JOIV : Int. J. Inform. Visualization, 8(1) - March 2024 535-541

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Offline Handwriting Writer Identification using Depth-wise Separable Convolution with Siamese Network

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Abstract*— Offline handwriting writer identification has significant implications for forensic investigations and biometric authentication. Handwriting, as a distinctive biometric trait, provides insights into individual identity. Despite advancements in handcrafted algorithms and deep learning techniques, the persistent challenges related to intra-variability and inter-writer similarity continue to drive research efforts. In this study, we build on well-separated convolution architectures like the Xception architecture, which has proven to be robust in our previous research comparing various deep learning architectures such as MobileNet, EfficientNet, ResNet50, and VGG16, where Xception demonstrated minimal training-validation disparities for writer identification. Expanding on this, we use a model based on similarity or dissimilarity approaches to identify offline writers' handwriting, known as the Siamese Network, that incorporates the Xception architecture. Similarity or dissimilarity measurements are based on the Manhattan or L1 distance between representation vectors of each input pair. We train publicly available IAM and CVL datasets; our approach achieves accuracy rates of 99.81% for IAM and 99.88% for CVL. The model was evaluated using evaluation metrics, which revealed only two error predictions in the IAM dataset, resulting in 99.75% accuracy, and five error predictions for CVL, resulting in 99.57% accuracy. These findings modestly surpass existing achievements, highlighting the potential inherent in our methodology to enhance writer identification accuracy. This study underscores the effectiveness of integrating the Siamese Network with depth-wise separable convolution, emphasizing the practical implications for supporting writer identification in real-world applications.

***Keywords*— Offline handwriting; writer identification; Siamese network; similarity approach; depth-wise separable convolution.**

Manuscript received 26 Sep. 2023; revised 24 Dec. 2023; accepted 19 Jan. 2024. Date of publication 31 Mar. 2024.

I. INTRODUCTION

Identifying offline handwriting authors remains an open research problem due to the diversity in handwriting, which extends beyond alphabet forms to include scripts like Chinese and Indian scripts and regional variations such as Javanese scripts in Indonesia, among others. In the context of writer identification, those scripts are a substantial advancement of feature extraction techniques and the comprehensive methodologies employed by numerous researchers for writer identification. For instance, scripts such as Urdu and Hindi exhibit strikingly similar strokes despite originating from distinct writing systems, resembling writer identity styles and characteristics. Moreover, the similarity between writers' handwriting and the high intra-variability among authors continue to be subjects of investigation to find optimal methods for writer identification, particularly in the offline context. This research has broad applications in forensics, psychology, historical and ancient documents, authentication of wills, bank signatures, and more. For instance, in forensic science, experts can utilize the findings of this research to identify the author of a handwritten will or threat letter and determine its authenticity. In general, Online handwriting involves using a mouse or pen on tablets to generate data in real-time.

Conversely, offline handwriting employs ink on paper, creating the document through scanned images. Online and offline handwriting produce distinctive characteristics based on the writer's hand movements and has even become a biometric trait. In this study, due to the well-established performance of Optical Character Recognition (OCR) technology in addressing online handwriting, we emphasize authors who engage in offline handwriting. Furthermore, given the high intra-variability, similarities among writers, and linguistic diversity worldwide, this issue remains an open research problem in offline handwritten text. Identifying authors from offline handwriting employs two approaches: conventional handcrafted algorithms and deep learning [1]. Notable examples of handcrafted algorithm approaches include texture-based descriptors [2], scale-invariant feature transform [3], [4], and the utilization of transform-based [5], which have demonstrated promising research outcomes. However, with the emergence of deep learning, automatic feature extraction has become feasible, as shown by [6]–[9] utilizing a CNN architecture and harnessing frozen layers coupled with a machine learning algorithm as a classifier.

A similar approach, but with dissimilarity techniques, has been undertaken by [10]. Furthermore, several researchers have explored a focus on feature learning, both in unsupervised manners such as [11] and semi-supervised manners like [12], aiming to enhance writer identification accuracy [13]. The proposed FragNet involves a segregated network comprising a feature pyramid for feature map extraction from word data and a fragment pathway trained for author identity prediction. Kumar and Sharma [14] also employed CNN with a segmentation-free approach to the utilized data. Additionally, [15] used a multi-stream structure-based CNN approach to enhance prediction accuracy, while [16] pursued a combined approach incorporating conventional methods with deep learning techniques.

From our previous study [17], we endeavored to evaluate several deep learning architectures, including VGG, ResNet, Xception, EfficientNet, and MobileNet, to ascertain the optimal ground truth for selecting a deep learning architecture appropriate for addressing the problem of author identification in handwriting. The findings highlighted that XceptionNet exhibited a small convergence gap between training and validation.

Furthermore, several researchers have employed the Siamese Neural Network (SNN) approach, where this technique aims to discover the similarity between two inputs once they enter a neural network. SNN has found application in verifying the authenticity of offline signatures, as demonstrated in previous studies [18]–[20]. Despite these approaches being used in offline writer signatures, this approach in the context of offline handwriting writer identification was pursued by [21] with Bengali handwritten from India, [22] with additional SIFT algorithm and modified Principal Component Analysis (PCA) trained on omniglot dataset. A unique database 19 called NIST-SD19 was incorporated with SNN by [23] to verify handwritten authors. With all that has been explained above, it is noteworthy that the offline handwriting of authors can also be categorized as the same objects, albeit possessing distinct biometrics.

This research aims to enhance accuracy and validation for offline handwriting writer identification. We utilize the publicly available IAM and CVL datasets as benchmarks. Following this, the resultant model will undergo an assessment using metrics based on the confusion matrix to determine the performance of the suggested model.

II. Materials and Method

The method proposed in this research is visually depicted in Fig. 1. Initially, we acquire the publicly available image datasets IAM and CVL. A preprocessing phase follows, involving thorough cleaning and preparation steps, which will be detailed in the dedicated preprocessing subsection. Subsequently, the data is segmented into inputs: Input 1 and 2.

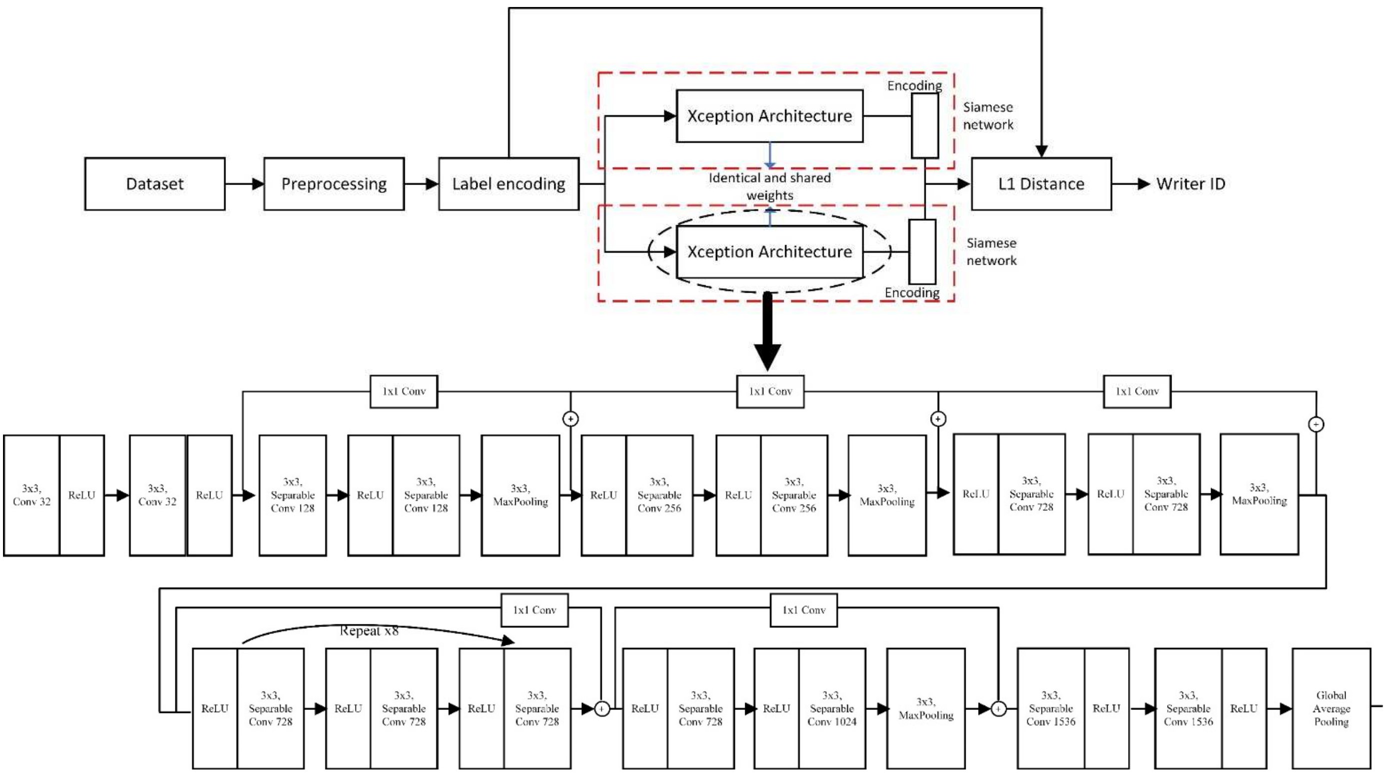

Fig. 1 Proposed Method

These inputs are directed into a Siamese network, where a CNN incorporates a depth-wise separable convolution to serve as a feature extractor. The Siamese network generates an encoded representation that simplifies the computation of the L1 distance, facilitating the evaluation of similarity or dissimilarity and also extracts the writer's identification label.

A. IAM Dataset

The IAM dataset [24] constitutes an openly accessible compilation of offline handwriting samples in the English language. It covers 658 unique writers, each designated with IDs spanning from 000 to 657. This dataset includes well-segmented data units such as words, sentences, and pages. However, in segmenting into words, certain characters remain unresolved. Additionally, special characters like commas, quotation marks, and colons, which can be challenging to interpret in an author's handwriting, are removed. The Word of IAM dataset has a total of 100350 images. These images were split into two halves, resulting in 50175 images for each input. Within each input set, a further division was made: 70% of the data (35123) was allocated for data training, and 30% (15053) was used for validation and testing. Specifically, 90% of the validation subset comprised 1355 images, and the remaining 10% constituted 151 images for testing. The data distribution for each writer becomes uneven when the dataset is segmented into words. However, this uneven distribution proves advantageous in our proposed Siamese approach, which capitalizes on one-shot classification and mitigates the need for an extensive dataset size. Examples of the IAM dataset in page and word formats are presented in Fig. 2.

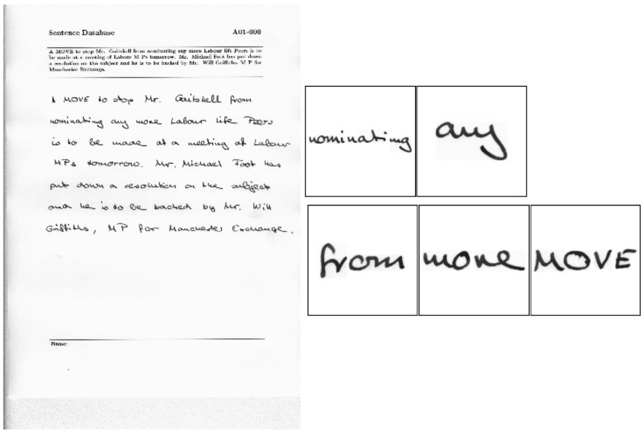

Fig. 2 Example of IAM dataset

B. CVL Dataset

The CVL dataset [25] is an openly accessible English and German offline handwriting dataset, encompassing contributions from 310 writers. Similar to the IAM dataset, the CVL dataset is structured to accommodate word, sentence, and page data, primarily focusing on identifying author identities. The dataset contains a total of 99904-word images. These images were divided equally into two sets, resulting in 49952 images for each input. An additional partition was implemented within these input sets, with 70% (34966 images) allocated for training purposes and 30%, 14986 handwritten images reserved for testing and validation. Within the validation subset, 90% (13487 images) of the divided data was utilized, leaving the remaining 10% (1498 images) for the testing phase. Unlike the IAM dataset, the CVL dataset exhibits a relatively even distribution of page data across each writer. Fig. 3 showcases several segmentation results of word data extracted from page data within this dataset.

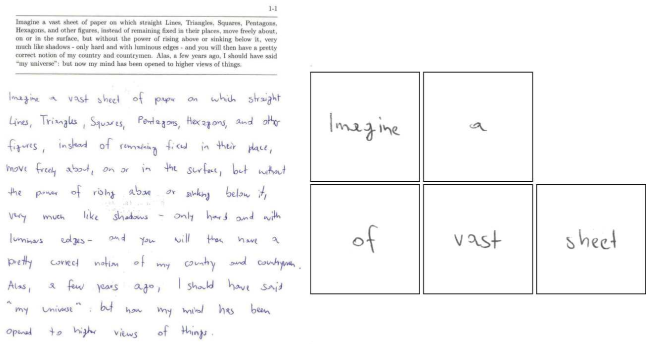

Fig. 3 Example of CVL dataset

C. Preprocessing

The datasets obtained from the earlier sources comprise raw data extracted from scans of paper documents. As a result, the handwritten content within these datasets retains noise originating from the inherent randomness of handwriting despite certain sections being discernible. The preprocessing phase incorporates two distinct stages to mitigate the dataset's variability. The primary stage is dedicated to data cleansing, as illustrated in Fig. 4

Fig. 4 The initial stage of cleaning preprocessing for IAM and CVL datasets.

In the initial preprocessing stage, it is observed that the handwritten content within the dataset occasionally contains colors other than black. As a result, a conversion to grayscale is performed. Subsequently, certain writings need more strokes and noise. A morphological operation called "morphology" is applied to address these issues, precisely an opening operation, to effectively remove noise during image segmentation. Further refining is achieved using a Gaussian filter to mitigate Gaussian noise. Binarization is then applied to establish a consistent black-and-white color scheme for the images. Finally, Otsu thresholding is utilized to automatically determine a threshold separating foreground and background pixels. The outcomes of this initial preprocessing stage are illustrated in Fig. 4.

Following the data cleansing process in the initial preprocessing stage, the second stage involves preparing the data before it enters the Xception architecture within the

Siamese network. All the handwritten images must be divided into training, testing, and validation sets. For this purpose, the data is split into two equal portions, each comprising 50%, which will serve as Input 1 and 2. Subsequently, further partitioning is performed within each input set, with 70% for training, 10% for testing, and 20% for validation. Given that the handwritten images are structured around words, a standardized input size of 299x299x3 for Xception architecture is established after the preprocessing phase. This preprocessed data is then input into the neural network for subsequent processing.

D. Depth-wise Separable Convolution

The Xception architecture [26] is an artificial neural network that leverages depth-wise separable convolution, featuring a depth of 36 layers and more than 20 million parameters. This convolution approach is known for its computational efficiency, significantly reducing the computational workload through separate channel computations. In architectures like MobileNet, customary nonlinear layers, batch normalization, and ReLU activation are typically placed after each convolution layer. However, in the context of Xception, batch norm, and activation of ReLU are exclusively utilized after depth-wise separable convolution, which is followed by point-wise convolution.

Experimental results have shown improved accuracy compared to architectures where batch normalization is applied after every convolution, as seen in MobileNets. Our previous research evaluated various deep learning architectures, including VGG, ResNet, Xception, EfficientNet, and MobileNet, to identify the most suitable architecture for addressing the author identification problem in handwriting. The findings highlighted that ResNet achieved the highest accuracy rates. However, XceptionNet exhibited a smaller convergence gap between training and validation, rendering it more suitable for real-world applications. The architectural configuration is illustrated in the previous Fig. 1.

E. Siamese Network

The Siamese network employs identical neural subnets with uniform weights. The Siamese Neural Network (SNN) is designed to match a pair of representation vectors and ascertain their semantics to distinguish one from another. This configuration enables vector representation data to group similar instances while distinguishing dissimilar ones [27]. The SNN framework finds applicability across various research domains, mainly focusing on image processing and computer vision, for example, face recognition, signature verification, object tracking, anomaly detection, and one-shot learning [28]–[30]. Upon traversing the neural network, the feature extraction process yields encodings utilized for calculating the discrepancy between two inputs, referred to as loss function. In selecting the loss function, we opt for the contrastive loss based on the Manhattan or L1 distance metric, as mathematically represented in equation (1):

$$d(p,q) = \sum_{i=1}^{n} |q_i - p_i| \quad (1)$$

where d is the distance between q_i and p_i, two representation feature vectors. This distance is then incorporated in contrastive loss calculation, which is commonly used in SNN as depicted in equation (2):

$$Y = (1-B)\frac{1}{2}(D)^2 + (B)\frac{1}{2}\{\text{maximum}\ (0, l-D)\}^2 \quad (2)$$

where Y represents loss, B indicates two-ways, as if siamese inputs offline handwriting from the same writer ID or not, in this case, B = 0 if similar, and B = 1 on the contrary, a margin l that we set to 0.7 to be allowed, and D as calculated L1 distance from equation (1). Suppose B = 0 and the distance D below 0.7, the second term of the contrastive loss formula will be zero. If D exceeds 0.7, the network will be penalized for not keeping dissimilar pairs separated by at least the margin. This situation encourages the network to learn feature representations that maintain a clear margin between different writers in the feature space. That also means lower loss values indicate that the network effectively distinguishes between pairs, whereas higher loss values suggest that the network struggles to differentiate between specific pairs. For the Manhattan distance, as an illustrative example, following the preprocessing steps described above, the IAM dataset is processed through the designed CNN architecture. The distance of similarity or dissimilarity for the input data is calculated based on the L1 distance computation, as illustrated in Table 1

TABLE I
EXAMPLES OF L1 DISTANCE COMPARISON

ID Input 1	**Input 2** 164	269	658
164	[0.63863564] (similar)	[0.10000002] (dissimilar)	[0.10000288] (dissimilar)
269	[0.10000002] (dissimilar)	[0.63863564] (similar)	[0.10000002] (dissimilar)
316	[0.11547202] (dissimilar)	[0.10000014] (dissimilar)	[0.1000002] (dissimilar)
396	[0.10000002] (dissimilar)	[0.10000008] (dissimilar)	[0.10000002] (dissimilar)
658	[0.10000014] (dissimilar)	[0.10043496] (dissimilar)	[0.63863564] (similar)

F. Configuration

Upon completing the preprocessing steps, which involved cleaning and preparing the dataset to dimensions 299x299x3, we utilized the Xception architecture as a feature extractor. The parameter "include_top" was false, leading to the fully connected layers being omitted from the architecture's output. Additionally, we executed 25 epochs during the training process. Subsequently, we introduced a flattened layer to convert the features generated by the Xception model into a singular vector. Moreover, we calculated the L1 distance (Manhattan distance) between the two obtained features, resulting in a similarity score.

Additionally, a prediction was generated to determine whether the two images were similar or dissimilar based on the computed distance. To optimize the Siamese model, reduce errors, and enhance performance, we employed the optimizer “Adam” with a 0.0001 learning rate. For binary classification, we selected the binary_crossentropy as the loss function. This experiment was conducted using the processor Intel Pentium i9 with a clock of 2.50 GHz, along with 32GB of RAM. The system was further enhanced with an NVIDIA

GeForce RTX 3080 TI GPU featuring 12GB of VRAM. The duration of the training process spanned around five to seven days for its completion.

III. Results and Discussion

During the training process for the IAM dataset, it became evident that by the 22nd epoch, the training accuracy had reached a point where further improvements were not noticeable, prompting us to conclude the training. The training accuracy outcomes of our proposed method have been illustrated in Fig. 5 and Fig. 6 in the order mentioned. The graphical representation showcases that the IAM dataset achieved convergence between training and validation accuracy by the fifth epoch, nearing 98%. This convergence gradually improved with successive epochs. In contrast, the CVL dataset exhibited accuracy convergence later, specifically around the eighth epoch, achieving a commendable accuracy level of 98%. This observation implies that the CVL dataset possesses more intra-variation or similarity than the IAM dataset.

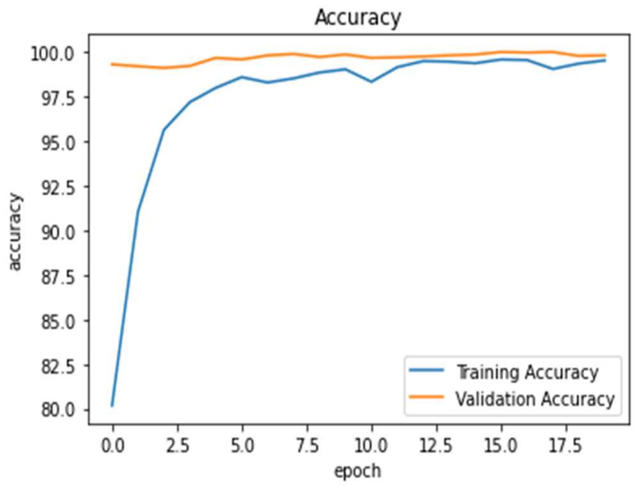

Fig. 5 Graphic of IAM dataset training accuracy

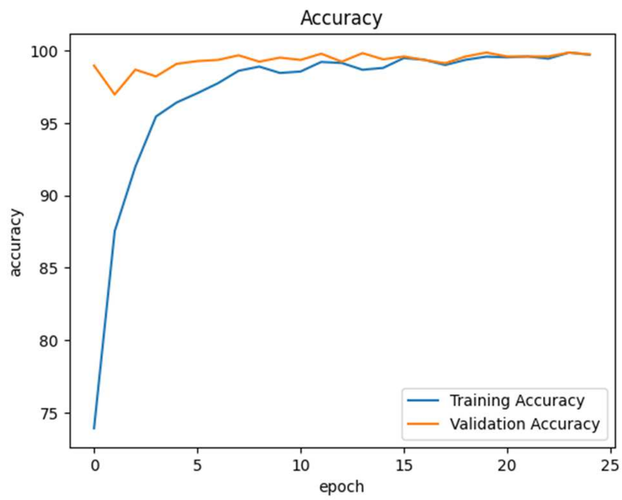

Fig. 6 Graphic of CVL dataset training accuracy

A comprehensive evaluation of each training iteration was conducted. The results indicated that the highest achieved accuracy rates were notably impressive, 99.81% for the IAM dataset and an even more remarkable 99.88% for the CVL dataset. Additionally, the model underwent rigorous testing utilizing an independent set of image pairs, constituting 10% of previously unobserved data. During this evaluation, the model's predictions were compared to the actual author identification IDs, allowing for an assessment of their accuracy. When these predictions align with the ground truth, the corresponding label encoding is assigned to the authentic or original images, and the author IDs are subsequently extracted, as depicted in Fig. 7.

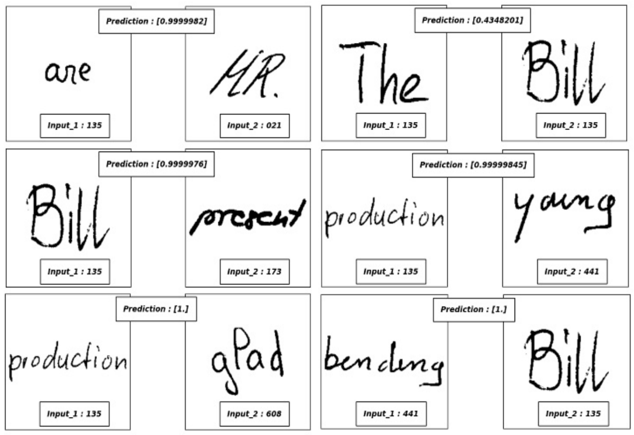

Fig. 7 Few predictions of data test

From Fig. 7, in the first column and row, it can be observed that input 1 with ID 135 is paired with input 2 with ID 021. The prediction result indicates a distance of 0.9999982, suggesting dissimilarity. Conversely, in the first row and second column, where the IDs are the same, the distance result is 0.4348201, signifying that this text is from the same author. This pattern continues for the remaining comparison results. These outcomes demonstrate that the predictions for unseen test data have performed remarkably well. However, a comprehensive evaluation of prediction results for the entire dataset is necessary to assess its performance, as detailed in the following subsection.

A. Evaluation Metrics

Since the predictions' output is binary, indicating similarity or dissimilarity, we do not employ metrics such as Top1, Top5, Top10, Hard N, or Soft N accuracy because these metrics are utilized for classification tasks where the output is not binary but involves multiple classes. Following the testing phase, the forecasted results on similarity and dissimilarity within the 10% dataset are Assessed through evaluation metrics, namely recall, F1-score, accuracy, and precision from the confusion matrix, as depicted in Fig. 8 and Fig. 9 for both datasets above.

The confusion matrix for IAM dataset indicates that the model correctly predicted class 1 (similar) for 722 instances and class 0 (dissimilar) for 782 cases, incorrectly predicted class 1 for zero instances, and incorrectly predicted class 0 for two instances. This result shows high accuracy and low error, with only two incorrect predictions.

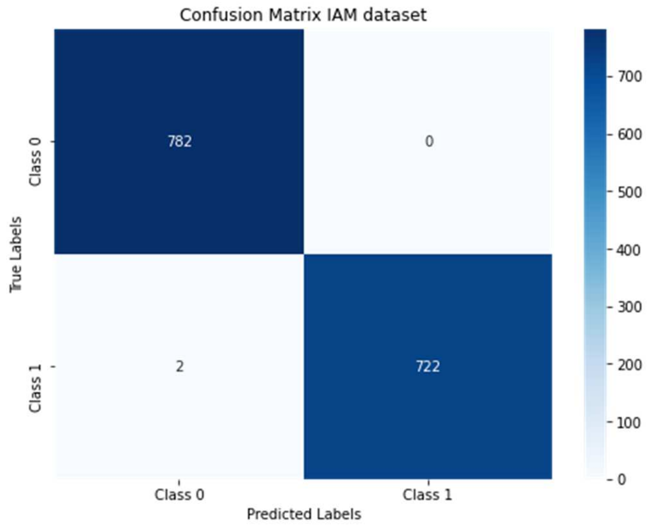

Fig. 8 Matrix of "Confusion" for the IAM dataset

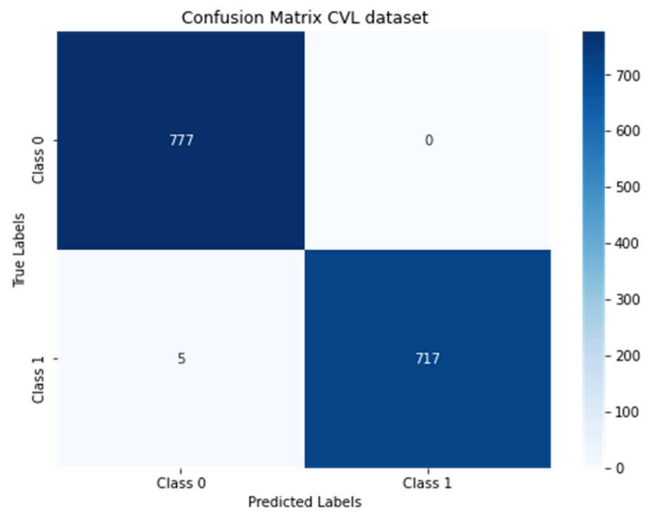

Fig. 9 Matrix of "Confusion" for CVL dataset

From Fig. 9 for the CVL dataset, class 1 (similar) has 717 true positives and zero false positives, and class 0 (dissimilar) has 777 true negatives and five false negatives. These outcomes also mean the model performs exceptionally well, with only five incorrect predictions. The assessment metrics result is presented in Table 2.

TABLE II
EFFICIENCY EVALUATION METRICS MODEL

	Dataset	
Metrics	**IAM**	**CVL**
Accuracy	99.81%	99.88%
Precision	99.75%	99.57%
Recall	99.75%	99.57%
F-1 score	99.75%	99.57%

These findings illustrate the frequency with which the model generates accurate predictions across the evaluated dataset. However, it is essential to acknowledge that not all predictions are entirely precise, as approximately 0.2% were inaccurate for the IAM dataset and 0.3% for the CVL dataset. These inaccuracies underscore both dataset's significant inter-class similarity and intra-class variation. Our approach focuses on a binary task, precisely predicting whether a pair of input data is similar or dissimilar while identifying author IDs.

B. *State-of-the-art Comparison*

Compared to our findings, we gathered data from the comprehensive survey paper on state-of-the-art writer identification authored by Purohit and Anwar [1]. To ensure fair and unbiased comparisons, we specifically focused on the datasets IAM and CVL. Subsequently, we juxtaposed the outcomes attained through cutting-edge methodologies with those achieved using our suggested methodology. This comparative evaluation is visually presented in Table 3 for IAM and CVL for Table 4.

TABLE III
STATE-OF-THE-ART COMPARISON WITH IAM DATASET

Authors	**Method**	**Accuracy (%)**
Abdelilah *et al.* [7]	ResNet-34	99.5
He and Schomaker [8]	Adaptive CNN	85.2
He and Schomaker [13]	FragNet-64	85.1
He and Schomaker [9]	GR-RNN	96.4
Kumar and Sharma [14]	SEG-WI model	97.27
Sulaiman *et al.* [16]	CNN + LBP	96.1
Xing and Xiao [15]	CNN	98.23
Proposed method	**(xception+siamese)**	**99.81**

TABLE IV
STATE-OF-THE-ART COMPARISON WITH CVL DATASET

Authors	**Method**	**Accuracy (%)**
Christlein *et al.* [4]	CNN + GMM super vector encoding	99.4
Abdelilah *et al.* [7]	ResNet-34	99.5
He and Schomaker [22]	GR-RNN	90.2
Helal *et al.* [10]	CNN	99.80
Chen *et al.* [12]	ResNet-50	99.2
Kumar and Sharma [14]	SEG-WI model	99.35
He and Schomaker [13]	FragNet-64	85.1
Sulaiman *et al.* [16]	CNN + LBP	99.69
He and Schomaker [8]	Adaptive CNN	94.3
Christlein *et al.* [11]	CNN + VLAD encoding	99.5
Proposed method	**(xception+siamese)**	**99.88**

IV. CONCLUSION

This research introduces an innovative identification technique for offline handwriting writers utilizing a Siamese network with the Xception architecture as the feature extractor. This study employs a unique approach to achieve cutting-edge results in writer identification from offline handwriting samples. The testing outcomes exhibit an accuracy of 99.81% for the IAM dataset and 99.88% for the CVL dataset. These results highlight the competitiveness of the Siamese neural network approach compared to existing methods. Additionally, integrating the Xception architecture from our previous work has effectively narrowed the gap between training and validation accuracy convergence. This enhancement renders the approach more applicable in real-world scenarios. While the accuracy and evaluation metrics achieved are commendable, there is a trade-off in the training computation time, which took five to seven days. This trade-off prompts us to contemplate future endeavors that involve exploring datasets beyond the English language and personal datasets.

ACKNOWLEDGMENT

This research was funded by the Budget and Annual Work Plan of the Research and Community Engagement Institute of Universitas Pendidikan Indonesia for the Fiscal Year 2023, under the Decree of the Rector Number: No. 535/UN40/PT.01.02/2023.

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