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Detection of Personality Traits Using Handwriting and Deep Learning

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Abstract: A series of studies and research have shown the existence of a link between handwriting and a person's personality traits. There are numerous fields that require a psychological assessment of individuals, where there is a need to determine personality traits in a faster and more efficient manner than that based on classic questionnaires or graphological analysis. The development of image processing and recognition algorithms based on machine learning and deep neural networks has led to a series of applications in the field of graphology. In the present study, a system for automatically extracting handwriting characteristics from written documents and correlating them with Myers–Briggs type indicator is implemented. The system has an architecture composed of three levels, the main level being formed by four convolutional neural networks. To train the networks, a database with different types of handwriting was created. The experimental results show an accuracy ranging between 89% and 96% for handwritten features' recognition and results ranging between 83% and 91% in determining Myers–Briggs indicators.

Keywords: convolutional neural networks; handwriting analysis; personality classification

1. Introduction

Although the development and widespread use of digital equipment has led to a substantial reduction in the number of handwritten documents, handwriting is a valuable skill that contributes to personal, educational, and emotional development. Even though modern technology facilitates electronic communication, maintaining the habit of handwriting can bring significant benefits. Handwriting helps develop hand–eye coordination and dexterity. These skills are essential not only for writing but also for other daily activities. Research suggests that handwriting can improve information retention [1]. The process of writing words by hand helps to understand and retain concepts, compared to typing. The activity of handwriting can have a calming effect, helping to reduce anxiety and organize thoughts. Handwriting requires more attention than typing, which can lead to better concentration and a deeper understanding of the material studied.

Handwriting analysis, also known as graphology, has several applications in various fields:

- Psychology and personal development: Graphology can provide clues about a person's personality traits, temperament, and emotions. It is used to better understand individual behaviors and motivations [2].
- Human resources: Some companies use handwriting analysis in the recruitment process to assess the characteristics of candidates. Graphologists can provide insights into compatibility with an organizational culture or interpersonal skills [3].

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- Forensic science: In crime investigations, handwriting analysis can help identify the authors of anonymous letters or establish the authenticity of documents. Comparing handwriting can provide clues about the identity of a suspect [4].
- Education: In education, handwriting analysis can be used to assess learning styles and personalize teaching methods, depending on the needs of each student [5].
- Therapy: Handwriting is used in art therapy or occupational therapy to help express emotions and process trauma. Handwriting analysis can provide therapists with information about the emotional state of patients [6].
- Interpersonal relationships: Graphology can be used to improve communication in personal or professional relationships, providing insights into communication styles and preferences of partners [7].
- Market research: In marketing, handwriting analysis can help understand consumer preferences and create more effective campaigns [8].

Graphologists focus on the vertical and horizontal features of a person's handwriting. In the vertical plane, the writing direction (in relation to the horizontal axis) is observed along with the proportions and size of the letters. When a person begins to write a word or a phrase, they look back to the past, but the ends of the words and sentences expose the writer's future outlook. The angle of writing the characters horizontally has the most information about the personality of the person.

The analysis then continued in depth and looked at the shape of the letters, the spacing between them, and the pressure of the writing. Of course, all these analyses cannot be generalized, and we must consider the fact that graphologists analyze writing through the lens of all associated graphic elements.

Personality models are theories and frameworks that describe and classify people's traits, behaviors, and thought patterns. They are used in psychology to understand human diversity and predict behavior in various contexts. Here are some of the most well-known types of personality models:

- The Big Five Model—this is one of the most widely accepted models in modern psychology and includes five major dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [9].
- HEXACO Model—similar to the Big Five model but adds an additional dimension: Honesty-Humility [10].
- Enneagram—describes personality into nine basic types, each with distinct motivations, fears, and behaviors [11].
- The Minnesota Multiphasic Personality Inventory—one of the most widely used and validated psychological instruments for assessing personality and identifying psychological disorders [12].
- Myers–Briggs type indicator (MBTI)—classifies personality into 16 types based on four dimensions: Introversion (I) vs. Extraversion (E), Sensing (S) vs. Intuitive (N), Thinking (T) vs. Feeling (F), and Judging (J) vs. Perceiving (P) [13].

The Myers–Briggs type indicator is a widely used personality assessment tool, especially by individuals and organizations. The MBTI is widely recognized and used in corporate settings, self-help literature, and pop culture, making it more relatable to the general public. The MBTI categorizes people into 16 distinct personality types (e.g., INFJ, ENTP), which are easy to grasp and remember. This simplicity makes it appealing for non-experts. The MBTI focuses on identifying strengths and preferences rather than pathologizing or highlighting negative traits. This makes it more appealing for personal development and team-building exercises. Also, unlike some models that include traits like neuroticism (Big Five) or honesty-humility (HEXACO), the MBTI avoids labeling traits as "good" or "bad", which can feel less threatening to individuals. It is often used in workplaces to improve team dynamics, communication, and collaboration. Its intuitive framework helps people understand differences in how others think and behave. Many people find the MBTI helpful for exploring career paths that align with their personality type, even if the scientific validity is limited. The MBTI prompts individuals to reflect on their preferences (e.g., introversion vs. extroversion, thinking vs. feeling), which can be a valuable exercise in self-awareness. The MBTI has been around since the mid-20th century and has been integrated into many organizational and educational systems. Its historical presence gives it a sense of legitimacy, even if it lacks scientific rigor.

Expertise and specialized training are typically required to accurately determine handwriting characteristics and to establish the appropriate personality traits. However, the advent of artificial intelligence algorithms, particularly deep neural networks, has enabled the development of highly accurate data classification applications. In the field of image analysis, convolutional neural networks have yielded the best results.

In this paper, using convolutional neural networks, an application was developed to automate the extraction of main features from handwritten texts and their correlation with the main personality traits using the Myers–Briggs model.

Convolutional neural networks are a popular choice for image information extraction because they can automatically learn and extract relevant features from images without the need for human intervention to manually define these features. CNNs are able to detect objects or features regardless of their position in the image. This is due to the use of convolutional filters that apply the same operation to the entire image.

The main contributions of this study are as follows:

- Automatic assessment of Myers–Briggs personality indicators.
- Objective determination of personality traits.
- Identification of the main features of handwriting.
- Integration of traditional psychological knowledge into machine learning algorithms.

The following section presents a series of results in which artificial intelligence algorithms were used to extract hand characteristics and establish personality traits. The following sections present the characteristics analyzed in this study and the connection with the Myers–Briggs indicators.

2. Related Work

With the development of machine learning image-processing techniques, the number of graphological analysis studies based on these techniques has increased considerably. Below, we present a series of results that exploit the use of handwriting analysis to identify certain personality traits with the help of artificial intelligence.

2.1. Personality Traits Determined from Handwriting and Applications

Even though there is no consensus among psychology specialists, there are numerous studies and results that demonstrate the connection between handwriting and a series of personality traits [1,14].

The literature surrounding handwriting analysis as an instrument of detecting personality traits has evolved significantly in recent years, reflecting a growing interest in the intersection of psychology and graphology. The foundational work by Gowda et al. [2] suggests that handwriting analysis is not merely an art but a scientific process that can reveal physiological and psychological insights, particularly in children. Their study correlates clinical diagnoses with graphological analysis, utilizing tools such as the Children's Personality Questionnaire to interpret personality dimensions through handwriting. This early work underscores the potential of handwriting analysis to discern personality traits, setting a precedent for future inquiries into the field.

Building on this foundation, Golbeck [15] explores the realm of online communication, examining how linguistic features in digital texts can be used to infer personality traits. His research delves into various platforms to assess the stability of personality traits across different textual samples. This inquiry expands the traditional boundaries of handwriting analysis to include digital expressions of personality, suggesting that the principles of graphology may extend into the analysis of online language, thereby enriching our understanding of personality detection in contemporary contexts.

Furthering the discourse, Schiegg and Thorpe [16] provide a historical perspective on handwriting analysis within psychiatric settings. Their investigation into letters written by psychiatric patients reveals significant insights into cognitive and motor disruptions associated with various psychological disorders. By highlighting the historical underpinnings of handwriting as a diagnostic tool, they illuminate the complexities of graphology, while also acknowledging its controversial status in modern scholarship. This historical analysis not only reinforces the notion that handwriting can reflect mental states but also calls for a reevaluation of its relevance in contemporary psychological assessments.

In a more recent contribution, Chernov and Caspers [17] introduce a formalized, computer-aided approach to handwriting psychology through their HSDetect system. This innovative methodology combines manual evaluation by experts with algorithmic calculations of psychological traits based on handwriting signs. By creating a structured database linking handwriting characteristics to psychological assessments, they enhance the reliability and validity of handwriting analysis in psychological contexts. This integration of technology into handwriting analysis signifies a pivotal shift towards more systematic and empirical methodologies in the field.

In [3], job compatibility can be identified from handwriting analysis with personality recognition. Candidates' skills like creativity, activeness, leadership, and work dedication are recognized. In [8], the handwriting analysis with machine learning classification is used for analyzing financial behavior. It shows where the individual is a risk seeker, risk-tolerant, or risk-averse.

2.2. Computer-Assisted Techniques Used for Handwriting Analysis

With the development of image-processing algorithms, numerous results have been reported on the determination of certain personality traits through computer-assisted analysis.

Studies in the field of personality traits' detection based on handwriting analysis using machine learning and deep learning generally exhibit the following characteristics:

- They explore links between handwriting patterns and psychological or behavioral tendencies [18]. Most studies are grounded in widely accepted frameworks like the Big Five (OCEAN), MBTI, or HEXACO, providing a structured approach to trait analysis.
- The data are collected from diverse participants, in the form of written text and signatures. Data often include age, gender, cultural background, and sometimes psychological assessments [19].
- The handwriting characteristics analyzed can be classified into three categories:

Geometric: Stroke length, slant, size, spacing, pressure, and alignment [20].
Kinematic: Speed, acceleration, and smoothness of pen movement [21].
Graphological: Style-specific traits like loops, flourishes, and baseline adherence [22].

The main evaluation metrics of the proposed algorithms are accuracy, precision, recall, F1 score, and sometimes correlation coefficients to measure alignment with psychological assessments.

Automatic personality detection algorithms can be classified into two broad categories: machine learning algorithms and deep learning algorithms.

The first category includes classification methods based on algorithms such as Support Vector Machine (SVM), AdaBoost, and k-nearest neighbors (KNN). The second category (based on deep learning) includes algorithms that use multilayer perceptron neural networks (MLPs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), Long Short-Term Memory (LSTM), or Gated Recurrent Units (GRUs).

So, in [23], extracted features from handwriting are mapped with personality using the rule-based technique. In [24], the authors implement a series of empirical algorithms for spatial analysis of text. Personality traits are inferred based on the distance between lines, words, and characters of text.

SVM is a technique often used in handwriting analysis algorithms. SVM as a classifier was applied to analyze various handwriting features like the margin, word spacing, line skew, letter size, sharpness, text density, speed, slant, and regularity of writing, which are extracted from collected handwriting sample images of different individuals [9,25].

KNN is a simple classifier that computes the distance between the feature vectors. Algorithms based on KNN were used in [26] to improve the feature extraction from handwriting, such as the margin, the bar on the letter t, and the baseline.

In [9], an MLP is used to determine a Big Five personality model, and in [27], LSTM, RNN, and GRU are used for writer identification.

The paper [28] presents the use of convolutional neural networks for determining the profession using handwriting. The present work analyzes handwriting data collected from the writers from different professions and classifies them based on the top features that characterize their profession. Collectively, the studies to date illustrate the multifaceted nature of handwriting analysis in relation to personality traits.

These studies have highlighted a number of problems with traditional psychological methods, problems that can be solved using artificial intelligence in handwriting analysis:

- Subjectivity of traditional methods—The subjective interpretations and questionnaires used by psychologists as well as the variable level of expertise can influence the results of psychological analyses.
- Reduced scalability—Traditional handwriting analysis methods are time-consuming, limiting the scalability of psychological analyses.
- Intrusive methods—The use of intrusive psychological analysis methods can influence the authenticity of the subjects' responses.
- Cultural and linguistic diversity—Traditional psychological assessment methods are usually developed for specific cultural and linguistic contexts, leading to misinterpretations when addressing diverse categories of the population.

3. Handwriting Analysis

The Myers–Briggs type indicator (MBTI) is a psychological instrument used to identify personality types based on the theory of psychological types developed by Carl Gustav Jung. The indicator was created by Katharine Cook Briggs and her daughter, Isabel Briggs Myers [13], to give people a deeper understanding of their preferences and behaviors.

The personality the MBTI classifies personality based on four major dimensions, each representing a spectrum between two opposing preferences:

- Extraversion (E) vs. Introversion (I): Preference for social interactions and energy from the external environment (E) or for introspection and solitary activities (I).
- Sensing (S) vs. Intuition (N): How a person gathers information: through senses and concrete details (S) or through patterns, connections, and intuition (N).
- Thinking (T) vs. Feeling (F): How a person makes decisions: based on logic and objective reasoning (T) or personal values and emotions (F).

- Judging (J) vs. Perceiving (P): Preferred style of living life: structured, planned, and organization-oriented (J) or flexible, spontaneous, and open to change (P).

Combining the four dimensions, the MBTI generates 16 different personality types, each represented by a combination of four letters, such as ISTJ: Introversion, Sensing, Thinking, Judging or ENFP: Extraversion, Intuition, Feeling, Perceiving. The main objectives of this model are the following:

- Self-knowledge: Helps people understand their preferences.
- Communication and relationships: Supports improved interactions with others.
- Career guidance: Helps identify professional fields compatible with the personality type.

Several approaches to determining personality traits from handwriting analysis are presented in the literature [14]. In this paper, we used the following four handwriting characteristics: baseline of the sentences, characters' slant, word spacing, and writing pressure. The four personality dimensions must be correlated with certain characteristics of handwriting. These correlations are presented in Tables 1–4.

Several character traits can be identified from looking at writing's baseline. The baseline serves as a link between the primal urges of the lower zone and the societal expectations of the middle zone, along with the ideal desires of the upper zone. Some traits identified through the baseline are listed in Table 1.

Table 1. Main personality traits based on the baseline.

Description	Type	Characteristics	MBTI
Rising	as he sat down.	Ambition, optimism	E, F
Normal	Cormack was particularly	Orderliness, emotional stability	T, J
Falling	the tides in the affairs of,	Depression, unhappiness, fatigue	I, T

There are additional types of baselines, but they are rare and not included in this study. In the horizontal view, the spacing between letters and words, as well as the slope of the letters, are examined. The slope of the letters is measured as the angle formed between a letter's slope and the writing's baseline. Stick-like letters are typically used as a reference, while looped letters may cause some confusion.

Most individuals have right-tilted writing, and fully vertical writing is quite uncommon. A vertical style (without tilt) indicates a person who enjoys working alone, someone rational who does not let feelings affect them. Left-leaning writing may suggest hidden traits, often showing a person who is evasive and fearful of the future. Right-leaning writing (the typical style) is associated with outgoing individuals who think freely. However, an excessive lean in this direction can indicate impulsivity and poor self-control. The angle of the letters reflects emotional expression and social growth. The emotions that can be determined from the inclination of handwritten characters are briefly presented in Table 2.

Table 2. Main personality traits based on slant of the writing.

Description	Type	Characteristics	MBTI
Extreme left inclined (reclined)	This third mailing will be	Self-centered, egotistic, self-interested, react too little or too late	S, T
Left inclined (reclined)	details are still	Hard to express emotions, reflective	I, F
Vertical	home again rather exciting.	Judgmental, reserved personality, oriented to work alone	I, N
Right inclined (reclined)	Little of the ball,	Extrovert, expressive, responds strongly to emotions, lack of self-control	E, F
Extreme right inclined	Speak up for our friends!	Impulsive, unrestrained, intense, very expressive, low frustration tolerance	E, S

The distance between words used by a person indicates their way of relating to other people; it is the distance that the writer wants to keep from society. If they are a cautious, circumspect person, the words will be written next to each other (a clear sign of an introverted person). If a person is extroverted, expansive, then the words will be far from each other. The combination of small letters with wide spaces is usually found in female people. A normal-sized writing with a regular distance is characteristic of a balanced and flexible personality in relationships with others (see Table 3).

Table 3. Main personality traits based on word spacing.

Description	Type	Characteristics	MBTI
Narrow	good employers. Wrong target. The Labour	Affected by emotions	I, F
Normal	Speak up for our friends!	Healthy vitality and willpower	J, T
Wide	Said there is at the moment	Sensitive and impressionable	E, S

The force (or pressure) with which words are written indicates the energy available for achieving a goal or for work. People who exert heavy pressure when writing are tenacious people, fearless of change, critical, irritable, and opinionated. Medium pressure is an indication of healthy vitality and willpower. When the writing pressure is light, it is a sign of a certain delicacy of feelings. The character is empathetic and emotionally receptive. One may note grandeur and innovation; however, the opportunities never seem to be captured, as it appears that these writers have an issue internalizing their encounters. The willpower is not steady, so the light-pressure writer is easily overwhelmed by the more powerful writer (see Table 4).

Table 4. Main personality traits based on pen pressure.

Description	Type	Characteristics	MBTI
Light	home again rather exciting.	Low self-esteem	N, P
Medium	most of the research	Healthy vitality and willpower	N, T
Heavy	WAS inside.	Sensitive and impressionable	S, J

4. Proposed Architecture

The proposed system is composed of three levels (see Figure 1). The first level is dedicated to preprocessing and segmentation. The second level is designed to extract handwriting features, and the third level converts these features into personality traits according to the Myers–Briggs model.

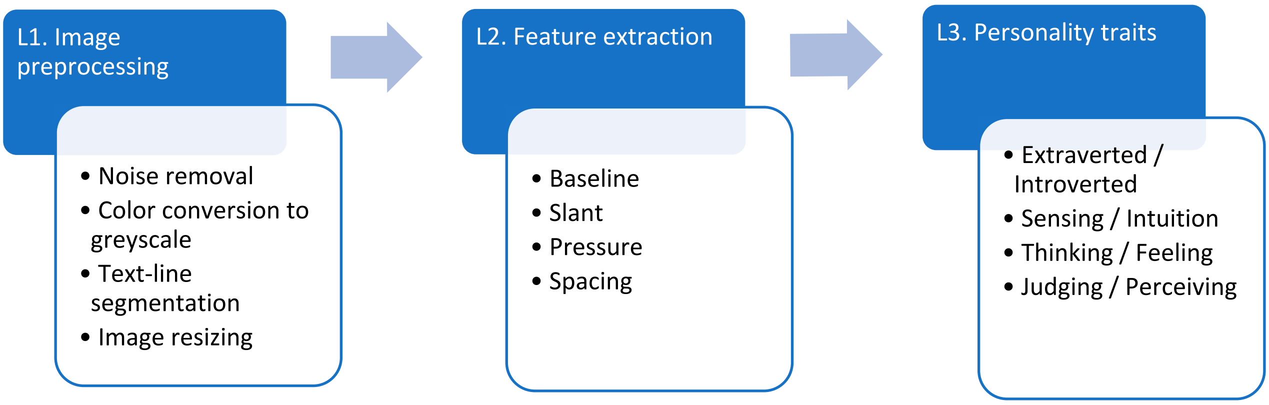

Figure 1. Proposed architecture—overview.

4.1. Level 1—Image Preprocessing

At this level, a series of processing steps takes place on the scanned image so that it can be used by a CNN for feature extraction. Preprocessing consists of the following operations performed on the scanned document: noise removal, conversion to greyscale, segmentation to extract lines from the text, and resizing the images so that they can be processed by neural networks.

4.1.1. Noise Removal

Noise removal from scanned images is an essential process in digital image processing, used to improve visual quality and facilitate further analysis. Image noise can be caused by factors such as poor lighting conditions, low-quality camera sensors, or image compression. To remove the noise, we used a Gaussian filter, weighing the neighboring pixels according to their distance from the central pixel.

4.1.2. Color Conversion to Grayscale

Converting a color image to a grayscale image is a common process in digital image processing. There are several methods to perform this operation, including the Single-Channel Method, Average Method, Desaturation Method, etc. In this work, the Weighted Luminosity Method was used, a method used in many image-processing applications.

Each color channel (R, G, B) contributes differently to the perception of luminosity, because the human eye is more sensitive to green than to red or blue. The formula used is the following:

$$Gray = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B$$

where

R: Red channel intensity.
G: Green channel intensity.
B: Blue channel intensity.

Using a threshold value, the image is transformed into a black and white image.

4.1.3. Line Segmentation

The segmentation operation is performed to obtain images with the lines of text. The method used is the one based on vertical projection and described in [29]. The method is based on determining the number of pixels on each line and establishing the boundary between two consecutive lines at the point with the fewest pixels (see Figure 2). Thus, rectangular images are obtained, containing the lines extracted from the text. The images obtained after segmentation are resized to 200 × 800 pixels.

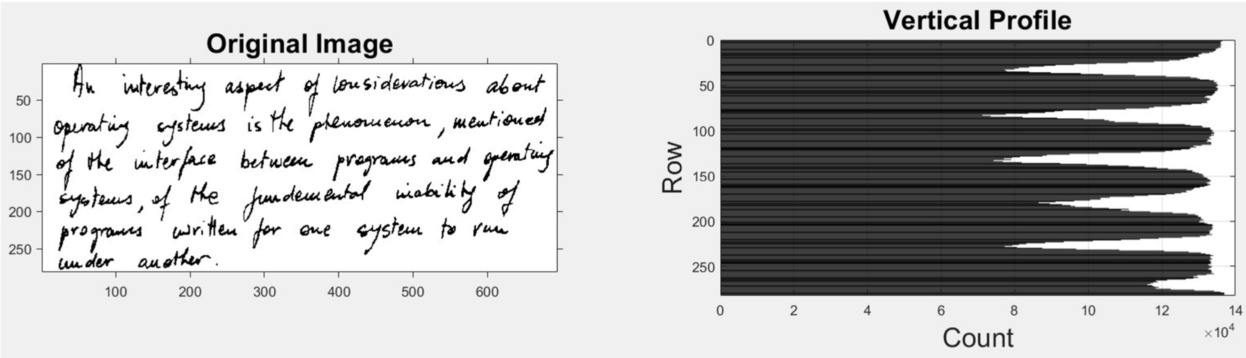

Figure 2. Vertical projection.

4.2. Level 2—Feature Extraction

The second layer is composed of four convolutional neural networks that analyze the four features of the handwritten text: baseline, slope, word spacing, and word pressure.

In image-processing-based object classification applications, the best results have been obtained using deep convolutional neural networks. CNNs are used in image feature extraction, object classification and detection, or image segmentation applications. There are several pretrained CNNs for recognizing numerous object classes, the best-known being ResNet, GoogLeNet, AlexNet, VGG, and Inception. CNNs have a number of features that make them extremely popular and lead them to be commonly used in image classification applications. Below, we present some of these features.

CNNs automatically learn relevant features (e.g., edges, textures, shapes) directly from the data, eliminating the need for manual extraction. This process is achieved through successive convolutional layers, where the initial levels detect simple features and the deep ones identify complex patterns. The pooling layer (e.g., max-pooling) reduces the spatial dimension of the data, ensuring invariance to minor translations or distortions. This allows for object recognition regardless of their position in the frame. The CNN architecture efficiently handles large image sizes (e.g., millions of pixels) by reducing parameters and preserving spatial relationships. Convolutional operations are parallelizable, allowing for fast training on specialized hardware (e.g., GPUs). CNNs dominate image classification competitions (e.g., ImageNet), outperforming traditional methods due to their high accuracy.

As disadvantages, we can mention the fact that CNNs fail if images are out of context or are seen for the first time; they need a lot of training data correctly labeled, which are difficult to obtain; and they are computationally expensive and require a high computing power and significant memory resources.

A CNN is composed of an input layer (which receives a digital color or grayscale image), an output layer (which usually returns the probability that the image belongs to a certain class), and several hidden layers. The hidden layers perform three operations: convolution, activation, and pooling.

To determine the various features in an image, a CNN can have dozens or hundreds of hidden layers. The basic idea is to use small matrices, called filters, which are applied by convolution over the original image. Then, after using an activation function (usually of the ReLU type), the pooling operation reduces the size of the output vector by reducing the number of parameters to be learned. These operations are repeated several times, with each hidden layer learning certain features of the object on which the training is performed.

In the final part, the matrix is linearized (transformed into a vector), which will represent the input for a multilayer perceptron neural network. In this paper, the structure of a CNN used for feature extraction is shown in Figure 3.

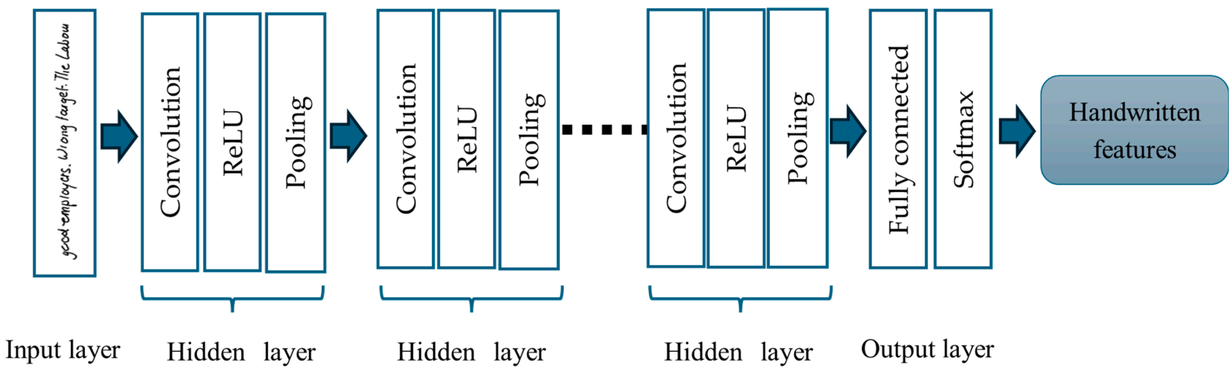

Figure 3. Structure of deep convolutional network.

4.3. Level 3—Determining Personality Traits

At the third level, MBTI personality traits are determined based on the results provided by the four neural networks. Each neural network determines a characteristic of writing (CNN1—baseline, CNN2—slant, CNN3—pressure, and CNN4—spacing), characteristics that can then be used by a specialist or computer application to determine the main personality traits.

Our application provides a score for the eight Myers–Briggs personality indicators, a score that is equal to the probability provided by the softmax output layer. The final score given to an indicator is the sum of the scores given by the four neural networks to each indicator. Finally, the Myers–Briggs personality traits are those in the top four positions according to the scores obtained (Figure 4).

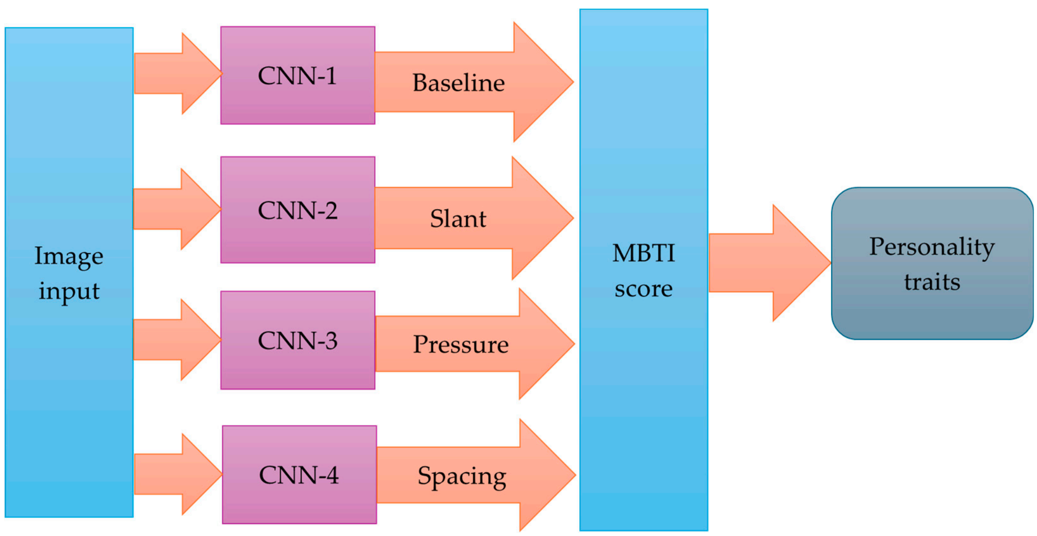

Figure 4. Determining Myers–Briggs indicators.

5. Experimental Results

5.1. Training Dataset

The most difficult part of the application is building a database for training the neural networks. To this end, four labeled databases corresponding to the four features were built. Each class has 100 images. In order to create the training data, the IAM database was used. This repository contains handwritten words and phrases in English [30]. IAM is a public database and was developed to create and test algorithms for the automatic recognition of handwritten characters and words.

It contains 13,353 isolated and labeled text lines from 657 writers who contributed samples of their handwriting. We selected and labeled sentence-type texts from the IAM database and then grouped them into training data and validation data (75 images for training and 25 for validation).

Since each handwriting characteristic (baseline of the sentences, characters' slant, word spacing, and writing pressure) has three or five features, we built fourteen datasets (one for each feature). Since the CNN-based classification algorithm uses fixed-size images as inputs, all images were resized to 200 × 800 pixels.

5.2. CNN Model

The CNN architecture shown in Figure 3 was implemented in MATLAB R2021b using the Deep Network Designer (see Figure 5). The neural network has one input layer, three hidden layers, and one output layer.

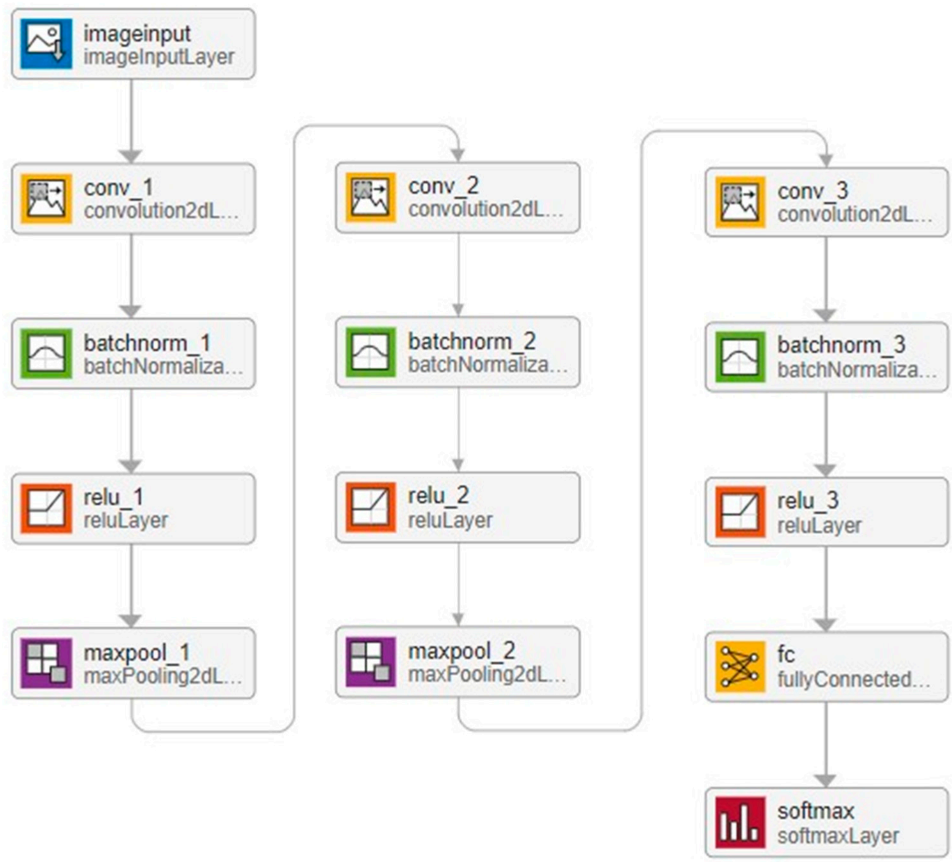

Figure 5. Software implementation (MATLAB R2021b) of CNN (1 input layer, 3 hidden layers, and 1 output layer).

Choosing the parameters of a convolutional neural network (CNN) involves several key decisions that depend on the specific task (e.g., image classification, object detection) and the dataset you are working with. These parameters can be grouped into three classes depending on the elements they refer to: convolutional layer parameters, dense layer parameters, and training algorithm parameters. Convolutional layer parameters are the number of layers, the number of convolutional filters of each layer, the size of filters, the activation function for each convolutional layer, and the size of the pooling filters. The problem we have to solve is of low complexity (each neural network must classify 3–5 types of handwriting), and the structure we have chosen has a small size. Thus, the network is made up of three convolutional layers with the following parameters: layer 1 uses 32 7×7 filters, layer 2 uses 16 5×5 filters, and layer 3 uses 16 3×3 filters. The first layer detects simple features (edges, textures), while the last layer detects complex features. Each convolution is followed by a max pooling operation with a 2×2 window and a stride of 2. We also use batch normalization, which is an important technique used in deep neural networks, including CNNs, to help improve training stability and speed. As activation functions, we used ReLU (rectified linear unit) functions, which are the standard choice for convolutional networks. After flattening the output from convolutional/pooling layers, we used three dense layers with 128 nodes. The final layer size matches the number of classes for classification (in our case, three or five) with softmax as the activation function.

The training options are the following:

- Optimization algorithm: stochastic gradient descent with momentum;
- Initial learning rate: 0.01;
- Maximum number of epochs: 10;
- Objective metric: loss;
- Minibatch size: 20.

The parameters of the neural network are presented in Table 5.

Table 5. Parameters of convolutional neural network.

Nr. Crt.	Layer	Type	Parameters
1	'imageinput'	Image Input	$200 \times 800 \times 1$ images
2	'conv_1'	Convolution	$7 \times 7 \times 32$ convolutions with stride [1 1] and padding [0 0 0 0]
3	'batchnorm_1'	Batch Normalization	Batch normalization with 16 channels
4	'relu_1'	ReLU	ReLU
5	'maxpool_1'	Max Pooling	2×2 max pooling with stride [2 2] and padding [0 0 0 0]
6	'conv_2'	Convolution	$5 \times 5 \times 16$ convolutions with stride [1 1] and padding [0 0 0 0]
7	'batchnorm_2'	Batch Normalization	Batch normalization with 16 channels
8	'relu_2'	ReLU	ReLU
9	'maxpool_2'	Max Pooling	2×2 max pooling with stride [2 2] and padding [0 0 0 0]
10	'conv_3'	Convolution	$3 \times 3 \times 16$ convolutions with stride [1 1] and padding [0 0 0 0]
11	'batchnorm_3'	Batch Normalization	Batch normalization with 16 channels
12	'relu_3'	ReLU	ReLU
13	'fc'	Fully Connected	3 fully connected layers
14	'softmax'	Softmax	softmax
15	'classoutput'	Classification Output	cross-entropy

The program was run on a PC with the following specifications: GPU processor 7th generation i7-7700HQ, 2.80 GHz, NVIDIA GeForce GTX 1050 Ti, and DDR4 16 GB (NVIDIA, Santa Clara, CA, USA). The training progress of a CNN for handwriting baseline analysis is shown in Figure 6.

In this example, we set a maximum of 10 epochs with seven iterations per epoch. It can be seen that the algorithm converges after only two epochs, and the training time is very short. The accuracy achieved is 95%.

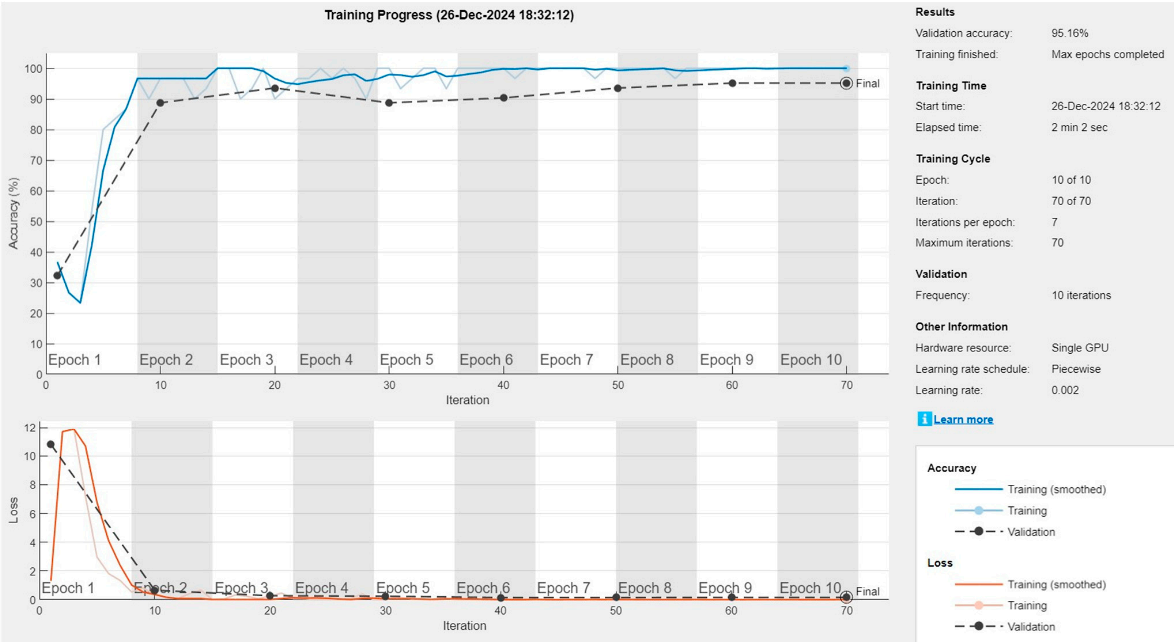

Figure 6. Training progress for baseline analysis.

5.3. Results

Using the standard indicators for evaluating machine learning models and their performance—true positive (TP), true negative (TN), false positive (FP), and false negative (FN)—we evaluated the classification performance using the following measures: accuracy, precision, recall, and F1 score. The performance measures were calculated using the following equations:

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$$

$$\text{F1 score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall})$$

The results obtained after training the networks are presented in Table 6.

Table 6. Handwriting feature prediction accuracies.

Handwriting Feature	Type	Accuracy	Precision	Recall	F1 Score
Baseline	Rising	0.96	0.89	1.00	0.94
	Normal	0.90	0.81	0.92	0.86
	Falling	0.91	0.84	0.91	0.88
Slant	Extreme left inclined	0.89	0.72	0.81	0.76
	Left inclined	0.90	0.76	0.81	0.79
	Vertical	0.94	0.81	0.93	0.87
	Right inclined	0.90	0.73	0.79	0.76
	Extreme right inclined	0.89	0.70	0.88	0.78
Spacing	Narrow	0.93	0.81	1.00	0.89
	Normal	0.90	0.85	0.88	0.87
	Wide	0.93	0.88	0.92	0.90
Pressure	Light	0.96	0.90	1.00	0.95
	Medium	0.93	0.83	1.00	0.91
	Heavy	0.91	0.85	0.92	0.88

To test the system, we asked 70 subjects aged between 18 and 30 to complete the MBTI questionnaire online at the web address [31] and to provide 1–2 pages of written text. Figure 7 shows part of the text written by one of the subjects. The recognition accuracy of the four Myers–Briggs indicators is presented in Table 7.

Table 7. MBTI prediction accuracies.

MBTI	Accuracy
Extraversion (E) vs. Introversion (I)	91%
Sensing (S) vs. Intuition (N)	85%
Thinking (T) vs. Feeling (F)	88%
Judging (J) vs. Perceiving (P)	83%

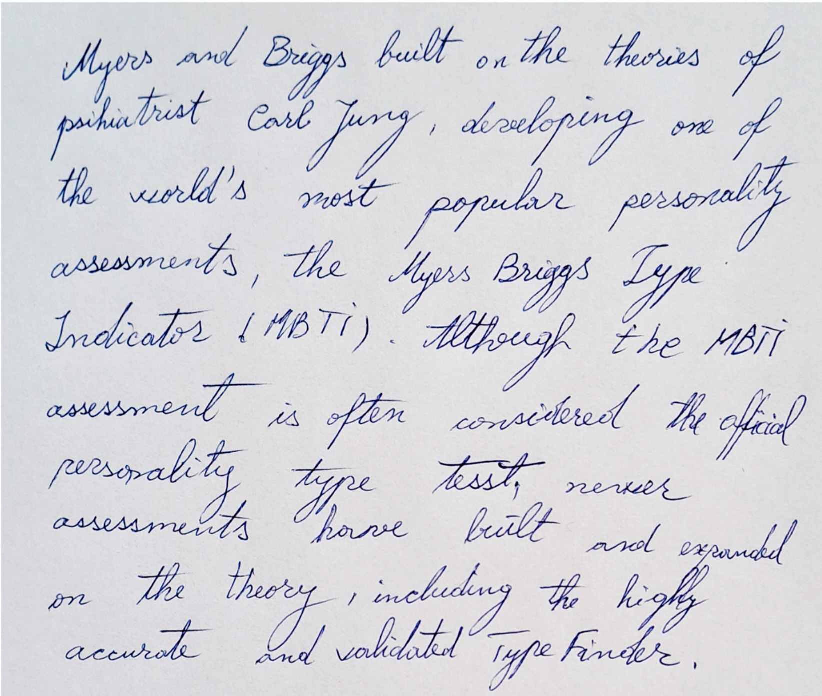

Figure 7. Handwriting sample text written by one of the subjects.

From the results presented in Tables 6 and 7, it can be seen that there is a correlation between handwriting characteristics and Myers–Briggs indicators. Although the data used to train the neural network (extracted from the IAM database) are different from those used to test the application, the results obtained are very good.

6. Discussion

As can be seen from the previous section, the convolutional neural network performs very well even though it is composed of a relatively small number of hidden layers, and the time required for training is very short (a few minutes). Also, although a small number of training data items were used, the CNN is able to extract the main features of handwriting.

Below, we present a comparison of the results obtained in this study with some results obtained in similar studies, limitations in our approach, and future research directions.

6.1. Comparison with State of the Art

Since there are no public databases that correlate handwriting samples with personality traits, the comparisons presented below are based on the data obtained and published by each author.

In Fallah (2016) [32], a handwriting feature detection algorithm using multilayer perceptron (MLP) is used. The features analyzed are character size, line spacing, word slant, and horizontal-to-vertical ratio of characters. The personality traits are obtained via Minnesota Multiphasic Personality Inventory tests. The results presented are based on tests applied to 70 subjects (50 for training and 20 for validation) and have an accuracy between 69% and 76%.

In Gavrilescu (2018) [9], a feed-forward neural network is used to determine the so-called Big Five personality type. The results presented are obtained based on handwriting samples obtained from 128 people. The handwriting characteristics analyzed are the baseline, the slope, connecting strokes between characters, and certain characteristics of the letter f. The results obtained range between 77% for Agreeableness and Conscientiousness and 84% for Openness to Experience.

In Joshi (2019) [3], an algorithm based on Support Vector Machine is presented. The features analyzed are the text margin, baseline, character size, and letter t analysis. The database used consists of 1890 handwriting samples obtained from a group of students aged between 20 and 24 years old. The accuracy of the results is 93%.

In Rahman (2022) [20], text feature extraction is performed using a Semi-supervised Generative Adversarial Network (SGAN) and a graph-based character representation. The model used is the Big Five personality traits. The database built for this application contains 1038 instances (800 for training and 208 for testing). The accuracy of the algorithm varies between 86% and 91%.

A summary of these results is presented in Table 8.

Table 8. Comparison with similar studies.

Paper	Text Features	Classifier	Dataset	Accuracy
Fallah 2016 [32]	Character size, line spacing, word slant, horizontal-to-vertical ratio of characters	Multilayer Perceptron	70 subjects	0.69–0.76
Gavrilescu 2018 [9]	Baseline, the slope, connecting strokes between characters and letter f	Feed-Forward Neural Network	128 subjects	0.77–0.84
Joshi 2018 [3]	Text margin, baseline, character size, letter t	Support Vector Machine	1890 samples	0.93
Rahman 2022 [20]	Handwriting strokes, shapes, structure	Semi-supervised Generative Adversarial Network	1038 samples	0.86–0.91
Current work	Baseline, characters' slope, pen pressure, spacing	Convolutional Neural Network	1400 samples	0.83–0.91

6.2. Limitations

Although the results obtained are quite good, there are a number of aspects and limitations that must be taken into account when applying this method of determining personality traits:

- Subjectivity of personality traits: Personality traits are abstract and subjective concepts, making it difficult to associate them with physical characteristics of handwriting. There are psychological studies that consider the number of personality traits to be in the hundreds, which makes it impossible to classify people into just a few classes.
- Lack of standardized datasets: Available datasets are often small, unbalanced, or lacking in diversity, which limits the ability of models to generalize the results.
- Handwriting variability: Handwriting can vary depending on the emotional state, context, health status, or even the writing instrument used, which introduces noise into the data.

- Ethical issues: Using these techniques in sensitive areas (such as recruitment or psychological assessment) raises ethical questions related to confidentiality and bias.

6.3. Future Research Directions

Each person has a unique handwriting style, which makes it an interesting topic for user identification research and practical for a number of uses, including biometric analysis, personal identity, pattern recognition, digital forensics, criminalistics, fingerprint analysis, signature verification, etc. As future research directions in this area, we wish to mention the following:

- Improving datasets by creating larger, more diverse, and well-labeled datasets is essential for advancing research in this area.
- Improving accuracy of personality trait predictions is key, by analyzing other handwriting features together with the four ones already analyzed in our study.
- Modal fusion by combining handwriting data with other modalities (such as facial expressions, voice, or online behavior) can improve the accuracy of predictions.
- Advanced deep learning models—Using more advanced architectures (such as recursive neural networks—RNNs, or transformers—Transformers) may capture complex dependencies in the data.
- Interdisciplinary validation—Collaboration between machine learning experts, psychologists, and graphologists can lead to more robust and accurate approaches.
- Dynamic data (e.g., writing speed, pen pressure) can be captured using digital tablets [33].

7. Conclusions

In this study, a system for automatic recognition of handwriting features using convolutional neural networks was developed. The basic idea is to replace the cumbersome and impractical questionnaires used by psychologists to determine the main personality traits with a non-invasive system based on artificial intelligence. The main advantages of the system developed in this study are the speed of image processing and the extraction of the main features of handwriting: baseline, slope, spacing between words, and writing pressure. Based on these features, the system also provides an estimate of the Myers–Briggs personality indicators. The system consists of three levels, the most important part being the second level composed of four neural networks trained to extract handwriting features. Convolutional neural networks were chosen because they present a number of advantages over other types of neural networks, with advantages proven for numerous practical applications in image processing and recognition. The dataset used for training and validation contains 1400 images taken from the public IAM database. The system offers an accuracy between 89% and 96% for handwritten feature recognition and results ranging between 83% and 91% in determining Myers–Briggs indicators. It also computes the results in less than 1 min, making the system practical for determining the MBTI personality types through handwriting. It could be successfully implemented in applications such as human resources, forensic science, education, health assistance, or personal development.

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Data Availability Statement: The dataset is accessible from the public repository, Computer Vision and Artificial Intelligence, and is accessible on the following URL: https://www.kaggle.com/datasets/naderabdalghani/iam-handwritten-forms-dataset (accessed on 14 October 2024).

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Abbreviations

The following abbreviations are used in this manuscript:

MBTI	Myers–Briggs Personality Indicators
CNN	Convolutional Neuronal Network
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
KNN	k-Nearest Neighbors
SVM	Support Vector Machine
RNN	Recurrent Neural Network
ReLU	Three-Letter Acronym
MLP	Multilayer Perceptron Neural Network

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