Handwriting-based personality classification on Indian samples using long-short term memory

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ABSTRACT

Traditional handwriting analysis methods have historically faced criticism for their lack of scientific basis, but more contemporary models based on layered artificial neural network (ANN) architecture have evidently been more successful. In the proposed model, a deep neural network (DNN) layered, long-short term memory (LSTM) model with contextual analysis has been proposed for handwriting-based personality classification. The model has been trained over a manually curated verbose dataset of ~6,000 Indian handwriting sample images, varying across genders, age groups, and regions. The classification is based on the five major personality traits. The proposed framework achieved an accuracy of 97.75%, which is over 10% better than the next best performing model on a comparably numerically bigger dataset; demonstrating the enhanced potential of context based neural networks on handwriting-based personality prediction when coupled with an appropriately varied and unbiased dataset.

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1. INTRODUCTION

Graphology, or handwriting analysis, aims to reveal an individual's character, emotions, and behavior through their writing patterns a concept dating back to ancient Greece and Rome. Traditional personality assessment methods such as questionnaires and interviews are often subjective, time-consuming, and prone to bias. Handwriting, long associated with personality, offers a more natural, behavioral form of expression, yet most analytical approaches remain qualitative rather than scientific. With personality profiling becoming essential in domains like recruitment, forensics, security, and mental health monitoring, there is a growing demand for objective and data-driven personality prediction methods. The handwriting analysis and behavioral biometrics market is projected to reach USD 4.3 billion by 2027, driven by advances in AI-based non-invasive evaluation systems [1].

Modern computational models enable the digital extraction and measurement of handwriting features once analyzed manually [2], [3]. Based on psychological frameworks like the Big Five model [4], machine learning (ML) algorithms such as support vector machines (SVM), random forests (RF), and neural networks learn correlations between handwriting attributes and personality scores. the accuracy of such systems heavily depends on the dataset's diversity and labeling quality [5].

The present study introduces a novel dataset of 6,000 handwritten samples representing five distinct personality categories: introvert, extrovert, optimist, pessimist, and stable mindset. Unlike prior research centered on Big Five or Myers-Briggs type indicator (MBTI) traits, this work expands personality modeling through new behavioral dimensions. Long-short term memory (LSTM)-based architecture is developed to analyze handwriting sequentially, leveraging temporal, and stroke-related information for enhanced accuracy. The proposed model achieved 97.75% accuracy, outperforming existing methods. This approach demonstrates how handwriting analysis can evolve from a subjective art to a reliable, data-driven discipline, with broad applications in forensics, employment screening, psychometric evaluation, education, and clinical diagnostics [6]. It helps in better understanding humans and allows a number of analyses and decisions-making, as shown in Figure 1.

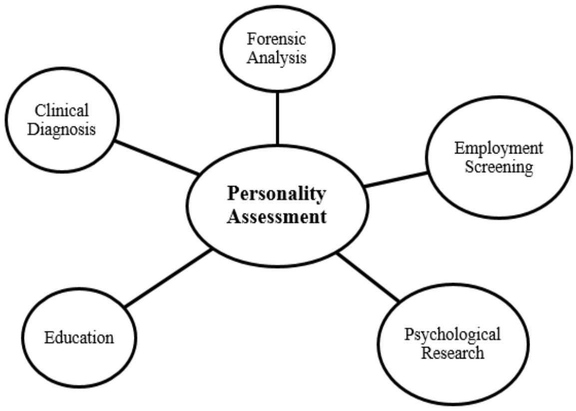


Figure 1. Graphology application areas

2. LITERATURE REVIEW

The study of handwriting, or graphology, is basically based on the belief that the way a person writes can reveal important personality traits. Initial research mainly concerned with proving links between handwriting traits and personality characteristics. As ML techniques have improved, researchers have constantly come up with several ideas to improve the objectivity and reliability of such predictions. However, authenticity of this process has been questioned over time as well [7]. A brief literature review of such related work is tabulated in Table 1. Study conducted on Arabic handwriting utilizing four different classification algorithms achieved a maximum accuracy of 68.67%. Another study indicated that the MBTI test could be automated through the use of neural networks and natural language processing, thereby eliminating human bias [8]. Further contributions focused on developing datasets and models for handwriting-based personality prediction. A hybrid model using artificial neural network (ANN) and a convolutional neural network (CNN)-based model known as PersonaNet mapped handwriting to the Big Five personality traits. This highlights the usefulness of conventional and deep learning models [9]. The averaging of synthetic minority over-sampling technique (SMOTE) multi-label SVM-CNN (AvgMlSC), automated handwriting analysis system achieved a performance of 92% accuracy, 0.94 area under the curve (AUC), and 90% F1-score by applying ML and graphological rules. The evaluation of the graphologists and the Big Five questionnaires also showed significant correlations according to this study [10]. A different study using the five-factor model (FFM) achieved accuracy 95.9% for non-binary continuous traits [11]. Besides handwriting researchers are looking at other types of personality prediction. Fuzzy logic and genetic algorithms were used to classes social photos with good accuracy using a dataset of 5,000 images per class [12].

Nevertheless, handwriting has remained a focal point: an SVM-based approach reported 95.05% accuracy [13], while another study introduced a graph-based handwriting representation with semi-supervised generative adversarial networks (SGANs), attaining 91.3% accuracy on 173 participants [14]. Recent works have also leveraged textual data and advanced deep learning. A knowledge graph-driven framework predicted Big Five traits from text by exploiting semantic relationships [15], while another applied dominance, influence, steadiness, and compliance (DISC) model-based language analysis, with adaptive boosting (AdaBoost) emerging as the best-performing classifier [16]. Integrative approaches have further advanced the field: a CNN-multi-layer perceptron (MLP) hybrid system was developed to simultaneously identify multiple traits from handwriting images [3]. Transfer learning models (VGG-16, ResNet-50, and GoogleNet) have also been fine-tuned for personality prediction tasks, with ResNet-50 delivering the highest accuracy [17]. In similar directions, physiological, and behavioral signals such as electrodermal activity (EDA) have been used for predicting traits in risky driving situations, evaluated through AUC scores [18]. Within handwriting-focused research, various novel methods such as utility of Gaussian filter with principal component analysis (PCA)-based normalized global image structure template (GIST) descriptors for preprocessing and feature extraction have been used to enhance performance of the recognition system in general [19].

According to Pratiwi *et al.* [20], feature descriptors based on invariant moments consistent with the Enneagram model classified personality types with 85.7% accuracy. Collectively, these studies highlight the progression from traditional graphological analyses to modern AI-driven frameworks. While methods vary across handwriting, text, images, and physiological data, the central challenge remains improving prediction accuracy, generalizability, and scientific credibility. This motivates our proposed work, which leverages an LSTM-based architecture and a newly developed handwriting dataset to advance personality prediction with superior performance [21]. This study explores a hybrid methodology that combines CNNs with traditional ML classifiers to improve recognition accuracy. Transfer learning is employed with four pre-trained CNN architectures AlexNet, VGG-16, VGG-19 and ResNet-50 which are utilized as feature extractors [22]. In this study, the proposed system is structured in three levels, with the primary level consisting of four CNNs [23]. This study introduces advanced deep learning framework designed to enhance detection accuracy of ancient Chinese characters in complex scenes and ensures high accuracy as compared to state-of-the-art methodology.

Table 1. Comparison of related recent work

Ref	Methodology/ model	Input modality	Personality model	Dataset size	Accuracy/ performance	Gap
[7]	4 ML classifiers	Arabic handwriting	Personality types	Not specified	68.67%	Small dataset, No cross-language handwriting evaluation, low accuracy,
[8]	Neural networks + NLP	Text (MBTI test responses)	MBTI	Custom responses	Not reported (focus on automation)	KNN scalability limitations, Accuracy / Performance not reported, small dataset size
[9]	ANN + CNN (PersonaNet)	Handwriting images	Big Five	Custom dataset	Not reported	Dataset diversity limited, Accuracy/Performance not reported, limited experimental validation
[10]	AvgMlSC (graphological rules + ML)	Handwriting	Big Five	Not specified	93% accuracy, 0.94 AUC, 90% F-score	Limited dataset, optimization lacking
[11]	ML-based prediction	Handwriting	FFM	Not specified	95.9% (non-binary traits)	Small no. of participants, limited cross-device
[12]	Fuzzy + genetic algorithm + FCNN	Social photos	Personality traits	5000 images/class (5 classes)	High accuracy (exact not stated)	Accuracy/Performance not quantified
[13]	SVM classifier	Handwriting	Personality traits	Not specified	95.05%	Dataset size is not specified
[14]	Graph-based features + Semi-supervised GAN	Handwriting	Big Five	173 participants	91.30%	Limited data, Early detection limitations
[15]	Knowledge Graph-based framework	Text	Big Five	Not specified	Improved accuracy (not quantified)	Accuracy / Performance Not quantified, small dataset size, Modern deep learning absent
[16]	AdaBoost, RF	Text (DISC analysis)	DISC model	Not specified	AdaBoost best performance	Accuracy/Performance Not quantified
[3]	CNN + MLP (integrated model)	Handwriting images	Multiple traits	Not specified	High accuracy	Real-time performance unvalidated
[17]	Transfer Learning (VGG16, ResNet50, GoogleNet)	Images (personality cues)	Personality traits	Not specified	ResNet50 highest accuracy	Accuracy/Performance Not quantified
[18]	ML algorithms (5 tested)	Physiological & behavioral data (EDA)	Big Five + STAI	63 participants	Evaluated by AUC	Small dataset size
[19]	Optimized DL + PCA-based GIST descriptor	Handwriting	Personality traits	Custom dataset	Improved accuracy (not quantified)	Accuracy/Performance Not quantified
[20]	Invariant Moments + Enneagram model	Handwriting	Enneagram	49 samples (120 reference profiles)	85.70%	Moderate accuracy, that may be increased with better methodology and classifiers

Motivation for this research is: i) limited dataset diversity and size: the prevalent datasets and models at the moment do not carry diversity. Most models do use a limited dataset. All models have very limited data; ii) subjectivity in personality labeling: many studies utilize self-identified or manually assigned personality labels, both of which are inherently subjective in nature; and iii) underexplored deep learning architectures: numerous research papers and publications seem to employ classical ML architectures such as SVM and RF. The authors utilized the Big Five inventory (BFI) questionnaire to collect data on participants' personality traits and applied ML algorithms such as K-star, k-nearest neighbor, and MLP to build their predictive model. They evaluated the performance of models using train-test split of 67:33 and cross-validation.

3. MATERIALS AND METHOD
3.1. Dataset
The dataset encompasses contributions from approximately two thousand writers who have provided both Devnagari and English text samples, a distribution is provided in Table 2. It comprises of multi-textual data, incorporating Devnagari, English, and comprehensive information about the writers, including their personality analysis. The dataset's creation underwent a meticulous scientific process, ensuring its integrity and reliability.

The dataset is available to the public on GitHub at https://github.com/PradeepMishra76/Hand---Written_DataSet, the dataset is organized using a relational database structure, facilitating efficient data management and retrieval. This sets this dataset apart is its inclusion of personality analysis and other pertinent information, such as writing style and individual characteristics. These aspects make it a valuable resource for research in handwriting analysis and related fields. Its potential applications span various domains, including text recognition, handwriting individuality analysis, writer identification, and personality estimation, underscoring its versatility and significance in advancing research. Researchers and practitioners anticipate that this dataset will provide valuable insights and contribute to the advancement of knowledge in the field of handwriting analysis and its related areas.

Table 2. Dataset sample distribution

Handwritten Devnagari text		Handwritten English text		Total samples
Unconstrained	constrained	Unconstrained	Constrained	
1,500	1,500	1,500	1,500	6,000

3.2. Proposed model
Traditional handwriting analysis methods are often costly, time-consuming, and reliant on human expertise. To address this, ML-based model capable of predicting an individual's personality from handwriting samples without human intervention was developed as demonstrated in Algorithm 1. The proposed system introduces an automated handwriting analysis framework shown in Figure 2, extracts unique handwriting features, which are then used to infer corresponding personality traits.

Algorithm 1. Handwriting personality classification using CNN–LSTM
Input: Handwriting image dataset $D = \{(I_1, y_1), (I_2, y_2), ..., (I_N, y_N)\}$
    where $y_i \in$ {introvert, extrovert, optimist, pessimist, stable}
Output: Trained model M capable of predicting personality type
1: Initialize parameters:
    learning_rate ← 0.001
    batch_size ← 64
    epochs ← 50
2: For each image I_i in dataset D do
    a. Convert I_i to grayscale
    b. Resize I_i to (128 × 128)
    c. Normalize pixel values to [0, 1]
  End For
3: Extract CNN features:
    For each preprocessed image I_i:
        Fi ← CNN_encoder(I_i)
    End For
4: Form sequential feature vectors:
    $S = [F_1, F2, \ldots, F_t]$ where t = number of feature frames

5: Feed sequential features into LSTM:
h = LSTM(S)
6: Pass through fully connected layers:
z = Dense(h)
7: Apply Softmax activation:
P = softmax(z)
8: Compute categorical cross-entropy loss:
L = -Σ y_i * log(Pi)
9: Optimize model parameters using Adam optimizer
10: Repeat steps 2–9 for all epochs until convergence
11: Evaluate model on test dataset using:
Accuracy, precision, recall, F1-score
Return M

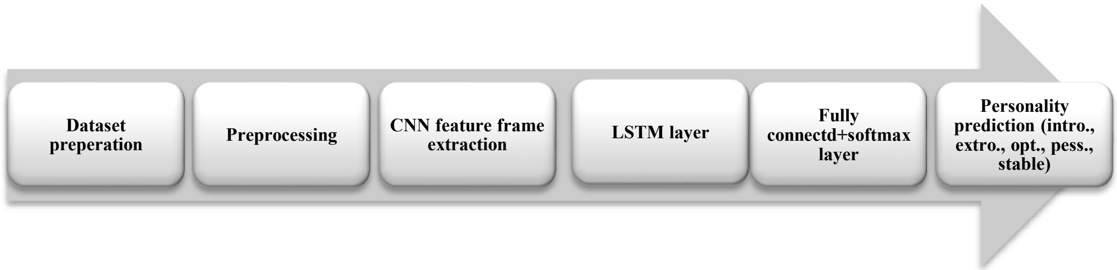


Figure 2. Steps used in personality prediction

3.2.1. Data pre-processing

To make your handwritten image data for analysis, the data needs preparation to improve quality and reduce noise and inconsistencies of the data. During the procedure, image binarization is performed post grayscale conversion. Images are then resized to 128×128. And all pixels are normalized to a range of [0, 1]. The images are hence standardized and primed for CNN feature extraction, sample shown in Figure 3, where Figure 3(a) shows originally scanned image and Figure 3(b) shows image after pre-processing. The dataset is prepped for 80-20 train-test split.

Let $I = (x, y)$ be an image of the handwritten text, where x and y are the pixel coordinates. Binarization and resizing: convert the grayscale image to a binary image $I_i(x, y)$ (where $0 \leq x, y \leq 127$) using a threshold T as in (1).

$$I_i(x,y) = \begin{cases} 1 & if\ I(x,y) > T \\ 0 & if I(x,y) \leq T \end{cases} \quad (1)$$

3.2.2. Convolutional neural network feature frame extraction

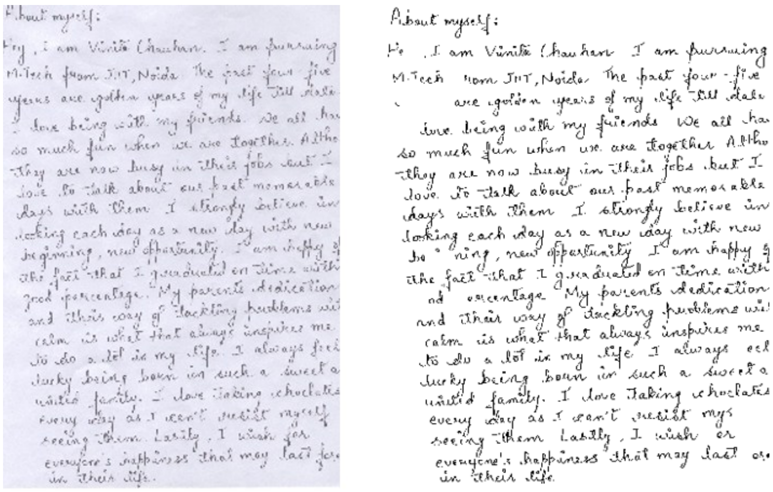
All preprocessed images I_i are then led through the CNN encoder layer to extract relevant features into a feature frame Fi. These feature sets are then collected into corresponding feature vectors 'S'. Such as S = [F_1, F_2, …, F_t] where t is number of feature frames.

3.2.3. Long-short term memory

All sequential feature vectors 'S' extracted from the CNN architecture are then led into the LSTM layer for contextual analysis through attention mechanism. The output of this layer is passed through a sequence of fully connected dense layers. This technique achieves a relative error rate decrease of 20-40% across most languages, completely replacing our old segment-and-decode-based approach. The system achieves noticeably faster identification speeds by combining sequence recognition methods with a unique input representation based on Bézier curves. The strategy was tested on multiple public benchmark datasets and determine the ideal model configuration after substantial experimentation [21].

3.2.4. Softmax activation

Feature vectors passed through LSTM and fully connected dense layers are then sent to the softmax layer for activation as shown in Figure 4. The output thus obtained is used for computation of cross-entropy loss. These parameters are optimized using the commonly used Adam optimizer for fair comparison of results and performance of the model. The parameters and dataset specifics are shown in Tables 3 and 4.



(a) (b)

Figure 3. Sample handwriting dataset of (a) originally scanned image and (b) image after pre-processing

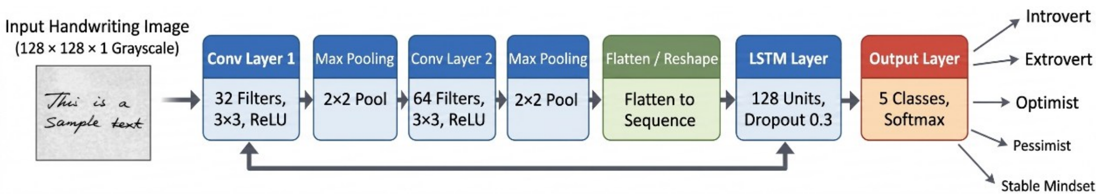


Figure 4. CNN–LSTM architecture diagram

Table 3. CNN–LSTM architecture parameters

Layer type	No. of filters / units	Kernel size	Activation	Additional parameters
Input	–	–	–	128×128×1 image
Conv2D-1	32	3×3	ReLU	Padding = same
MaxPooling-1	–	2×2	–	–
Conv2D-2	64	3×3	ReLU	Padding = same
MaxPooling-2	–	2×2	–	–
Conv2D-3	128	3×3	ReLU	Padding = same
MaxPooling-3	–	2×2	–	–
Flatten / Reshape	–	–	–	Converts spatial → temporal
LSTM	128 units	–	tanh	Dropout = 0.3
Dense	64 units	–	ReLU	–
Output Dense	5 units	–	Softmax	Personality classes

Table 4. Dataset size and value

Parameter	Value
Dataset size	6,000 handwritten samples
Train–test split	80% training / 20% testing
Epochs	50
Batch size	32
Optimizer	Adam
Learning rate	0.001
Loss function	Categorical cross-entropy
Evaluation metric	Accuracy
Regularization	Dropout (0.3)
Hardware	GPU-accelerated training

4. RESULTS AND DISCUSSION

The results obtained from the proposed handwriting-based personality prediction model demonstrate highly promising performance. Using a hybrid CNN–LSTM architecture, the system effectively captures both spatial and sequential features from handwriting samples to classify individuals into five distinct personality categories: introvert, extrovert, optimist, pessimist, and stable mindset. With a dataset of 6,000 handwriting images, the model achieved an impressive accuracy of 97.75%, indicating its strong capability to learn complex handwriting patterns that correlate with personality traits.

The confusion matrix shown in Figure 5, implies that the model exhibits balanced and consistent performance across all personality types, with only minimal misclassifications among similar classes, such as between optimist and stable mindset. The precision, recall, and F1-scores are calculated and shown in Table 5, all averaging above 0.98, confirm that the classifier maintains both high sensitivity and specificity. The F1-scores of individual categories ranging from 0.980 to 0.988 reflect robust generalization and low bias toward any particular class.

This high accuracy (as can be seen in Table 6) can be attributed to the combination of convolutional layers, which efficiently extract visual and structural handwriting patterns, and LSTM layers, which capture temporal dependencies and subtle variations in stroke dynamics. The model's reliability suggests that handwriting carries meaningful indicators of psychological tendencies, and the proposed deep learning approach is successful in decoding them. Overall, these results validate the effectiveness of deep neural networks (DNN) for behavioral and personality assessment, establishing a foundation for future multi-modal extensions combining handwriting.

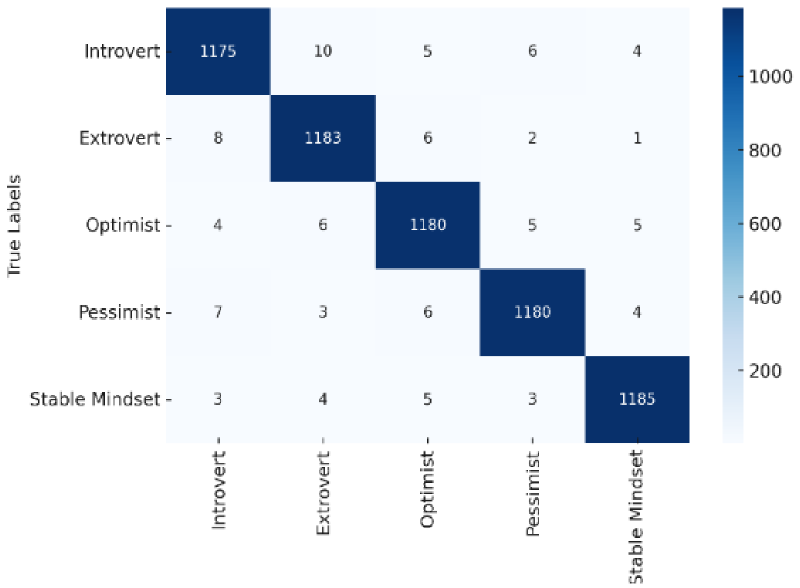


Figure 5. Confusion matrix for handwriting based personality prediction

Table 5. Performance evaluation metrics for each personality class

Personality type	Precision	Recall	F1-score
Introvert	0.9816	0.9792	0.9804
Extrovert	0.9809	0.9858	0.9834
Optimist	0.9817	0.9833	0.9825
Pessimist	0.9866	0.9833	0.9850
Stable mindset	0.9883	0.9875	0.9879

Table 6. Comparative results with existing and proposed approaches

Reference/year	Dataset and personality framework	Method/model	Accuracy/results
[24], 2018	128 samples, Big Five personality traits	Neural network (three-layer)	84.4% (intra-subject) / 80.5% (inter-subject)
[23], 2022	~1,038 instances, Big Five framework	DNN	83%–91%
[25], 2022	Real-time handwriting data, multiple personality traits	Deep CNN models	71%–74%
Proposed work	6,000 handwritten samples (Indian participants), 5 classes (introvert, extrovert, optimist, pessimist, stable mindset)	CNN + LSTM hybrid model	97.75%

5. CONCLUSION

The proposed work employs deep learning techniques to automatically predict personality traits from handwriting samples. Personality traits represent enduring patterns of thought, emotion, and behavior that define an individual’s psychological makeup. In this study, a hybrid CNN–LSTM architecture was developed specifically for the manually curated dataset. This proposed architecture classified the handwriting samples into five distinct personality types i.e., introvert, extrovert, optimist, pessimist, and stable mindset with a remarkable accuracy of 97.75%. This performance is especially outstanding given the fact that it was trained over a dataset of high cardinality with ample variety keeping the bias to a minimum. The integration of convolutional layers enabled the extraction of spatial handwriting features, while the LSTM network effectively captured sequential dependencies and stroke dynamics has improved the overall performance of the proposed model. These findings demonstrate that deep learning-based handwriting analysis can deliver a more objective, consistent, and efficient alternative to traditional graphological assessments. Moreover, the study reinforces the potential of ML-driven personality prediction as a reliable and cost-effective tool. Beyond advancing the field of computational graphology, the proposed approach contributes to affective computing by providing practical applications in forensic psychology, human–computer interaction, educational guidance, and recruitment systems, where personality insights are crucial for decision-making. The proposed methodology may be applied to forensic and human resource screening systems, which will be very useful for the remarkable outcomes. The authors still however would suggest that cultural generalization of personality in a diverse country like India is something hard to achieve and acceptable results are difficult to find hence this tool should be used objectively person to person that too for assistance in hiring and screening processes and not as an alone and self-standing model.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declared that there is no complicit of interest in this research

DATA AVAILABILITY

The dataset is available in Github at https://github.com/PradeepMishra76/Hand---Written_DataSet.

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