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Research article

Personality Type Analysis through Handwriting Characteristics Mapping using Invariant Moment Descriptors

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ABSTRACT

Handwriting patterns are unique to each individual and can offer valuable insights into their mental health conditions, personality traits, behavioral tendencies, mindsets, and more. To effectively analyze someone's personality or solve a problem using their handwriting, it is crucial to employ suitable descriptors that accurately represent the essential information it contains. Therefore, this study aims to explore the application of invariant moments as descriptors to map personality types using the psychological technique of enneagrams in conjunction with handwriting patterns. The main procedures in this research involve pre-processing, texture-based feature extraction utilizing seven invariant moment values, and applying the chi-square similarity measure. Through testing with 49 handwriting samples and 120 reference data points, it was discovered that 42 writings were successfully and accurately mapped to their corresponding personalities, achieving an impressive accuracy rate of 85.7%. This research also reaffirms the validity of personality analysis through a system that utilizes graphological techniques, as demonstrated by a 4.1% increase in accuracy through the inclusion of invariant moment descriptors when compared to psychologist analysis.

1. Introduction

The technology for analyzing handwriting is currently limited and has not been widely developed, despite its potential to assist in various areas such as verifying the authenticity of written documents for forensic purposes or understanding someone's personality. Graphology assesses not only behavior but also medical and mental health aspects, as well as a person's talents.In Indonesia, the number of graphology experts remains limited due to the perception that graphology is not widely recognized as a genuine science, but rather as a pseudosciencebecause of the difficulty in establishing a definitive link between a person's psyche or personality and the characteristics of their handwriting [1].However, graphology has been applied in practice to aid in criminal investigations by analyzing perpetrator characteristics[2]and to assist psychologists in clinically assessing Attention Deficit Hyperactivity Disorder (ADHD) in children[3].In their book, graphology experts from the United States argue that handwriting characteristics can indeed describe a person's character and personality. This is because writing involves both knowledge and skills, as well as the infusion of emotions, desires, and feelings. Since these emotions are unique to each individual, they tend to correlate with the inherent nature and character of the person[4].However, due to the challenges in providing definitive evidence, the field of graphology has developed slowly and is rarely implemented. This research aims to address this challenge by exploring the application of graphology to computer devices, specifically utilizing the invariant moment descriptor, in order to help analyze human personality through the mapping of handwriting features. By merging graphology with technology, the researchers hope to contribute to the advancement of this field and its potential applications.

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Previous studies conducted by researchers have provided evidence for the validity of graphology. They have established correlations between personality analysis based on graphology and psychology using the Region Of Interest (ROI) method [5][6]. The connection between a person's personality and their writing style has been validated through the use of the Enneagram, a personality test employed by psychologists, which has demonstrated an accuracy rate of approximately 81.6%. Chaudhari and Thakkar [7] have also explored various psychological assessment mechanisms to establish the relationship between an individual's nature and their writing style. Additionally, other researchers have utilized methods such as Deep Convolutional Neural Network [8], Support Vector Machine [9], and Particle Swarm Optimization [10] to analyze personality based on handwriting characteristics.

Handwriting possesses features that extend beyond personality recognition, making it applicable for various purposes. Previous research has successfully employed handwriting in forensic graphology and document security with relatively high accuracy. This was achieved through the combination of methods such as the Inner Product with Support Vector Machine (SVM), as well as Fisher Score with Learning Vector Quantization [11][12][13]. Moreover, handwriting has proven to be a useful tool for assessing the mental preparedness and psychological state of pilots before flight [14]. Building upon these successful studies, the researchersaimed to further explore the utilization of handwriting in this research to enhance personality assessment tools accessible to a wide range of users. This was accomplished through the utilization of the Invariant Moment descriptor and Chi-Square similarity measure.

Researchers have previously utilized the Invariant Moment as a feature in the context of verifying the authenticity of English handwriting owners, yielding results with a notably high level of accuracy [15]. While this research employs similar features, it differs in terms of the similarity measure technique and the categorization of data into four groups: Slant, Size, Breaks, and Baseline. The goal of this study is to develop a model capable of accurately analyzing personality types based on the assessment results from psychologists.

2. Materials and Methods

This research primarily utilizes the method of writing feature extraction based on Invariant Moment and employs pattern recognition through the calculation of Chi-Square Distance.

2.1. Materials

2.1.1. Invariant Moments

The crucial stage in pattern recognition is obtaining the features within the pattern that enable learning and recognition by the system. The accuracy of feature selection significantly impacts subsequent processes, computational load, and the success rate of the system [11]. Shape is a fundamental feature that can be extracted from image data. When analyzing shape characteristics, it can be approached in two ways: a general manner, known as global feature extraction, or with specific details, known as local feature extraction. The resulting features are stored in vector form as feature vectors. In this study, the focus is on extracting global features, specifically moment invariant values.

Moments provide distinctive characteristics of an object that uniquely represent its shape. Recognition of invariant shapes is achieved through classification in the multi-dimensional moment invariant feature space. Various techniques have been developed to derive invariant features of moment objects for object representation and recognition. These techniques differ in their moment definitions, the type of data being utilized, and the methods employed to derive the invariant value of the image moment. The moment invariant value remains unchanged in the presence of translation, scaling, and shape rotation. Calculation of the moment invariant relies on information derived from the shape boundary and its interior area. While moments are used to form continuously defined moment invariants, practical implementations typically involve discrete calculations. The formula for computing the invariant moment is as follows:

$$M_{pq} = \iint x^p y^q f(x,y)dxdy \quad (1)$$

The two-dimensional moment of the function f(x, y) is denoted as Mpq, where p and q are natural numbers representing the order of the moment. In digital implementations, the equation is modified as follows:

$$M_{pq} = \sum_x \sum_y x^p y^q f(x,y) \quad (2)$$

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In order to normalize the invariant moment within the image plane, the centroid of the image is utilized to determine the center point. The coordinates of the image's center of gravity are calculated using equation (2) and are expressed as follows:

$$\bar{X} = \frac{M_{10}}{M_{00}} \text{ and } \bar{Y} = \frac{M_{01}}{M_{00}} \quad (3)$$

Additionally, the central moment can be discretely calculated using the following formula:

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q \quad (4)$$

Subsequently, the moment is normalized to account for the scaling effect:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \quad (5)$$

Using the normalization factor:

$$\gamma = \left(\frac{p+q}{2}\right) + 1 \quad (6)$$

The seven invariant values can be determined from the normalized central moment:

$$\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2 \\
\phi_5 &= (3\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 \\
&\qquad - (\eta_{21} + \eta_{03})^2] \\
\phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} - \eta_{12})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 \\
&\qquad - (\eta_{21} + \eta_{30})^2]
\end{aligned} \quad (7)$$

Hu has demonstrated and proven that the seven invariant moment values are independent of rotation [16]. However, it is important to note that these values are calculated based on the outer boundaries and interior region of the object.

2.1.2. Chi-Square Distance

Pattern recognition is a field within the realm of artificial intelligence that aims to identify distinctive features or characteristics within a given dataset and classify them accordingly [17]. This stage is commonly employed in image recognition and analysis to identify complex structures, regions, shapes, and patterns that may be challenging to discern [18]. There are various approaches to pattern recognition, and one such approach involves the utilization of similarity measures.

Similarity measures are techniques used to assess the resemblance between two objects by calculating the distance between them [19]. Multiple methods exist for distance calculation within similarity measures, including Manhattan Distance, Euclidean Distance, Chi-square Distance, and Cosine Distance. In this research, the Chi-square distance is employed for distance calculation.

$$x^2 = \sum_{i=0}^{n} \frac{(H_i - S_i)^2}{H_i + S_i}$$

In the formula for the chi-square distance, x represents the value of the distance, while H and S denote the variable values of object H and object S, respectively.

Chi-square is a straightforward method for quantifying the similarity between objects based on their statistical probability values [20]. Chi-square is particularly suitable for analyzing the correspondence or correlation of data among multiple variables, making it a suitable choice for this study. The variables considered in this research are those that determine handwriting characteristics according to graphology, which are known to correlate with personality types. These variables include slant, size, baseline, and breaks.

2.1.3. Interpretation ofGraphology and Psychology

Graphology is a scientific discipline that explores techniques for interpreting human characteristics through handwriting from various perspectives [4]. According to recommendations from graphologists, handwriting can reveal an individual's strengths and weaknesses, behavioral tendencies in problem-solving, and even their mental health condition. These experts employ a range of viewpoints when analyzing handwriting, such as examining spacing between letters, the slant of writing, size, speed, and many other factors [21]. Different perspectives yield diverse analyses of behavior and personality, emphasizing the importance of selecting the most interpretable aspects of the written text.

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In psychology, various tests are available to analyze behavior, character, and personality, similar to graphology. Structured psychological tests provide insight into selected behaviors, with each test category serving a different purpose. One such category is the personality test, designed to reveal patterns of thinking, feeling, and behaving. These tests can also assess emotional levels and detect deviant behavior. Several graphic personality test methods, including Baum Tree, DAP, HTP, Wartegg, as well as questionnaire-based tests like Enneagram, MBTI, MAPP, and EPPS, are utilized [22]. In previous research, researchers successfully demonstrated a correlation between handwriting characteristics and a person's personality, employing enneagram mapping in collaboration with psychologists [6].

Table 1.Personality Traits based on Graphology

Category	Feature	Characteristics
Slant	Left	Not independent, difficult to get along with, quiet, selfish, anxious, oriented to the past, lacking self-awareness, prone to inner rebellion, resistant to accepting progress or change.
	Vertical	Independent, analytical, considerate, logical, unobtrusive, having a personal charm that draws others close.
	Right	Easily sympathizing, emotional, sentimental, irresponsible, openly displaying feelings, future-oriented, sincere in relationships.
Baseline	Up	Explosive, unrealistic, ambitious, restless, optimistically active
	Down	Overly sensitive, easily broken hearted, morose, depressed, melancholic
	Flat	Stable, reliable, firm, having good self-control
Size	Large	Extroverted, enjoying luxury, seeking attention, disliking being alone, enthusiastic, optimistic, expansive, restless, struggling with concentration
	Medium	Realistic, practical, adaptable to conventional circumstances, having a balanced mind
	Small	Simple, having a strong academic mentality, paying attention to details, modest, able to concentrate, not very communicative except with close friends, occasionally experiencing feelings of inferiority
Breaks	Dashed	Relaxed, keen observer, inspiring thinking, relying on instincts, individualistic, extroverted, inconsistent, moody, restless, shy, quick to understand, possesses a vivid imagination
	Connected	Logical, often restless, loving reading and studying, analytical, rational, introverted, self-understanding, reliable, consistent, systematic thinker, disliking interruptions, persevering

The mapping technique mentioned above was utilized once again to evaluate a person's psychological condition and personality by analyzing the written characters produced in each test data.

2.2. Methods

In this research, the methodology involves several key stages, which are depicted in the flowchart presented in Figure 1.

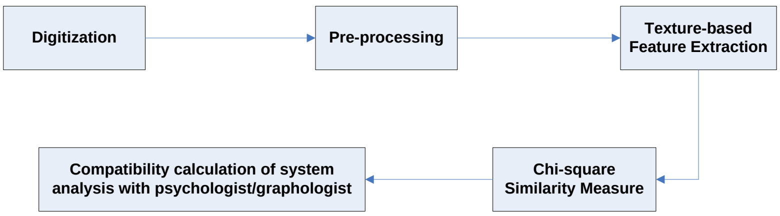

Fig. 1. Research Flowchart

The initial step of the research, as shown in Figure 1, was the collection of data in the form of handwritten documents. The data collection process involved sourcing handwritten samples from various available sources or utilizing graphology books that provide references with accompanying personality assessments [4], as illustrated in Figure 2 (a) and (b). Each handwritten document was then converted into digital format using a scanner, resulting in JPEG images of the handwritten data. For the sample reference data (training), 30 data points per category of handwritten characters were collected,

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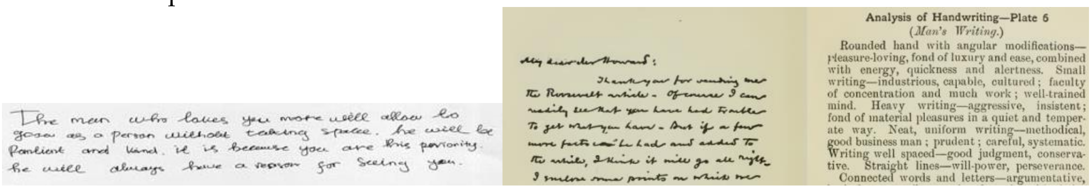
with a total of 4 categories: slant (8 left, 11 right, 11 vertical), size (13 large, 11 medium, 6 small), breaks (14 dashed, 16 connected), and baseline (7 up, 13 down, 10 flat). In the testing phase, handwriting data from 50 participants were used. Consequently, a total of 170 data points were utilized for this study. Here are some examples of the data used:



(a) (b)

Fig. 2.Example of Handwritten Data: (a) Testing data; (b) Reference data with graphological analysis

The collected samples meet the requirements for correlation research and multivariate experiments, which necessitate a minimum of 30 data points per group to ensure representative results[23]. Subsequently, each data point undergoes image processing, involving RGB to grayscale color conversion and the segmentation of writing objects using thresholding techniques.A threshold value of 128 wasdetermined, representing the midpoint of the color interval. This value separates the foreground area (writing object), where pixels with grayscale values below the threshold are assigned to the foreground, while those above the threshold were set to 255, representing a white background.Texture features were then extracted from each category of graphological characteristics for every data point, resulting in seven moment invariant values(*Φ1, Φ2, Φ3, Φ4, Φ5, Φ6,Φ7*). These values were stored as reference data in an SQLite database, serving as a basis for comparison with the test data. During the testing phase, the same steps were repeated for the test data. To determine the personality type associated with the test data, the similarity measure approach was employed to calculate the shortest distance to the reference data. A smaller distance indicates a higher similarity to the corresponding category. After obtaining the distance results and the relevant graphological categories, the system-generated personality types were compared with the assessments made by experts (graphologists and psychologists). A higher degree of alignment between the resulting personality types and expert assessments indicates improved system accuracy.

3. Results and Discussion

In this research, characteristic values have been obtained from all reference data in the form of seven moment invariant values for each handwriting pattern. This was achieved through an application developed to implement feature extraction. The handwriting patterns of the 120 reference data encompass various combinations of Baseline, Breaks, Slant, and Size, which were previously mapped to enneagram types in the studies conducted in the previous year [5] [6]. From these patterns, feature values were extracted and averaged to create reference patterns for determining personality types from the test data. The following table displays the invariant moment values used as references for each enneagram type on Table 2.

Table 2. Reference Average Invariant Moment Descriptor Values for Enneagram Mapping

Enneagram	**Average Invariant Moment Value**						
Type	**Φ1**	**Φ2**	**Φ3**	**Φ4**	**Φ5**	**Φ6**	**Φ7**
1	1.5926	3.0655	4.0355	5.01121	7.5643	9.2186	11.032
2	1.638	3.0942	4.2422	5.7734	6.5768	8.1216	10.456
3	1.995571	3.291857	4.192286	5.552143	6.799429	8.704143	11.28
4	1.84975	2.6365	4.15425	5.45125	7.33675	8.67775	10.83
5	1.57825	2.50525	3.679	5.3245	6.718	8.818	10.8145
6	1.81625	2.6625	4.27325	6.11	7.62	8.828	10.9675
7	2.0115	2.95975	4.46525	5.991375	7.3305	8.57875	11.22625
8	1.933	3.522	3.852333	5.617	6.371333	8.026667	10.79
9	1.799625	3.179875	4.41125	6.143375	7.385	8.77	10.90588

To facilitate the analysis of the correlation between the moment invariant values and the enneagram type, the researchers visualized the data in the following graphical format on Figure 3.

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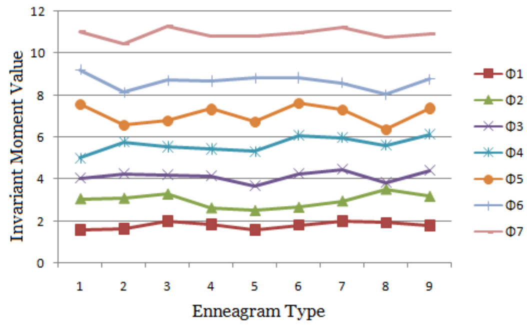

Fig. 3. Graph illustrating the Correlation Analysis of Moment Invariant Values with Enneagram Types

When examining the graph in Figure 3, it is evident that the moment invariant values across enneagram types do not exhibit a consistent pattern. This is because the moment invariant values within each enneagram type have distinct intervals. However, significant differences can be observed in the patterns of moment invariant values. Specifically, the first invariant is smaller than the second invariant, the second invariant is smaller than the third invariant, and so forth. These distinct patterns are what contribute to the unique characteristics of each enneagram type. In this study, to determine the enneagram type based on a handwriting pattern, a similarity measure calculation using the Chi-square distance was employed. The subsequent table presents the test results obtained from analyzing 50 handwritten data samples collected from 50 participants on Table 3.

When examining Table 3, the test results are highly satisfactory. Although there are still variations in the analysis of personality types within some of the data, the number of matches between the graphology application developed and the enneagram analysis performed by psychologists remains higher. Out of the 50 participants' handwriting samples analyzed (with one data point excluded due to human error), 42 handwritings were successfully and accurately analyzed, while 7 data points yielded inconsistent results. The current accuracy rate stands at 85.7%. This accuracy value demonstrates an improvement compared to previous research conducted in 2017, where the accuracy increased by 4.1%, from 81.6% [6]. Consequently, this study concludes that the application of Invariant Moment as a descriptor or feature value for handwriting pattern recognition enhances accuracy by 4.1% compared to the utilization of ROI descriptors with the same amount of final test data. This improvement may be attributed to the fact that the invariant moment value is unaffected by potential transformations during the pre-processing stage. This notion is supported by research conducted by Syafie et al. [24] in recognizing numeric data on electricity meters through a blurring process, as well as by Narudin et al.'s research [25] in analyzing transformed images. As a result, the accuracy obtained in this study reached 85.7%. Nevertheless, it is important to note that further investigation is necessary to validate the immunity of moment invariant values to transformation effects in handwriting patterns. Future studies should explore various types of transformations, such as changes in position, size, and slope, to validate this assertion.

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Table 3. Results of Personality Type Matching through the Enneagram and Graphology using Invariant Moment Descriptors and Chi-square distance

Participant Pseudonyms	Types of Personality		Invariant Moments						
	Enneagram	Graphology	Φ1	Φ2	Φ3	Φ4	Φ5	Φ6	Φ7
Marcella	3 / 7 / 9	3	2.331	3.702	3.998	5.163	7.203	7.355	10.56
Unknown	3	3	1.924	3.331	4.058	4.897	5.079	8.203	11.02
Nathania	9	9	2.21	2.602	3.992	5.707	7.333	8.034	10.27
Unknown	2/3/5	5	1.058	1.947	2.344	4.212	5.239	7.673	9.988
Unknown	5/9	5	1.344	3.234	4.201	6.391	6.992	8.522	10.01
Unknown	3/8	8	2.904	3.823	5.053	6.202	7.302	9.011	10.63
Unknown	9	4	2.21	2.904	3.764	5.987	7.45	9.004	10.9
Unknown	2	2	1.18	2.033	4.022	5.992	6.310	8.024	10.43
Unknown	4	4	1.534	2.139	4.212	6.031	8.32	10.32	11.98
Unknown	-	-	-	-	-	-	-	-	-
Zilzikridini	4	9	2.35	3.677	4.904	6.911	7.453	8.056	9.98
Veni E.	3	3	1.802	3.023	4.029	6.102	8.221	10.22	12.29
Yayang N.	7	7	1.39	2.066	4.203	5.326	7.043	9.201	11.51
Vitria R.C.	7/9	9	2.085	4.302	5.997	6.667	8.039	10.55	12.597
Nadine A.S	7	4	2.787	3.973	5.011	6.85	7.982	9.202	11.04
Sarah	3	3	1.223	3.108	4.292	6.027	8.208	10.14	11.78
Titania R. N.	4	4	1.024	2.502	4.043	5.982	6.074	8.032	9.88
Khumaira	6/9	6	2.315	3.408	5.032	7.854	9.304	11.02	13.20
Tara A.A.P	9	9	1.503	3.022	4.694	6.391	7.025	9.92	11.31
Niken	7	7	1.28	2.233	4.322	5.992	6.810	8.124	11.43
Nurul M.P.	9	9	1.39	2.066	4.303	5.326	7.343	9.201	11.51
Putri	3	3	1.824	3.231	4.158	4.897	5.179	8.203	11.02
Labiba	7	7	2.531	3.702	3.998	5.263	7.203	7.355	11.56
Melinda	9	9	2.831	3.302	3.198	5.563	7.703	7.355	10.56
Nur F.	4/7/9	7	1.534	3.139	4.882	6.231	8.32	10.32	11.98
Tiara	7	7	2.112	2.602	3.992	5.707	7.333	8.034	10.27
Ranyta D.	5	1	1.924	3.331	4.058	5.897	7.079	9.903	13.17
Sarah W.	6	6	1.58	2.038	4.077	5.992	6.310	8.024	10.13
Lady M.	2	2	2.631	3.001	4.598	5.503	7.503	7.355	10.56
Rania B.	9	9	1.55	2.602	3.792	5.507	7.533	8.034	11.27
Sisilya E.	3/7/8	3	2.831	3.302	3.198	5.563	7.703	7.355	10.56
Safira	5	1	1.19	2.233	4.062	5.992	6.110	7.924	10.43
Nissa	1/9	1	1.033	3.903	4.301	6.391	6.332	8.822	11.81
Ari S.	8	8	1.924	3.331	4.058	4.897	5.079	8.203	11.02
Robert M.	5	5	1.534	2.139	4.312	6.031	8.32	10.32	11.28
Tiffany M.	2/6/7/9	6	2.11	2.602	3.992	5.807	7.333	8.234	10.27
Tiffany	2/9	9	1.344	3.234	4.201	6.391	6.992	8.522	10.01
Qotrunnadya	9	1	2.001	3.902	3.598	5.563	6.703	8.355	10.56
Siti Salediah	2	2	1.18	2.033	4.022	5.992	6.310	8.024	10.43
Namira	6	6	1.26	2.602	3.992	4.787	7.533	8.034	10.27
Petra Mario S.	2	2	2.031	3.702	3.998	5.163	7.203	7.355	10.16
Lea Insani	5/6/9	5	2.531	3.702	3.998	5.063	7.203	9.355	11.56
Marcellina	7	7	2.904	3.823	5.753	7.202	7.302	9.011	10.63
Sherli Betris	1	1	1.534	2.139	4.212	6.031	8.32	10.32	11.98
Viola	2	2	1.012	3.73	4.158	4.87	5.079	8.003	10.22
Shazlin	1	1	1.134	2.039	4.212	5.031	8.32	10.32	11.98
Manindya	9	7	2.131	3.511	4.58	6.503	7.3	8.551	12.16
Miranti V	8	8	1.044	3.933	4.301	6.391	6.332	8.522	10.3 1
Stella Febrina	1/7	1	2.631	3.302	3.598	5.563	7.503	7.355	10.56
RM	3	3	1.26	2.602	3.992	5.707	7.533	8.034	10.27

4. Conclusion

After testing 50 different handwriting samples from various participants (with one sample being excluded due to human error), 42 writings were successfully matched with personality analysis, resulting in a system accuracy rate of 85.7%. These results not only reaffirm the correlation between graphological analysis (system) and assessments conducted by psychologists but also highlight the improved accuracy achieved through the utilization of the invariant moment descriptor. The invariant

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moment descriptor effectively represents handwriting features, resulting in a 4.1% increase in accuracy. Furthermore, the use of invariant moments reduces the number of matched features and reduces the computational burden compared to other studies employing different feature sets [26].

Author Contributions

D. Pratiwi: Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, and writing - review & editing. S. Syaifudin: Conceptualization, formal analysis, funding acquisition, investigation, project administration, and validation. A. Fauzy: Investigation, software, and visualization. M. Khasan: Formal analysis, resources, and validation.

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