Handwriting Intra-Variability Across Surface Transitions: Implications for Writer Identification

Kumari Priya[1[0009-0001-7078-0490]], Chandranath Adak[1[0000-0002-9085-2770]], Bidyut B. Chaudhuri[2], and Michael Blumenstein[3[0000-0002-9908-3744]]

[1] Dept. of CSE, Indian Institute of Technology Patna, India-801106
[2] Dept. of CSE, Techno India University, Salt Lake City, Kolkata, India-700091
[3] FEIT, University of Technology Sydney, Australia-2007
{priya_2321cs02,chandranath}@iitp.ac.in

Abstract. Handwriting exhibits intra-variability within the same writer due to friction between different writing surfaces, such as transitioning from paper to a computer tablet. This study investigates such intra-variability in handwriting characteristics across different writing surfaces and its implications for writer identification. An empirical study is conducted to assess the performance of state-of-the-art deep architectures in identifying writers amidst such intra-variation. Additionally, a transformer-based model is proposed to capture writer identification under these intra-variable circumstances. A dataset comprising 1560 handwritten English text-line images from 130 writers is created and utilized for experimentation. The results reveal insightful outcomes regarding the utilization of deep architectures and the proposed model in handling intra-variability for writer identification. This study contributes to advancing the understanding of intra-variability in handwriting and offers practical implications for forensic analysis and document authentication in the digital age.

Keywords: Biometric · Computer Forensics · Handwriting Intra-Variability · Transformer Networks · Writer Identification

1 Introduction

In the realm of forensic investigation and beyond, the analysis of handwriting has long been a fundamental tool for identifying individuals and authenticating documents. However, with the advent of digital technology, traditional pen-and-paper writing is progressively giving way to computer tablets for various writing tasks [14]. This shift raises pertinent questions about the consistency and reliability of handwriting characteristics across different writing surfaces. Forensic contexts, such as writer identification in legal documents or criminal investigations, necessitate a deep understanding of handwriting intra-variability (variations within an individual's writing) [2] across surface transitions to ensure accurate analysis and interpretation [25,10]. Moreover, in the education sector, studying handwriting analysis amidst surface transitions can provide valuable insights into students' adaptability [15].

The friction between the writing instrument and the writing surface plays a pivotal role in shaping handwriting [15]. For instance, on a computer tablet, factors like pressure sensitivity, screen responsiveness, and the angle of the writing instrument contribute to variations in writing output. As individuals adapt their writing behaviors to accommodate digital mediums, it becomes imperative to examine the degree of intra-variability that may emerge within their handwriting patterns [3]. Writings among different writers are distinguished by unique styles, known as inter-class variance or *inter-variability*. Moreover, within the writings of a single person, considerable variations can occur due to various mechanical, physical, and psychological factors [22], termed intra-class variance or *intra-variability* [4]. Despite significant intra-variations in ink-strokes among handwritten samples of a writer, individuals familiar with certain writing over an extended period may still identify it. This ability may stem from implicit stroke characteristics present in the writing [1].

This paper explores the intra-variability inherent in individual handwriting across surface transitions, particularly focusing on the transition from paper to computer tablets, and its implications for writer identification. While the field of pattern recognition lacks studies similar to ours, research in the domains of education and psychology has addressed related topics [14,15]. Gerth et al. [15] studied whether age-related effects exist in graphomotor execution due to variations in writing surfaces. Their another research [14] also indicated that proficient writers can adjust their handwriting movements to suit the writing surface. The study by Alamargot et al. [6] examined the impact of writing on tablet screens on students' graphomotor skills across different grade levels. Some past studies also explored the impact of varying writing instruments (e.g., pen, and pencil) on individual handwriting, revealing insights into these tools' influence on intra-variability [23,19].

In this paper, we recognize the potential of transformer networks in addressing the challenges posed by handwriting intra-variability across different writing surfaces. Through our empirical study, we aim to assess the effectiveness of deep architectures in accurately identifying writers amidst intra-variation and discerning subtle nuances in handwriting patterns. The past researches on writer identification can be found in [26,8,36]. In recent days, contemporary deep convolutional architectures have also been employed for writer identification, including models like CaffeNet [13], AlexNet [27], SqueezeNet, GoogLeNet, Xception Net, VGG, ResNet, etc. [2]. Integration of global and local features in architectures can also be seen, e.g., FragNet [17], GR-RNN [18]. Very recently, papers employing spatial attention [30] and multi-head self-attention [21,5] have emerged. By bridging the gap between traditional handwriting analysis and emerging digital technologies, our paper aims to provide valuable insights for practitioners across diverse fields.

Our **contributions** to this paper are outlined as follows:

(i) We conducted a thorough study on writer identification using the intra-variable characteristics found within an individual's handwriting. This involves a comprehensive and detailed investigation into the unique attributes and variations present in individual writing style.

(ii) We investigated both traditional pen-and-paper writing and computer tablet writing, demonstrating intra-variation influenced by a range of writing instruments. We systematically investigate the variables within each category to mimic real-world writing conditions, encompassing writing on paper, on-screen display tablets, and off-

screen graphics tablets. This comprehensive approach facilitates research in handwriting analysis by capturing the nuanced variations observed across different writing mediums and environments.

(iii) We have proposed a transformer-based network and conducted rigorous experiments aimed at thoroughly investigating the effects of intra-variability in handwriting. Through systematic testing and data collection, we aimed to gain a comprehensive understanding of how surface transitions influence handwriting characteristics within individuals. Our experiments were designed to provide insights into the nuances of intra-variability and its implications for handwriting analysis on surface changes, with the goal of enhancing the accuracy and reliability of automated systems for writer identification.

The rest of the paper is organized as follows. In Section 2, we mention the employed dataset details and associated challenges. Section 3 presents the proposed method. The experimental analysis and results are discussed in Section 4. Finally, Section 5 concludes this paper.

2 Dataset Details and Challenges

This study aims to examine intra-variability in handwriting across surface transitions and its significance for writer identification. Given the absence of publicly available datasets meeting our specific requirements, we undertook the task of creating our own dataset.

Writer details: Our dataset includes contributions from 130 distinct writers from various regions of India, all of whom have at least a professional working proficiency in English. None of the writers are known to be native English speakers, and all have completed at least a higher-secondary level of education with English as part of the curriculum. The ages of the writers range from 16 to 33 years, with an average age of 19.14 and a standard deviation of 2.22; among them, 101 are male, and 29 are female. The writers have different levels of experience with writing on computer tablets, ranging from extensive to minimal.

Text-dependent writing: In our dataset, all writers were tasked with writing a standard English pangram, "*The quick brown fox jumps over a lazy dog*". This enabled us to closely examine the characteristics of each English character in a text-dependent manner.

Writing surface: For each of the 130 writers, we engaged three writing surfaces as mentioned below:

(i) Paper: Each writer was provided with a standard form printed on 75 GSM white A4 paper, featuring blank 24.5 $cm \times 2$ cm sized rectangular boxes. Participants were instructed to scribble the above English palindrome within this designated box. We provided all the writers with the same 5 writing tools, i.e., pencil, gel pen, fountain pen, 0.5 mm and 1 mm ball pens. Here, we have incorporated 2 distinct *paper* surfaces to capture a comprehensive array of handwriting variations. Firstly, participants were provided with a stack of paper containing fifty A4 sheets as platform, on which they kept the printed paper form to write, allowing for a *regular* writing experience akin to standard note-taking conditions. Secondly, we offered a wooden exam clipboard as an alternative to place only the printed paper form, providing a *hard* platform for writing tasks. Here,

each writing tool offers unique tactile feedback and line thickness, contributing to the diverse range of handwriting styles observed in the dataset. By offering participants a selection of tools commonly encountered in everyday writing contexts, we aimed to capture the full spectrum of handwriting variability across different mediums and tools. Thus, using 5 tools on paper placed on both *regular* and *hard* platforms, each writer wrote 10 ($= 5 \times 2$) copies of the above palindrome. The pages were scanned on an autofed flatbed scanner (EPSON DS-1630) to convert into digital images.

(ii) On-screen display tablet: Each writer wrote 1 copy of the above palindrome on Wacom One Pen DTC133W0C Display Tablet (size: medium). We captured this writing as an image.

(iii) Off-screen display tablet: Each writer scribbled 1 copy of the abovementioned palindrome on Wacom Intuos CTL-4100/K0-CX Digital Graphics Tablet (size: small). This device features a decoupled writing surface without a built-in display, requiring the writer to view the connected computer screen while writing. Here also, the writing was captured as an image.

In this way, we have collected 12 ($= 10 + 1 + 1$) handwriting samples from each of the 130 writers. Therefore, our dataset contains a total of 1560 ($= 12 \times 130$) handwritten text lines.

Major challenges observed in dataset: This database offers valuable insights into intra-variant handwriting, which encompasses the natural variations in a person's handwriting due to diverse mechanical factors. We have observed various challenging cases in our database, some of which are mentioned below:

(i) Micro-structure intra-variation: This type of variation occurs when the writer is less accustomed to touch tablets and must concentrate on the screen to which the tablet is connected. It reflects the deviations in the micro-level details of handwriting strokes due to the writer's adjustment to the digital writing interface. These deviations are often observable in the subtle details of pen movement, line thickness, and overall flow of the handwriting, highlighting the impact of the digital medium on the intricacies of handwritten expression. Fig. 1 shows the impact of micro-structure variations in Fig. 1.(a3) where the writer has lost the smoothness of the writing that was maintained in Fig.s 1.(a1), (a2).

(ii) Stroke reduction intra-variation: It occurs due to the continuous surface of the tablet screen, which requires the writer to maintain contact without lifting the pen as frequently as with traditional paper writing. Consequently, the writing process on a tablet involves longer strokes and fewer interruptions in pen movement, leading to alterations in the typical patterns of handwriting strokes. This change in writing behavior can result in differences in stroke length, spacing between letters, and overall fluidity of the handwriting, reflecting the influence of the digital medium on the intricacies of writing style. Fig.s 1.(b1), (b2), (b3),(b4) reflect the stroke reduction in the handwriting samples.

(iii) Ink type intra-variation: It refers to the variations in handwriting characteristics resulting from the distinct visco-elastic properties of the inks used in these two types of pens. The gel pen's smooth, consistent lines from gel-based ink contrast with the intermittent flow of the ballpoint pen's oil-based ink, leading to varying stroke widths and intensities in handwriting. Fig.s 1.(c1), (c2), (c3),(c4) illustrate the variation in ink flow within the handwriting samples.

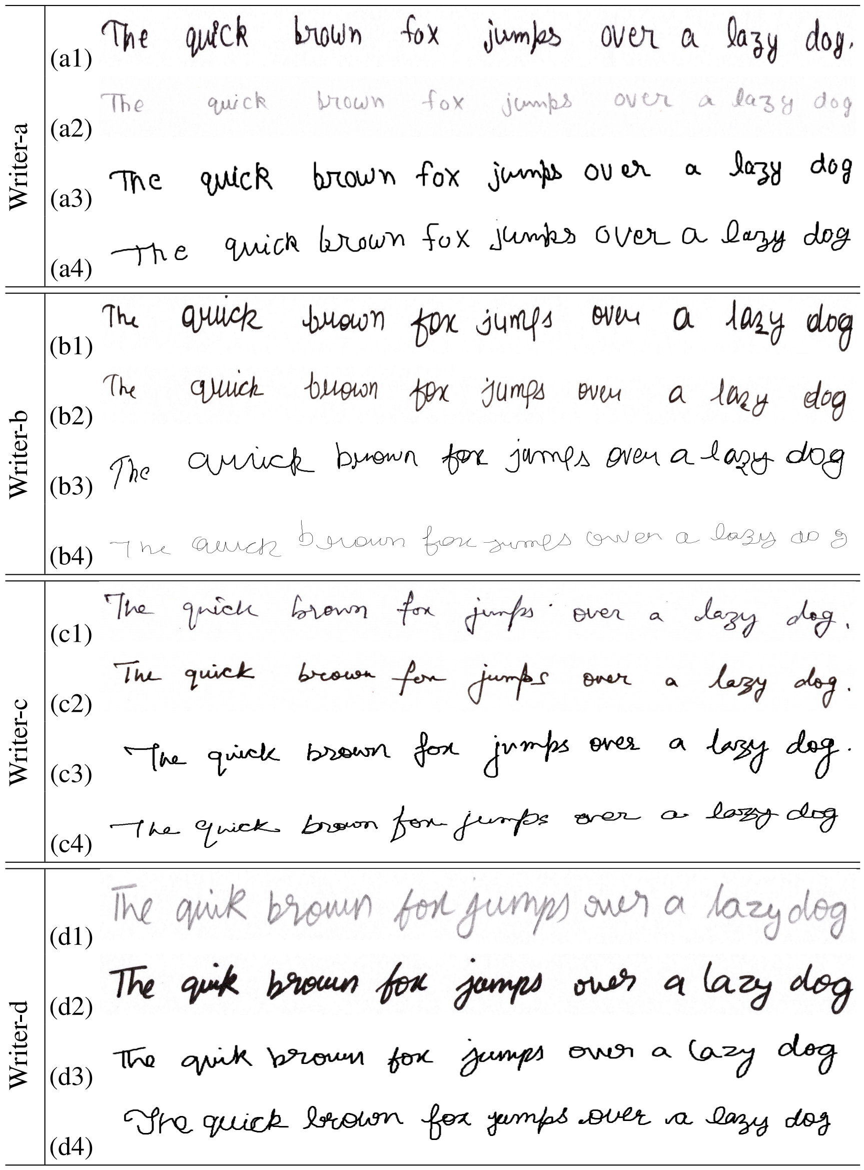

Fig. 1: Some samples from our database. Here, Writer-a has written four samples (a1)-(a4). Similarly, Writers-b, c, d have written (b1)-(b4), (c1)-(c4), (d1)-(d4), respectively.
(a1), (b1), (c1), (d1): Writing on *paper* while the paper is placed on a hard surface.
(a2), (b2), (c2), (d2): Scribbling on *paper* placed on a medium/ regular surface.
(a3), (b3), (c3), (d3): *On-screen* display tablet writing.
(a4), (b4), (c4), (d4): *Off-screen* graphics tablet scribbling.
Writing tools: (a2), (d1): pencil; (b1), (c2): gel pen; (d2): fountain pen; (b2): 0.5 mm ball pen; (a1), (c1): 1 mm ball pen.

(iv) Idiosyncratic intra-variation: Arises from the writer's tendency to employ different forms of letters while writing. This phenomenon reflects the unique stylistic choices and habits of the writer, resulting in variations in the shapes, sizes, and embellishments of individual letters within the handwriting samples. These idiosyncrasies contribute to the distinctive and personalized appearance of the handwriting, highlighting the individuality and nuances in the writer's writing style. In the writing structure of the first character 'T', we can see a clear difference in Fig. 1.($d4$) from Fig.s 1.(d1),(d2),(d3).

3 Proposed Methodology

The aim of this study is to examine handwriting intra-variability across transitions between various writing surfaces and explore its relevance to writer identification. Therefore, we first formally define the problem in the context of writer identification, and subsequently discuss the methodology to address it.

3.1 Problem Formulation

A handwriting image ($\mathcal{I}$) has been given as input. The task is to identify the writer (w_i) from a set of writers ($\mathcal{W}$), who has scribbled the text; for $i = 1, 2, \ldots, |\mathcal{W}|$. Therefore, we formulate the undertaken task as a multiclass classification problem to classify the correct writer-class $w_i \in \mathcal{W}$ of handwriting image $\mathcal{I}$. The database employed in this paper contains samples from 130 writers; i.e., $|\mathcal{W}| = 130$.

3.2 Solution Architecture

Before moving on to the main processing module, we conducted some preprocessing steps.

Pre-processing: A handwritten text-line image ($\mathcal{I}$) is input to our model, which is first resized into $d_h \times d_w$ sized $\mathcal{I}_T$ without distorting the aspect ratio. Such distortion is undesirable in the context of writer identification tasks due to preserving the ink-stroke individuality or writer inter-variability. We introduce zeros into certain rows or columns to maintain the aspect ratio. We here empirically fix $d_h = 192$, and $d_w = 1920$.

Transformer Network: For the task at hand, our approach involves utilizing a transformer network due to its minimal inductive bias and resilience to noise [12]. However, unlike directly employing the Vision Transformer (ViT) [12] that feeds raw image patches directly to the transformer encoder, our model initially extracts deep features from the image patches before embedding in the transformer encoder. This workflow is visually depicted in Fig. 2.

$\mathcal{I}_T$ is partitioned into a sequence of non-overlapping n_p patches denoted as x_p^i (for $i = 1, 2, \ldots, n_p$), each having dimensions $d_p \times d_p \times c_p$, where c_p represents the channel count of $\mathcal{I}_T$. Each patch x_p^i undergoes processing through a convolutional architecture f_C to extract the corresponding deep feature g_p^i with a dimension of d_g. In f_C, we utilize the layers before the global_average_pool of ResNeXt-50 [35], as it exhibited superior performance compared to contemporary models like VGG19 [29], ResNet [16],

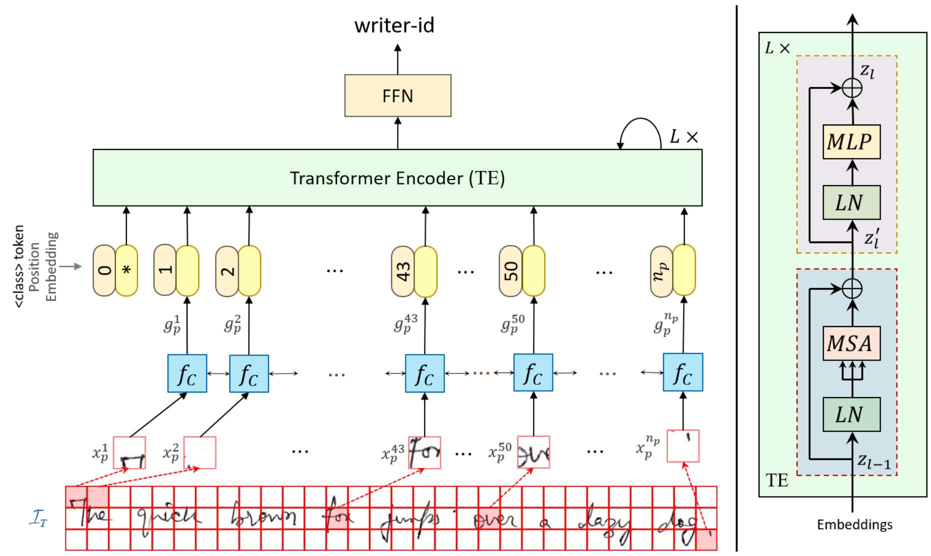

Fig. 2: Workflow of the proposed writer identification model

MobileNetV2 [28], etc. The weights of f_C's are shared across all patches. We refrain from utilizing a distinct objectness network [34] to delineate between background and foreground ink-stroke (object) patches, since transformer network inherently leverage the attention mechanism [33] to prioritize important patches. Here, $c_p = 3$, since $\mathcal{I}_T$ is an RGB image. Empirically, we fix $d_p = 64$; therefore, $n_p = \lfloor (d_h \times d_w)/(d_p \times d_p) \rfloor = \lfloor (192 \times 1920)/(64 \times 64) \rfloor = 90$. We also choose $d_g = 2048$.

Each g_p^i undergoes further flattening and is then transformed into a D-dimensional vector, i.e., embedding z_0 through transformer layers [12], utilizing the following linear projection:

$$z_0 = [g_{class}\ ;\ g_p^1\,\mathbb{E}\ ;\ g_p^2\,\mathbb{E}\ ;\ \ldots\ ;\ g_p^{n_p}\,\mathbb{E}] + \mathbb{E}_{pos} \tag{1}$$

Here, $\mathbb{E} \in \mathbb{R}^{d_g \times D}$ is the embedding projection matrix; $\mathbb{E}_{pos} \in \mathbb{R}^{(n_p+1)\times D}$ denotes the position embedding added to the deep feature embeddings extracted from patches, serving to retain positional information; $g_{class} = z_0^0$ refers to a learnable embedding [11]. Following the embedding space, a sequence of transformer encoder is incorporated [33,12]. The right-hand side of Fig. 2 depicts the internal structure of a transformer encoder, which consists of alternating layers of MSA (Multi-head Self-Attention) [12] and MLP (Multi-Layer Perceptron) [37] modules. LN (Layer Normalization) [7], and residual connections [37] are applied before and after each of these modules, respectively. This composition is formally presented in equation 2 with general semantics. The MLP module utilized here comprises two layers with $4D$ and D neurons, respectively, incorporating the GELU (Gaussian Error Linear Unit) non-linear activation function [12].

$$z'_l = MSA(LN(z_{l-1})) + z_{l-1};\ z_l = MLP(LN(z'_l)) + z'_l;\ l = 1, 2, \ldots, L \tag{2}$$

where, L denotes the total count of transformer blocks. The core element of the transformer encoder is MSA, which incorporates h (> 1) number of $heads$. Each $head^i$, $\forall\ i \in \{1, 2, ..., h\}$ uses SA (Scaled dot-product Attention) [12,33], wherein the input consists of query (Q), key (K), and value (V) matrices. The SA module calculates the attention assigned to the input patches. The results of SA computations across all heads are concatenated within the MSA module, as illustrated below.

$$\begin{aligned} MSA\,(Q, K, V) &= [head^1, head^2, \ldots, head^h]\ ; \\ head^i &= SA(Q \cdot W_q^i,\ K \cdot W_k^i,\ V \cdot W_v^i)\ ; \\ SA(Q, K, V) &= softmax\left(QK^T \big/ \sqrt{D_h}\right) V \end{aligned} \tag{3}$$

where, W_q, W_k, W_v are the weight matrices for the linear transformation; $D_h = D/h$. Following L transformer encoder blocks, the <class> token [11] is enriched with contextual information. The learnable embedding state resulting from the transformer encoder (z_L^0) serves as the image representation y [12]; $y = LN(z_L^0)$.

Feed Forward Network (FFN): The final stage of our model integrates an FFN consisting of two hidden layers, sequentially added with 1024 and D nodes, respectively, which engages GELU activation function. The output layer consists of n_w neurons with $softmax$, resulting in the distribution $s^{<j>}$, from which the writer-id w is identified as below.

$$w = \arg\max_j\ s^{<j>}\ ;\ \text{for } j = 1, 2, \ldots, n_w\ ; \tag{4}$$

where, n_w is the number of writers in the database, i.e., $n_w = |\mathcal{W}|$. Here, we utilize cross-entropy loss, as it has been found effective for multi-class classification tasks [37]. Furthermore, we employ the Adam optimizer [20]. The details regarding hyperparameter tuning and training are elaborated in Section 4.

4 Experiments and Discussions

This section starts with an outline of the dataset and experimental setups, followed by experimental results to evaluate the effectiveness of our model and some contemporary deep architectures for the undertaken task.

4.1 Dataset Employed and Experimental Setups

As mentioned in section 2, we have collected a total of 1560 handwritten English text-line images from 130 individuals. Each writer scribbled 10 samples on "*paper*", 1 sample on "*on-screen*" display tablet, and 1 sample on "*off-screen*" graphics tablet.

We have created 4 experimental setups (*ES*), as below:

- *ES-1:* All samples written on *paper* (i.e., 10×130 samples) were used as training set, and *on-screen* 1×130 samples were engaged for testing.
- *ES-2:* The training set was kept similar to *ES-1*, and *off-screen* 1×130 samples were used for testing.

• *ES-3:* The training set was the same as *ES-1*. The test set combined the *on-screen* and *off-screen* samples used for testing in *ES-1* and *ES-2* (i.e., 2×130 samples).
• *ES-4:* We randomly split all 1300 (= 10×130) samples written on *paper* only into training and test sets with a ratio of 8 : 2. We ensured that the training set included samples from all 130 writers.

In each of the above experimental setups, 10% of the training data was allocated for validation purposes. During model training, we augmented the training set samples by introducing random changes in image saturation, brightness, and contrast to mitigate overfitting.

4.2 Results

We performed the experiments on an Intel(R) Xeon(R) CPU @ 2.00 GHz with 52 GB RAM and Tesla T4 16 GB GPU. The hyperparameters of the employed models were tuned and fixed during the model training, considering the performance of the validation set [37]. For training, the mini-batch size was equal to 16. In this study, 100 epochs were used for model training. The Adam optimizer [20] parameters were selected as follows: the initial learning rate was set to 10^{-4}, the exponential decay rates for the 1^{st} and 2^{nd} moment estimates, β_1 and β_2, were set to 0.9 and 0.999, respectively, and the zero-denominator removal parameter (ϵ) was set to 10^{-8}. For transformer network, we empirically chose $L = 6$, $D = 192$, and $h = 12$. All results presented in this paper were obtained from the testing set. We utilize average *top-1 accuracy %* over all writers as the evaluation metric for assessing model performance [2].

Table 1 presents the performance of our model, and provides a comparison with some major baseline deep architectures [29,16,31,9,28,32,24] and state-of-the-art (SOTA)

Table 1: Performance analysis on various experimental setups and comparative study

	Methods	**Top-1 Accuracy %**			
		ES-1	*ES-2*	*ES-3*	*ES-4*
Baseline	VGG19 [29]	56.4391	56.3369	57.3468	67.4889
	ResNet50-V2 [16]	64.3467	64.2342	65.4734	79.3504
	Inception-V3 [31]	69.3458	69.3456	69.3456	80.0581
	Xception [9]	69.3563	69.3873	69.5647	80.1904
	MobileNet-V2 [28]	69.4737	69.3884	70.4098	80.4259
	EfficientNet-B3 [32]	72.3422	<u>72.8463</u>	<u>72.6833</u>	81.2626
	RAM [24]	<u>72.4523</u>	72.2346	72.5842	<u>81.4558</u>
SOTA	Fiel et al. [13]	54.5692	54.1956	54.8073	65.4442
	GR-RNN [18]	71.7432	71.6591	72.1226	81.0562
	Koepf et al. [21]	73.2389	73.2420	73.3460	81.6678
	Srivastava et al. [30]	75.1104	75.0188	75.3365	81.7277
	WiT [5]	75.3602	<u>75.3600</u>	75.5308	83.1328
	FragNet [17]	<u>75.3613</u>	75.0404	<u>76.2904</u>	<u>83.4105</u>
	Ours	**75.6061**	**75.5975**	**76.8509**	**83.6481**

writer identification methods [13,18,21,30,5,17] across abovementioned four experimental setups (i.e., *ES-1*, *ES-2*, *ES-3*, and *ES-4*).

From the results presented in Table 1, we have the following major **observations**:

(i) Our method outperformed major baseline deep architectures and SOTA methods by attaining 75.6061%, 75.5975%, 76.8509%, and 83.6481% top-1 accuracies for *ES-1*, *ES-2*, *ES-3*, and *ES-4*, respectively.

(ii) Among the compared baseline and SOTA methods, EfficientNet-B3 [24] and FragNet [17] obtained superior performances, respectively, in *ES-3*. In all individual setups, the best performances of baseline and SOTA methods are underlined in Tabel 1.

(iii) Overall, the comparable methods, including ours, achieved better performances in *ES-4* than other setups. One possible reason is that the training and test samples in *ES-4* encompass handwriting produced by various tools (e.g., pencil, gel pen, fountain pen, 0.5 mm and 1 mm ball pens) on *paper* while placed on regular and hard surfaces.

(iv) Overall, our method and some major baseline/ SOTA methods encountered challenges stemming from the surface transition from paper to computer tablets. This is evident from performances on *ES-1*, *ES-2*, and *ES-3* setups, where training samples were written on paper while test samples were scribbled on computer tablets.

(v) We also noted that overall, the comparable methods, including ours, demonstrated better performance in *ES-1* compared to *ES-2*. One plausible reason is that individuals encountered more challenges in *ES-2* when writing on an *off-screen* graphics tablet, which involves a decoupled writing surface while viewing the computer screen. However, for some writers, the act of scribbling on a *on-screen* relatively smoother surface of a display tablet posed challenges in *ES-1*.

These observations highlight the presence of intra-variation in handwriting resulting from surface transitions, as evidenced by the performance of writer identification methods. As a matter of fact, while baseline and state-of-the-art (SOTA) methods achieve high accuracy in benchmark datasets [36], their performance is notably poorer in the dataset examined in this paper.

Ablation Study : We also performed an ablation study by removing the f_C component from our model (refer to Fig. 2 and Section 3.2). After ablating f_C, we obtained top-1 accuracies of 73.2389%, 73.2420%, 73.3460%, and 81.6678% in *ES-1*, *ES-2*, *ES-3*, and *ES-4* setups, respectively. This ablation led to a decrease in accuracy ranging from 1% to 3.5%.

5 Conclusion

This paper studies the intricate challenge of understanding intra-variability in handwriting, which encompasses the variations observed across different writing surfaces, ranging from traditional paper sheets to modern computer tablets. The study explores these diverse writing contexts, including writing on both traditional paper and digital tablets, with and without visual displays, to shed light on how they influence the characteristics and patterns of handwriting. By examining the variations arising from these different conditions, the paper aims to provide insights into the underlying factors contributing to intra-variability in handwriting. We utilized a transformer network with deep features to assess performance in this study. We curated an intra-variable handwriting dataset across various surfaces, incorporating English handwriting samples from 130 distinct writers, totaling 1560 samples. Our model demonstrated an overall accuracy of 76.8509% on this dataset, showcasing promising outcomes. In future research endeavors, we aim to further investigate intra-variation stemming from various writing tools and explore multiple scripts to deepen our understanding of handwriting characteristics across diverse contexts.

Acknowledgment

The authors heartily thank all the writers/ volunteers, and interns/ trainees/ researchers, who helped in database generation. C. Adak acknowledges the partial support from the SERB, DST, Govt. of India, under grant no. SRG/2022/002151.

References

1. Adak, C.: A study on automated handwriting understanding. Ph.D. thesis, University of Technology Sydney, Australia (2019), `https://opus.lib.uts.edu.au/handle/10453/134139`
2. Adak, C., Chaudhuri, B.B., Blumenstein, M.: An empirical study on writer identification and verification from intra-variable individual handwriting. IEEE Access **7**, 24738–24758 (2019). https://doi.org/10.1109/ACCESS.2019.2899908
3. Adak, C., Chaudhuri, B.B., Blumenstein, M.: A deep reinforcement learning-based study on handwriting difficulty analysis. In: Advances in Pattern Recognition and Artificial Intelligence, pp. 97–117. World Scientific (2022). https://doi.org/10.1142/9789811239014_0006
4. Adak, C., Chaudhuri, B.B., Lin, C.T., Blumenstein, M.: Intra-variable handwriting inspection reinforced with idiosyncrasy analysis. IEEE TIFS **15**, 3567–3579 (2020). https://doi.org/10.1109/TIFS.2020.2991833
5. Adak, C., Jaswanth, B., Akhtar, Z., Kåsen, A., Chanda, S.: Writer identification from nordic historical manuscripts using transformer networks. In: IJCB. pp. 1–9 (2023). https://doi.org/10.1109/IJCB57857.2023.10448665
6. Alamargot, D., Morin, M.F.: Does handwriting on a tablet screen affect students' graphomotor execution? a comparison between grades two and nine. Human movement science **44**, 32–41 (2015). https://doi.org/10.1016/j.humov.2015.08.011
7. Ba, J.L., Kiros, J.R., Hinton, G.E.: Layer normalization. NIPS: Deep Learning Symposium (2016)
8. Bulacu, M., Schomaker, L.: Text-independent writer identification and verification using textural and allographic features. IEEE TPAMI **29**(4), 701–717 (2007). https://doi.org/10.1109/TPAMI.2007.1009
9. Chollet, F.: Xception: Deep learning with depthwise separable convolutions. In: CVPR. pp. 1251–1258 (2017). https://doi.org/10.1109/CVPR.2017.195
10. Costain, J.: Questioned documents and the law: Handwriting evidence in the federal court system. Journal of Forensic Sciences **22**(4), 799–806 (1977). https://doi.org/10.1520/JFS10422J
11. Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: BERT: Pre-training of deep bidirectional transformers for language understanding. In: NAACL-HLT. pp. 4171–4186. ACL (2019). https://doi.org/10.18653/v1/N19-1423
12. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., Houlsby, N.: An image is worth 16x16 words: Transformers for image recognition at scale. In: ICLR (2021), `https://openreview.net/forum?id=YicbFdNTTy`

13. Fiel, S., Sablatnig, R.: Writer identification and retrieval using a convolutional neural network. In: CAIP. pp. 26–37. Springer (2015). https://doi.org/10.1007/978-3-319-23117-4_3
14. Gerth, S., Dolk, T., Klassert, A., Fliesser, M., Fischer, M.H., Nottbusch, G., Festman, J.: Adapting to the surface: A comparison of handwriting measures when writing on a tablet computer and on paper. Human Movement Science **48**, 62–73 (2016). https://doi.org/10.1016/j.humov.2016.04.006
15. Gerth, S., Klassert, A., Dolk, T., Fliesser, M., Fischer, M.H., Nottbusch, G., Festman, J.: Is handwriting performance affected by the writing surface? comparing preschoolers', second graders', and adults' writing performance on a tablet vs. paper. Frontiers in psychology **7**, 211618 (2016). https://doi.org/10.3389/fpsyg.2016.01308
16. He, K., Zhang, X., Ren, S., Sun, J.: Identity mappings in deep residual networks. In: ECCV. pp. 630–645 (2016). https://doi.org/10.1007/978-3-319-46493-0_38
17. He, S., Schomaker, L.: Fragnet: Writer identification using deep fragment networks. IEEE TIFS **15**, 3013–3022 (2020). https://doi.org/10.1109/TIFS.2020.2981236
18. He, S., Schomaker, L.: GR-RNN: Global-context residual recurrent neural networks for writer identification. Pattern Recognition **117**, 107975 (2021). https://doi.org/10.1016/j.patcog.2021.107975
19. Hilton, O.: Effects of writing instruments on handwriting details. Journal of Forensic Sciences **29**(1), 80–86 (1984). https://doi.org/10.1520/JFS11637J
20. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. ICLR (Poster) (2015)
21. Koepf, M., Kleber, F., Sablatnig, R.: Writer identification and writer retrieval using vision transformer for forensic documents. In: DAS. pp. 352–366 (2022). https://doi.org/10.1007/978-3-031-06555-2_24
22. Koppenhaver, K.M.: Forensic document examination: principles and practice (2007)
23. Mathyer, J.: The influence of writing instruments on handwriting and signatures. J. Crim. L. Criminology & Police Sci. **60**, 102 (1969). https://doi.org/10.2307/1141743
24. Mnih, V., Heess, N., Graves, A., Kavukcuoglu, K.: Recurrent models of visual attention. NeurIPS **27** (2014), `https://dl.acm.org/doi/10.5555/2969033.2969073`
25. Morris, R.N.: Forensic handwriting identification: fundamental concepts and principles (2020)
26. Plamondon, R., Lorette, G.: Automatic signature verification and writer identification—the state of the art. Pattern recognition **22**(2), 107–131 (1989). https://doi.org/10.1016/0031-3203(89)90059-9
27. Rehman, A., Naz, S., Razzak, M.I., Hameed, I.A.: Automatic visual features for writer identification: a deep learning approach. IEEE Access **7**, 17149–17157 (2019). https://doi.org/10.1109/ACCESS.2018.2890810
28. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., Chen, L.C.: MobileNetV2: Inverted Residuals and Linear Bottlenecks. In: CVPR. pp. 4510–4520 (2018). https://doi.org/10.1109/CVPR.2018.00474
29. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. ICLR (2015)
30. Srivastava, A., Chanda, S., Pal, U.: Exploiting multi-scale fusion, spatial attention and patch interaction techniques for text-independent writer identification. In: ACPR. pp. 203–217 (2021). https://doi.org/10.1007/978-3-031-02444-3_15
31. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z.: Rethinking the inception architecture for computer vision. In: CVPR. pp. 2818–2826 (2016). https://doi.org/10.1109/cvpr.2016.308
32. Tan, M., Le, Q.: Efficientnet: Rethinking model scaling for convolutional neural networks. In: ICML. pp. 6105–6114. PMLR (2019), `https://proceedings.mlr.press/v97/tan19a.html`

33. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I.: Attention is all you need. NeurIPS **30** (2017)
34. Wang, J., Tao, X., Xu, M., Lu, J.: Boundary objectness network for object detection and localization. In: ICASSP. pp. 2336–2340 (2018). https://doi.org/10.1109/ICASSP.2018.8462434
35. Xie, S., Girshick, R., Dollár, P., Tu, Z., He, K.: Aggregated residual transformations for deep neural networks. In: CVPR. pp. 1492–1500 (2017). https://doi.org/10.1109/cvpr.2017.634
36. Xiong, Y.J., Lu, Y., Wang, P.S.: Off-line text-independent writer recognition: A survey. IJPRAI **31**(05), 1756008 (2017). https://doi.org/10.1142/S0218001417560080
37. Zhang, A., Lipton, Z.C., Li, M., Smola, A.J.: Dive into Deep Learning. Cambridge University Press (2023)