Journal of Positive School Psychology http://journalppw.com
2022, Vol. 6, No. 5, 3263-3273

Improved Methodology For Personality Assessment Using Handwritten Documents

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Abstract

This paper presents an analysis and design of an intelligent software that supports handwriting analysis-based system development. The software facilitates handwriting acquisition and collection, graphological analysis, and results sharing. A substantially large number of handwriting samples, collected and analyzed over a long period of time, should help in discovering the ground truths needed to validate and justify applications in biometrics, medicine, forensic, psychiatry, patient monitoring and the like domains. Although, studies indicate strong relationships between consciousness that results into graphic patterns like handwriting, but the ground truth would give further insight into the phenomenon that governs graphology processes. The paper also presents rules through feature learning and rule induction modules, and embedding intelligence through an inference mechanism so a system build using these features justify its decision. In these experiments 1000 number of people participated from CPAR dataset. The average acceptance percentage range between 84 to 96 percentages.

Keywords: Graphology, Personality Assessment, Handwritten document processing, personality traits

Introduction:

A handwriting sample depicts writer's emotional or dramatic expressions. In handwriting, all hand movements manifest and writer's tendencies give individuality to handwritings. In addition to this, the individuality comes from handwriting learning process; arms, wrist and finger movements, use of writing instruments, amount of practice, professional requirements, social imitation, and similar factors. Some of these factors, like arms, wrist and finger, get affected by writer's physical and/or mental conditions, and thereby influence writer's handwriting stroke attributes such as thickness, length, rigidity, or suppleness.

According to an estimate, the probability of two handwritings being identical is one in sixty-eight trillion (Downey, 1919). That is why, handwriting analysis results are being investigated for discovering knowledge about relationships between handwriting samples and writer's physical & mental health, and individuality. However, for a better understanding of sources providing knowledge for designing a handwriting processing system, a brief description, on recent advances in some important areas, is given below.

In criminology the handwriting analysis is used for solving crimes by identifying the writer of the handwritten notes that are discovered during the criminal investigation (Hepler, et al., 2012). In child development handwriting analysis (Jonason Peter K, 2017) is being very successfully applied children's examination performance evaluation (Lowis, and Mooney, 2001), handwriting assessment (Falk, et al. 2011), attention deficit hyperactivity disorder estimation (Shen, et al., 2012), liver cirrhosis (Mechtcheriakov S., et al., 2005), and (Impedovo Sebastiano, 2014).

The nature of these applications reveal that the development of handwriting analysis techniques requires knowledge of handwriting structure, as well as, their association with attributes that relate the handwriting constituents with some personality traits, illnesses, disabilities (Kushnirt, 2013), etc. A large number of techniques has been developed for the detection of structural constituents in handwriting. Such techniques are well developed for unconstrained handwritten alpha-numeric character and symbol (Liwicki et al., 2012); signature verification (Saikia and Sarma, 2011); and cursive word recognition (Günter and Bunke, 2005). There are ample amount of observational knowledge available about the association between handwriting constituent structures and personality traits, physical or mental disorders or other behavioral defects. But conclusions drawn on the basis of such subjective knowledge may not be scientifically acceptable. Although, decades of research efforts, indicate that systems that are being crafted for handwriting analysis applications are expected to touch the acceptable recognition performance level, but their acceptance will depend on the system's ability to provide the scientific explanation and justification of its decision(s) with reasoning (Sreeraj and Sumam, 2011), and embedding such explanation ability in systems is a challenging research issue. This research is an effort in this direction. Handwriting analysis based on individual traits (Abdul, Diana and Kumar, et al, 2013) Handwriting Analysis based Invidualistic Traits Predictions (Rahan Abdul et. Al, 2013) (HABIT) has been proposed. In this slant of baseline, pen pressure, slant of letters and size of writing were used for personality analysis. The roles and age and education be related with handwriting analysis (Farnaz, Gholami, and Madani, 2014). To analyze data descriptive statistics were used along with person correlation and multiple regression. Results shows that there is a strong correlation between handwriting and age and education. Robust soft-biometrics prediction from handwritten documents (Bouadjenek, Hassiba and Youcef, 2016) for a robust prediction of the writer's gender (Topaloglu Murat, 2017), age range and handedness. First, three prediction systems using SVM classifier and different features, that are pixel density, pixel distribution and gradient local binary patterns, are proposed. Since each system performs differently to the others, a combination method that aggregates a robust prediction from individual systems, is proposed. This combination uses Fuzzy MIN and MAX rules to combine membership degrees derived from predictor outputs according to their performances, which are modeled by Fuzzy measures. Experiments are conducted on two Arabic and English public handwriting datasets. A word plotting based information retrieval approach for medical prescriptions/reports written by doctors has been proposed (Partha Pratim et. al, 2017) To extract the in- formation from handwritten document images (Prescription), first extract the domain specific knowledge of doctors by identifying department names from the printed text that appears in letterhead part. From the letterhead text, the specialty/expertise of doctors is understood and this helps us to search only relevant prescription documents for word spotting in handwritten portion. Word spotting in letterhead part as well as in handwritten part has been performed using Hidden Markov Model. An efficient MLP (Multilayer Perceptron) based Tandem feature is proposed to improve the performance. From the experiment with 500 prescriptions, and obtained encouraging results. Section 2 details the benchmark dataset for handwriting section 3 describes the details about intelligent personality assessor, Section 4

2. Benchmark dataset for handwriting analysis

The handwriting analysis methods are generally trained and tested on non-standard in-house collected datasets. However, there some datasets that are available for benchmark studies for handwritten character, digit and handwriting recognition, and writer identification but, to the best of our information, no benchmark dataset is available for medical, forensic and personality assessment applications. To evaluate the performance of methods for these applications standard benchmark datasets is needed. In these applications, such a dataset will not only help in discovering clues to personality traits or illnesses for medical applications from the handwriting samples but also the discovered ground truth would help in authenticating the subjectivity of the handwriting related myths that are widely accepted. Therefore, without discovering the ground truth, embedded in handwriting it would be unrealistic to devise good handwriting processing methods. Thus, the system depicted in Figure 1 must have module to collect, compile, and store handwriting samples in an organized manner so that the data can be used and shared among researchers efficiently. To standardize the dataset all the writers must be asked to write a same piece of text that contains all possible combinations of alphabet. We are collecting dataset for Hindi, English and Arabic where writers are asked to write the text shown in Figure 2.

अवधनरेश क्षत्रीयवंशी कोशलाधीश, राजाओं के मुकुटमणि दशरथ के बड़े सुपुत्र , रूप के भंडार,
सर्वगुण संपन्न, मंजूल मनोहर रूप, ऋषि – ऋणि, रघुवंशमणि, भक्तों के ऊपर दया रखने वाले,
ज्ञानी, प्रातः स्मरणीय ऐसे ईश्वर श्री रामचंद्र जी ने गंगा सदृश्य सीता माँ के लिये छलीया, ठग,
ढोंगी और फरेबी राक्षस रावण का संहार किये ।

० १ २ ३ ४ ५ ६ ७ ८ ९

Figure 1 Hindi Text

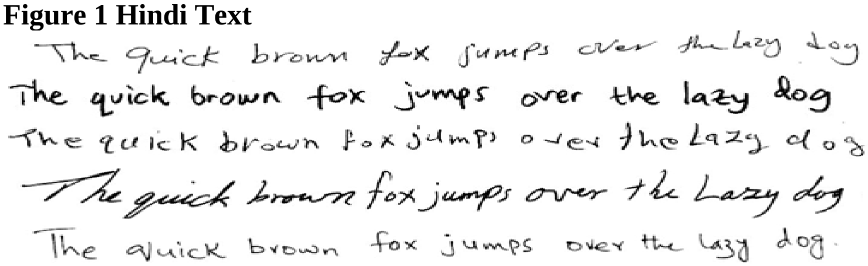


Figure 2 English Text

For Hindi language 13 most commonly used vowels, 14 modifiers and 36 consonants were used. The text was written by subjects of different **age** groups: ranging from 6 to 77 years; **genders**: male and female; **education** backgrounds: ranging from grade 3rd to post graduate levels; **professions** like: software engineer, professor, assistant professor, students, accountants, house wives, and retired persons; **regions**: states of Bihar, Uttar Pradesh, Haryana, Punjab, National Capital Region (NCR), Madhya Pradesh, Karnataka, Kerala, Rajasthan, and countries Nigeria, China and Nepal. Two thousand (2000) writers from these groups participated in this experiment. Similarly, for English & Arabic text 1000 writers from different educational and ethnic backgrounds, age groups, professions, nationalities and linguistics background participated in the experiments. The collected data is being prepared to be placed on a website, so that it can be shared among the researchers of this field. For personality assessment the handwriting samples must be collected from the writers having known personality traits. Such data is difficult to obtain. However, we are trying to create such a dataset from the handwriting samples of known personalities that are available through Internet.

3. An intelligent personality assessor

In this section we describe knowledge gathering and representation for the personality assessment application. The work presented in here is based on the knowledge that is preserved in graphology books (Downey June E., 1919; and Gilman John). Although, the scope of the work is limited to a particular domain but the antecedent part of the rules can be used (partially or fully) for other application domains. The sole objective of this section is to demonstrate the way the knowledge and fact bases can be develop from the ancient observations that are enshrined in historical documents, and being used by practitioners.

In practice, graphologists used coarse and finer handwriting analysis. In coarse analysis, similarity between prerecorded handwriting samples of known personality trait (referred to as prototypes), and samples of persons whose personality need to be assessed (referred to as test sample) is computed, and the personality attributes of the most similar prototype are assigned to the test sample writer. In finer analysis characteristics of handwriting constituents such as word spacing, line spacing, stroke formation (thickness, length, rigidity and suppleness), character shape formation, and the like features are considered as clues to some personality traits, and the overall assessment, on personality, is made on aggregating the knowledge provided by these clues.

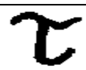
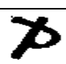
In order to computerize the coarse analysis process, knowledge is represented as an image of the handwriting sample while in finer analysis as feature vectors (or string) where vector elements depict some finer properties of the underlying handwriting. The simplest method for overall assessment that may be applied, in both analyses, is to form prototypes of personality types (prototypes can be determined manually or by applying an appropriate unsupervised learning method), compute similarity between prototypes and the test sample, and assign traits of the most similar prototype to the test sample. More sophisticated decision-theoretic, graph-theoretic, or syntactic methods can also be used to improve the assessment quality, but they have one disadvantage, i.e., they have no reasoning process embedded in their decision making process. Therefore, none of them can neither provide a justification of their decision nor explain the way they arrived to that decision.

A rule based knowledge representation can be an appropriate approach to embed these abilities. This approach has been successfully applied in developing the expert systems and it is supported by the well developed reasoning methods that provide justification as well as explanation of their decisions. One of the greatest advantages of this approach is that the knowledge can be accumulated dynamically in the form of rules and facts that can be automatically acquired or learned from experts. The performance of the approach depends largely on feature definition and extraction, knowledge representation (rule formulation) and reasoning procedure. Next, we describe feature definition, extraction and rule formulation from graphology the art/science of personality assessment form handwriting samples.

3.1 Feature extraction

General, basic, and accessory characteristics are the three types of measures used by graphologists. Graphologists categorize handwritings into harmonious (superior) and inharmonious (inferior) handwriting based on the broad measures that create an overall impression of handwriting. They look for clarity, precise balance and proportion, uniqueness, and the absence of superfluous pen motions when judging harmony. Strokes that are too big or little, too flourishing or bland, too heavy or faint, too regular or irregular, too slanted, and the like are common in inharmonious handwritings. Graphologists link personality qualities to stroke quality; for example, a tiny stroke in excellent handwritings indicates focus, whereas it measures pettiness in inferior handwritings. Similarly, with excellent handwriting, light, quick, sinuous, and unconnected strokes represent I delicacy and spirituality, (ii) spontaneity and vivacity, (iii) diplomacy, and (iv) insight. Similarly, they imply I weakness, (ii) impetuosity, (iii) prevarication deception, and (iv) illogical in poor handwriting. The foundations result in a basic categorization of handwriting samples. Eight fundamental genres are employed for this purpose. Slant, base line direction, letter size, continuity, shape, arrangement, pressure, and pace are among the genres. A slant indicates emotions, a base line direction indicates mood, a letter size indicates power, opinion of oneself, and one's role in life, continuity type handwriting indicates mode, quality, and coherence of thought, a form (shape) indicates natural impulse and free choice, arrangement indicates sense of organization and adaptability, pressure indicates intensity, strength, and appetites, and a letter size indicates power, opinion of oneself and one's role in life. It also represents vitality and spontaneity. Each of these characteristics has a wide range of values, and their finer quantification creates finer categories of the related qualities. For example, a finer value of tilt, such as reclining, reflects finer emotional introversion. Graphic symbols make up the Accessories. They give crucial evidence and show up on a regular basis. They are regarded as a trustworthy indication, despite the fact that handwriting quality can be influenced by a defective pen, poor writing position, or uneven writing surface. T-bars, i-dots, punctuation marks, capital letters, signatures, numerals, starting and terminal strokes, covering strokes, flourishes, upper and lower extensions or loops, and alphabet are all examples of accessories. The letter 't,' and how writers position the bar above it, indicate a lot about their personalities'-bars in various styles represent the writer's activeness and willpower. T-will Bar's manifests itself in the following ways.

Table 1 Manifestation in T-Bar [Gilman J., 2006]

Letter t	Characteristics and Significance
	Characteristics: Normal pressure and Evenly spaced bar at each side of the stem. Significance: Perfect balance, Calmness, Carefulness, Complete control of thought, and Complete control of action
	Characteristics: Descending with heavy pressure. Significance: Brutality, Destructiveness, Despotism, Obstinacy, Resistance, Aggressiveness, and Assertiveness
	Characteristics: Curving or waving like a pennant. Significance: Fantasy, Eccentricity, Wit. Pep, Gaiety, and Charm.
	Characteristics: No bar and no substitute stroke. Significance: Carelessness, absentmindedness, no will power at all, and possible despondency.
	Characteristics Stem final incurved for the bar. Significance: Jealousy

Handwritten specialists have also observed the features of a wide variety of handwriting symbols, such as capital letters in a word and loops and extensions, as well as their links to personality traits.

3.2 Rule formation

The rule syntax is: If <condition> Then < trait> {confidence factor}, where <condition> is formed using the extracted features, <trait> is as observed by handwriting experts, and confidence factor takes a value between 0 and 1 that signifies experts confidence in the rule. Some examples of rules are given below.

If t-bar (omitted) ^ i-dot (omitted) ^ p (without hump) **then** personality (absent-mindedness) {1}.

If arrangement (crowded word) ^ beginning-stroke (copy book) ^ final stroke (very short) ^ margin (no) ^ lower-loop (inflated) ^ m-humps(ovals □ half–ovals) ^ M-initial-stroke (curling) ^ M-final-stroke (curling) **then** personality (acquisitiveness) {1}.

Similarly, rules have been developed by handwriting experts for a large number of personality traits using global characteristics like handwriting style (Inferior/Superior), slant, size, speed, pressure, continuity, arrangement and form, special characteristics and important letter shapes Providing a comprehensive list of rules is beyond the scope of this paper. The features that can be found in special characters and important letters are listed here for the reasons: to expose features that may be observed in other applications and to assess complexity of their extraction method. Moreover, it can be seen from these tables that linguistic variables like medium, large, very large, short and very short are required to precisely define the features. Thus, integration of fuzzy logic module would also be required of to handle the linguistics variables.

4. Experimental details

This paper details the implementation of fundamental feature based components for personality assessment. These features are essentials for personality prediction while accessories and other features would be required for improving the prediction strength.

We describe below methods to estimate the values of features: slant, baseline direction, letter size, continuity, form, arrangement, pressure and speed. As can be accessed from their definitions, the estimation of these feature values is a challenging task. However, we have tried to emulate the process, as realistic as possible, as described by graphology experts. Our system stores the values obtained from all handwriting samples. Its' advantage is that the feature values can be scientifically quantized and that may provide better personality trait estimation.

4.1 Slant Estimation

A slant signifies emotions. Its values are: constantly changing, very-reclined, reclined, vertical, lightly inclined, inclined, very inclined and acutely inclined. Radon transforms are used for slant estimation.

4.2 Baseline Direction Estimation

A baseline direction signifies mood of the writer. Its values are: leveled, ascending, descending, varying, wavy or sinuous, convex and concave. The first step in baseline direction estimation is to find the line that separates handwritten lines. We obtained the line separators using horizontal projection profile of an image as shown in Fig 3 and drawing the separating line through the minima of smoothed profile as shown in Figure 3. In subsequent steps, we estimated the baseline directions from the text pixel distribution that are lying between two adjacent line separators. We describe the estimation process below.

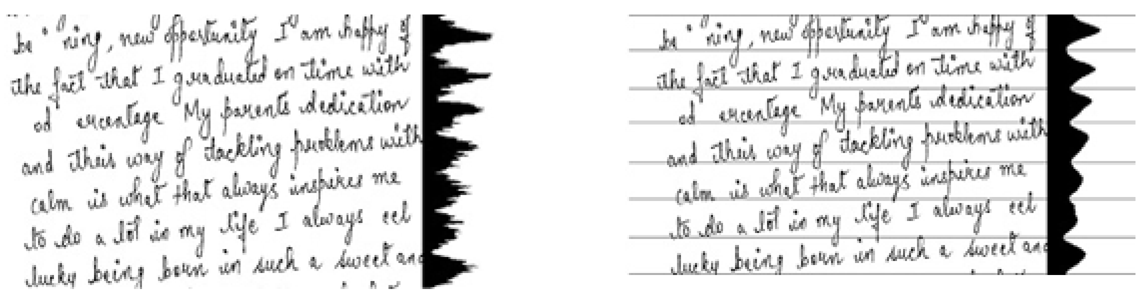


Figure 3 Baseline estimation.

In an $M \times N$ image, we consider baseline direction as a function f(x) of column x where $1 \le x \le N$ and f(x) is the lower last pixel of the stroke in column x, if present. In order to smooth the baseline, we partitioned N columns into K blocks and obtained K baseline values by averaging the baseline values of each block. Using these values, we classify baselines into leveled, ascending, descending, varying, wavy or sinuous, convex and concave. Figure 4 shows baselines trends discovered in handwriting samples using K=10 points.

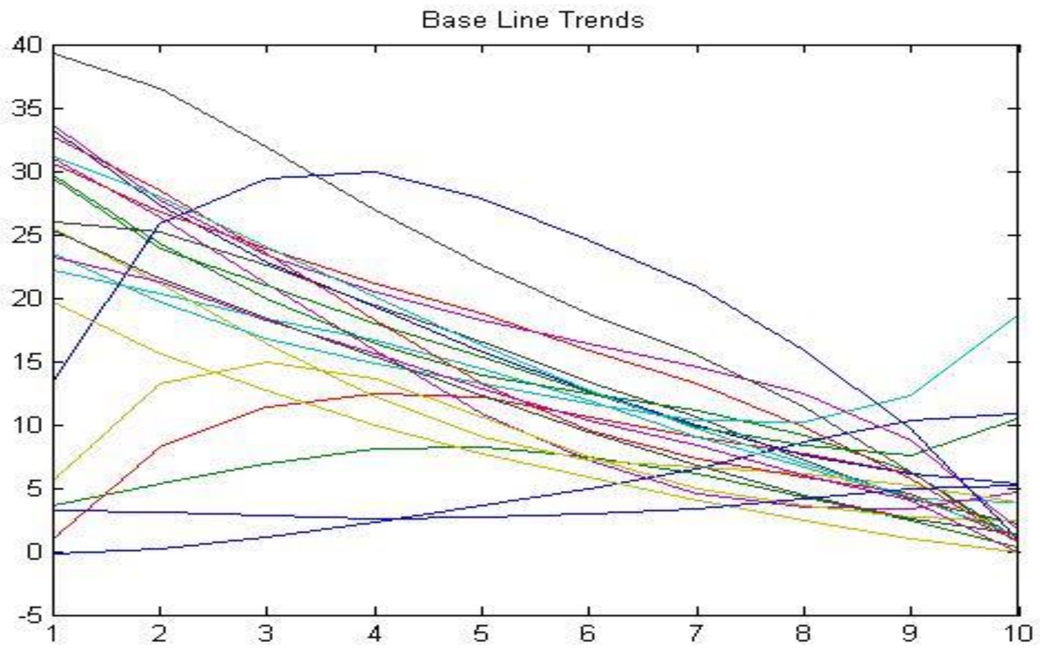


Figure 4 Baseline of different persons.

4.3 Letter Size Estimation

A letter size signifies power, opinion of oneself and one's role in life. The letter sizes that we estimated are: very large, large, medium, small, very small. We used vertical projection profile of a line to separate the words. Before computing the profile, the line was skew corrected by applying Radon transform. For word level skew correction, a use of connected component is under study. In this experiment, we considered average word height as a letter size. The graphology experts also use measurements such as large capitals, small, narrow capitals, capitals slightly higher than small letters, and capitals no higher than small letters. These measurements require a character recognition technique that distinguishes between capital and small letters.

4.4 Arrangement

Arrangement signifies sense of organization and adaptability. Measures of arrangements, in handwriting, are like well spaced and nicely disposed, badly spaced and disposed lines, widely spaced and crowded together words, tangled words and lines, legibility, illegibility and margins. Therefore, the arrangement estimation is subjective but the phonology experts, discovered that margins as good indicators for handwriting individuality. The margin characteristics that we have used in this study are: relatively even on both sides of the page, good proportion to paper size, wide left margin and disproportionate to paper size, wide right margins, wide margins all around the page including top and bottom of the page, the left margin widening as it descends, the left margin narrowing as it descends, narrow margins at both sides, no margins at all, and uneven margins. The arrangement was estimated by computing the margins and word spacing, the left margin was estimated by simply estimating the distance of the first pixel in a line from the left margin, similarly, the right margin of a line was estimated by recording the distance of the last pixel from the right margin of the paper, and the pressure was estimated by computing the average stroke thickness.

4.5 Personality Trait Estimation

We have created the fact base of the system. It consists of feature values along with associated personality traits. Both are represented as a vector pair (V_f, T_p), where V_f is a set of m values ($v_{f1}, v_{f2}, v_{f3}, \ldots, v_{fm}$) of feature f and associated with it are set of n personality traits $T_p=(t_{p1}, t_{p2}, t_{p3}, \ldots, t_{pn})$. To improve the prediction veracity, the system keeps on updating, regularly, the personality trait list T_p from experts' observations and graphology literature. To discover a set of personality traits in an unknown writer we have implemented a nearest neighbor-based procedure which is describe below.

1. Extract N feature vectors $V^u_{f,i} \quad \forall i = 1, N$ from an unknown handwriting image U
2. $\forall i = 1, N$, compute $T^u_{p,i} \leftarrow \Phi\left(V^u_{f,i}, V_f\right)$, where $\Phi\left(V^u_{f,i}, V_f\right)$ returns $T^u_{p,i}$ □ the traits of the nearest neighbor of the feature vector of the unknown handwriting $V^u_{f,i}$ in V_f .
3. Observed personality traits $T^u_p = \bigcup_{i=1}^{N} T^u_{p,i}$ in image U

A screen shot (see Figure 5) shows the observed personality traits along with their estimated values in the top right corner of the result window. A comparative analysis of each trait can be seen by clicking the trait. After the click, the current trait values are displayed along with its minimum, average, and maximum values that have been observed by the system. In this case the value of the mood trait is displayed. It is above minimum value but less than the population average.

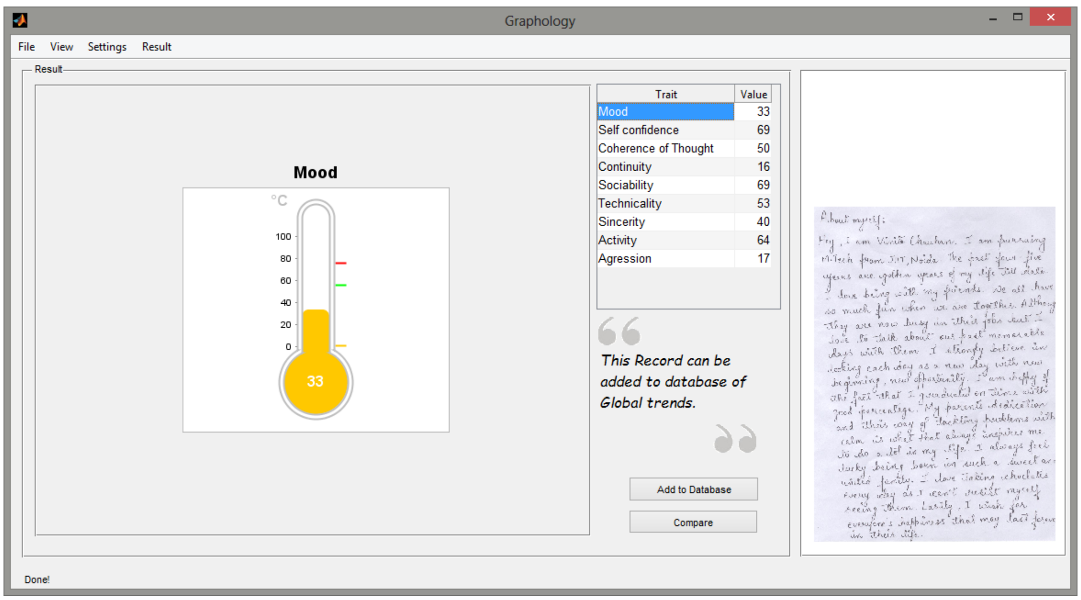


Figure 5 Graphical user interface design for personality assessment.

We discovered that a comparative analysis of the trait values of subject agins the population average provides information that can help in writer discrimination as well.

4.6 Performance evaluation

The performance evaluation of the system is difficult because of the involved subjectivity. However, we have used a pretest and posttests agreement measure. In pretest, we asked an individual to assess his/her traits as low, medium and high. After the test, we asked the individual to write their agreement with the result on the scale of 0 to 5 where indicating no to total agreements. In these experiments 1000 number of people participated. To assess the prediction variability among writers, we analyzed handwritings of writers were. The chart below shows the trait prediction results for 10 writers as shown in Figure 6. These results illustrate that the personality traits can be used to assess the handwriting individuality.

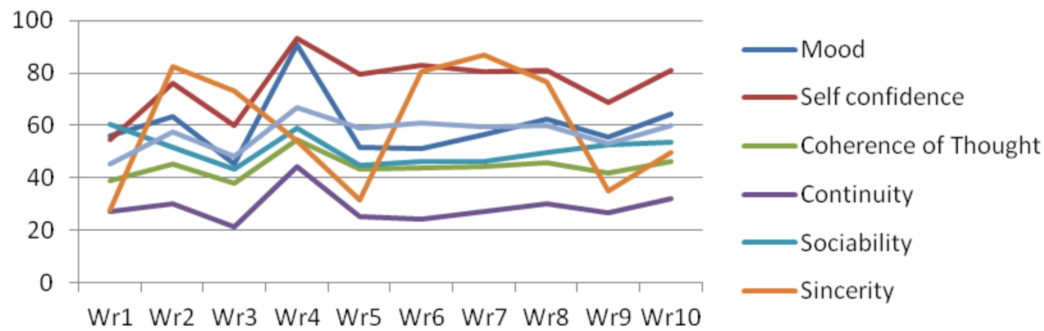


Figure 6 personalities of 10 different writers

Personality chart is also shown as pie-chart in Fig 7.

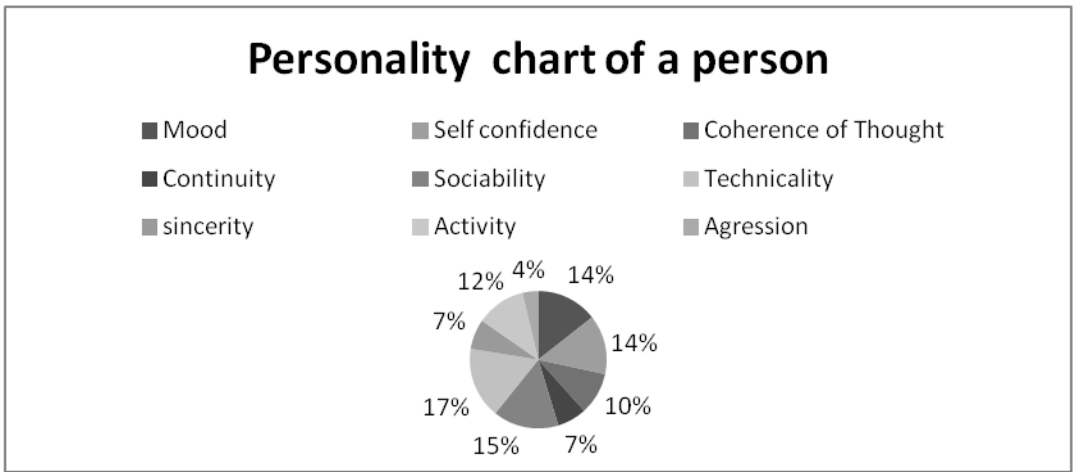


Figure 7 Personality chart of a person

The average agreement with prediction ranges between 84 to 96 percentage as shown if Figure 8.

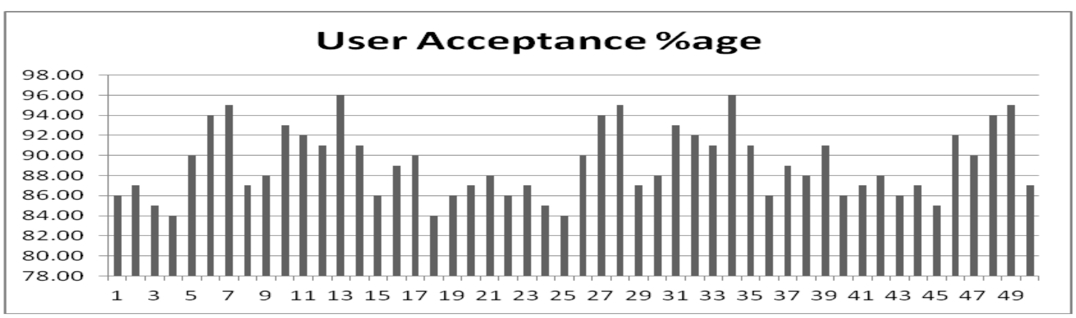


Figure 8 User acceptance percentage of fifty persons

5. Conclusion and future research

Handwriting analysis applications in diverse areas show its importance in exploring the hidden phenomena by a noninvasive means, but, the knowledge discovered from handwriting analysis need to be authenticated to provide the scientific basis. In this paper, we have presented an architecture of a system that allows continuous collection of handwriting samples from subjects having different personality traits, illnesses, learning disorders, criminal records, and other attributes that might help in exploring the writers mindset, compilation, store, retrieve and organize the samples for long term studies, discover knowledge from a large set of samples collected over a long period of time, and to make in scientifically viable authenticate the discovered knowledge. In addition to these, the system can provide justification of its decision along with the explanation of the process through which it reaches to a decision. These two characteristics can help greatly in knowledge justification process and it may guide in learning about the knowledge. To assess the viability of the system we have implemented a personality assessment module using the general and fundamental features. For this experiment, we have implemented simple and straight, forward algorithms to extract the speed, continuity, form, arrangement and pressure features. It gives the values of personality traits: emotions, mood, self-confidence, coherence of thought, strength and organization ability. We have not used yet the accessories features in this research. Development of algorithms to extract them is in progress and the knowledgebase consisting of production rules is being developed. Further, we intend to enlarge our test data set of handwriting samples of persons having known personality traits to test the reliability of the system. A total of 1000 participants from the CPAR dataset took part in these studies. The average proportion of approval ranges from 84 to 96 percent.

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