fig. 2. The high-level model demonstrates that the process of identifying the personality from handwriting is not a single-step action but consists of several key stages. It can also be seen that, both in the high-level model depicted in Fig. 2 and in the proposed model shown in Fig. 4, the preprocessing step is preserved. In the preprocessing approach depicted in Fig. 3, one can see the use of grayscale transformation, the use of scale-invariant feature transformation to select relevant areas, the extraction of fixed-size patches, and binarization according to the Otsu method for clear text separation. These steps play a key role because they reduce computational complexity, ensure scale invariance, and extract relevant regions.

Analyzing the proposed model shown in Fig. 4, we can see a simplification of the structure compared to the high-level structure given in Fig. 2, which is manifested in the absence of a feature extraction step. This is possible due to the fact that the Vision Transformer automatically learns to extract important features from images during training using attention weights. This eliminates the subjectivity of the selection of graphological features and the ambiguity of comparing features with indicators of personality types. Continuing the analysis of the proposed model in Fig. 4, one can see the use of the vision transformer in the ViT-Lite-7/8 variant. The architecture with 7 Transformer Encoder layers, 8 attention heads, and over 3.74 million parameters makes it possible for the model to detect subtle differences in handwriting and effectively train on small data sets typical of handwriting analysis tasks.

From the experimental validation side, analyzing the results of training the model for the classification approach in the plots of Fig. 7, 8, we can see the following results:

– looking at the validation accuracy indicator, we can see that the accuracy increased throughout the entire training of the model, which is a good sign;

– looking at the validation accuracy and training accuracy indicators together, we can see that despite the fact that from the 30th epoch the difference between the indicators increased, the validation accuracy did not start to level off and did not start to decrease, which demonstrates the absence of overtraining;

– looking at the training accuracy indicator, we can see that the training accuracy was generally higher than the validation accuracy and increased throughout the training of the model, which is expected for this indicator;

– looking at the validation loss indicator, we can see that the accuracy decreased throughout the training of the model, which means that the model is learning and reducing its errors over time;

– looking at the validation loss and training loss indicators together, we can see that the overall trend is descending. But despite the fact that from the 30th epoch the difference between the indicators increased, the validation loss began to slightly level off and did not begin to increase, which demonstrates the absence of signs of overtraining;

– looking at the Learning Loss indicator, we can see that the Learning Loss was generally lower than the Validation Loss and decreased throughout the entire training of the model, which is expected for this indicator.

Analyzing the results of training the model for the retrieval approach in the plots of Fig. 9, 10, we can see the following results:

– considering the validation accuracy indicator, we can see that the accuracy increased throughout the entire training of the model, this happened more slowly than the Training Accuracy, but this is expected for this indicator;

– considering the validation accuracy and training accuracy indicators together, we can see that despite the fact that from the 35th epoch the difference between the indicators increased, the validation accuracy began to level off slightly but did not begin to decrease, which demonstrates the absence of overtraining;

– considering the Training Accuracy indicator, we can see that the training accuracy was generally higher than the validation accuracy and increased throughout the entire training of the model, which is expected for this indicator;

– looking at the Validation Loss indicator, we can see that the accuracy decreased throughout the entire training of the model, which means that the model is learning and reducing its errors over time;

– looking at the Validation Loss and Learning Loss indicators together, we can see that the overall trend is descending. However, despite the fact that the difference between the indicators increased from epoch 35, the Validation Loss began to level off slightly and did not increase, which demonstrates the absence of signs of overtraining;

– looking at the Learning Loss indicator, we can see that the Learning Loss decreased throughout the entire training of the model and starting from epoch 30 was lower than the Validation Loss, which is expected for this indicator.

By analyzing the overall performance metrics for the classification approach, which are given in Table 3, the following improvements in personality identification can be seen:

– looking at the Accuracy metric, we can see that the overall accuracy percentage is high for all personality traits and has generally increased to an average of 97 %, with the lowest score being 94.84 % and the highest being 99.48 %;

– looking at the F1 Score metric, we can see that Agreeableness, Conscientiousness, Openness to Experience, and Neuroticism exhibit high F1 scores above 0.9, demonstrating a good balance in their predictions. Extraversion, with an F1 score of 0.82, may have a slight asymmetry towards precision or recall;

– looking at the Precision metric, we can see that Conscientiousness and Extraversion have perfect accuracy (1.0), which means that the model is very confident and accurate when predicting these traits. Other traits also have good accuracy scores, above 0.86;

– looking at the Recall score, we can see that Neuroticism has a perfect Recall (1.0), indicating that the model captures almost all cases of this trait. Other traits also show fairly high Recall scores, with the exception of Extraversion (0.70).

By analyzing the general metrics of ViT performance evaluation for the retrieval approach using Euclidean distance, which are given in Table 4, we can see the following improvements in personality detection:

– considering the Hard Top k indicator, we can see that the value of 0.84 for k=1 means that the model recommends the single most relevant item in 84 % of cases. For k=2, this indicator drops to 65 %, which indicates that finding the second best recommendation is more difficult;

– considering the Soft Top k indicator, we can see that these values are higher than Strict Top k, which indicates that the model ranks the relevant items in the top K positions better;

– considering the Precision indicator on k, we can see that the value of 0.84 for k=1 means that when the model recommends one item, it is correct in 84 % of cases. As K increases, the accuracy decreases, which means that the model is less accurate when it recommends more items;

– looking at the Recall indicator on k, we can see low values, especially for smaller K, indicating that the model has difficulty finding all relevant elements, even when considering a larger number of recommendations;

– looking at the Mean Average Precision metric, we can see that the value of 0.45 is a moderate indicator. This indicates that there is room for improvement in the model's ability to rank the corresponding items higher in the list.

Analyzing the results of the confusion matrix for the classification approach in the plot of Fig. 11, we can see that overall the model coped with the classification task, correctly identifying most of the cases with a small deviation for labels 1 and 2. This deviation is also confirmed by other metrics such as Recall and F1 score.

The results of the study showed that the Vision Transformer can significantly improve the identification of personality based on handwritten text, as it demonstrates greater accuracy.

Unlike work [8], in which the model largely depends on preprocessing steps such as normalization, segmentation, feature extraction, and intermediate representation formation, the vision transformer works with image patches and relies on transformation layers to learn the corresponding features, this difference solves the problem of ambiguity in matching features with indicators of personality types. At the same time, comparing the accuracy values for each individual trait, it can be seen that for Extraversion their model demonstrated 87.1 %, and the proposed approach 96.39 %, for Neuroticism – 86.3 %, and the proposed approach 97.93 %, for Agreeableness – 79.6 %, and the proposed approach 94.84 %, for Conscientiousness – 80.4 %, and the proposed approach 99.48 %, for Openness to Experience – 88.6 %, and the proposed approach 97.93 %.

Unlike work [15], in which a separate model was trained for each individual personality trait, in this work a single model was trained that distinguishes between five personality traits, this distinction makes it possible to reduce computational complexity. This becomes possible due to the self-attention mechanism, which makes it possible for the model to pay attention to different parts of the input data based on their relevance to the task. At the same time, comparing the accuracy values for each individual trait, it can be seen that for Extraversion their model demonstrated 85 %, and the proposed approach 96.39 %, for Neuroticism – 70 %, and the proposed approach 97.93 %, for Agreeableness – 75 %, and the proposed approach 94.84 %, for Conscientiousness – 65 %, and the proposed approach 99.48 %, for Openness to Experience – 65 %, and the proposed approach 97.93 %.

Unlike work [16], in which the model was trained using labeled, unlabeled, and generator-generated data, in this work the training was performed only using labeled data, this difference makes it possible to simplify the training process, reduce computational costs, and better control the quality of training and accuracy of results. This is possible due to the fact that the training of the vision transformer, unlike SGAN, is based exclusively on labeled data. At the same time, comparing the accuracy values, it can be seen that their model demonstrated 91.3 %, and the proposed approach demonstrated an average of 97 %.

Although the experiment successfully proved the work of the proposed approach, for the retrieval approach the results cannot be considered the best, but they can be considered satisfactory.

Thus, the approach to identifying personality based on handwritten text using machine learning methods has great practical potential for graphologists and handwriting experts, allowing them to perform analysis more efficiently during work. In addition to the conventional field of application – forensics and forensic examination, where this approach can accelerate and automate the process of determining the psychological portrait of the author, it can be successfully integrated into the field of HR and recruiting. Automated analysis of candidates' handwriting will allow for a quick and objective assessment of their personal qualities, such as the level of Extraversion, Neuroticism, Agreeableness, Conscientiousness, Openness to experience, which will significantly simplify the process of personnel selection.

The expected effects of implementing this approach include increasing the accuracy and objectivity of handwriting analysis, reducing the time required for examination, reducing the influence of the human factor and subjective assessments, as well as the ability to analyze large volumes of handwritten data. This, in turn, will lead to more efficient work of experts, improved quality of personnel selection and a deeper understanding of the psychological state of the person in different domains of activity.

The use of a public dataset in our research has a positive effect on the reproducibility of the study, but on the other hand, this dataset consists of handwritten texts only in German and English, which should be taken into account when applying the proposed approach. It is also assumed that before using the dataset, graphological analysis will be conducted and each sample of handwritten text will be marked with one of five marks according to the Big Five model (Extraversion, Neuroticism, Agreeableness, Conscientiousness, Openness to experience). When reproducing the results for the retrieval approach, it is important to use Euclidean distance; when using other methods of calculating the distance, the results may vary.

As a drawback, worth noting is that Extraversion is the trait where the model has the most room for improvement. Its lowest Recall and F1 scores among the other traits indicate that it may either not recognize some cases of Extraversion or incorrectly classify other traits as Extraversion, which can also be seen in the confusion matrix.

As a direction for further research, it may be interesting to use this approach to define personality using other personality trait theories such as the Myers-Briggs Type Indicator and others, as they have a larger number of personality types.

7. Conclusions

1. A functional model of personality identification based on handwritten text has been built by using machine learning methods. The functional model constructed makes it possible to build the process of handwriting analysis in such a way that by studying the differences between written samples and standard writing, an accurate personality identification is made. The use of the

machine learning method of the vision transformer in the development of a model of personality identification based on handwritten text makes it possible to remove the need to extract features as a separate step. This solves the problem of ambiguity in comparing features with indicators of personality types and eliminates the subjectivity of choosing graphological features. In addition, the use of a public dataset improves the transparency of the study and makes the study more accessible for comparison and reproducibility. The use of the Big Five type indicator allowed us to test the functional model not only as a tool for extracting graphological features but also as a full-fledged model of personality identification.

2. An experimental study was conducted on the proposed approach to personality identification, which showed that the accuracy of personality trait identification increased on average to 97 %, with the lowest indicator at 94.84 % and the highest at 99.48 %. The Precision indicator also improved compared to other models, as evidenced by the increased precision values for all personality traits, resulting in an increase in the average precision value from 0.65 to 0.94.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

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