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A Deep Learning Approach for Identifying Individuals Based on Their Handwriting

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Abstract: *Identifying the writer of handwritten text poses a significant challenge due to the diversity and variability inherent in handwriting styles. This paper proposes a novel approach based on Siamese neural network (SNN) for the task of writer identification in Khmer handwriting. The SNN architecture was leveraged for training and testing on a dataset specifically collected for this purpose. The dataset comprised 1400 samples collected from students, which were divided into training and testing sets containing 983 and 417 words, respectively. Promising results were achieved through extensive experimentation, with a training set accuracy of 96% and a testing set accuracy of 94%. The proposed SNN approach demonstrated effectiveness in handling the complexities of Khmer handwriting and accurately identifying the authorship of words. This research contributes to the advancement of writer identification techniques in the context of Khmer script, with potential applications in forensic analysis, document verification, and linguistic research. Future work may focus on enhancing the robustness and scalability of the model, as well as exploring additional features and optimization strategies to further improve performance.*

Keywords: Khmer handwriting; writer identification; identifying individuals; siamese neural network

1. INTRODUCTION

Biometric identification of an individual may be possible through many data elements including speech, fingerprints, facial features, and related data. Identifying the identity of individuals through characteristics of their handwriting is one of the most important challenges for security verification [1, 2], recognizing the individuality of handwriting including the psychological state of the writer. The ability to identify and authenticate individuals through pattern analysis of their handwriting has many potential applications including for bank account verification, criminal and judicial purposes, digital forensics, and for identifying the author of historical documents. Identification of a handwriter refers to the identification of a specific individual from samples of their handwriting characteristics, which are then analyzed across documents obtained from numerous writers. This identification is possible due to the handwriting style, which has multiple features of each word that represent the personality of the writer. Features include the letter slope, shape, stroke, and cursive [5, 1]. In this study, identification of a writer is divided into two modes, online and offline [6]. The offline writer identification mode receives static images of handwriting as features only, whereas the online writer identification mode receives more robust data including writing strokes, pen pressure, features, and especially the character's coordinates. An online writer identification system, however, has limited usage to electronic writing devices, as these systems require specialized hardware to capture the necessary dynamic writing data.

Adak et al., (2020) note that before the advent of machine learning, handwriting identification and forensic techniques targeted various physical facets, such as the writing media (paper) types, character orthography and size, and character and word level spacing. With advancements in deep learning—defined as a subset of machine learning methods based on neural networks with representation learning, characterized by the use of multiple layers in the network—writer identification can now utilize adaptive shape-based image feature extraction techniques that significantly improve accuracy.

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Language-specific handwriter identification systems have been developed for major languages such as Chinese [17], English [16], and Bengali [8]. Khmer script, an abugida orthography belonging to the Mon-Khmer subgroup within the broader Austroasiatic language family, is used to write the Khmer language. Khmer script presents fascinating and complex challenges to typographers and font designers worldwide [1, 21]. Annanurov & Noor (2016) note that the contemporary Khmer script consists of 33 primary consonant symbols, and includes 17 dependent vowel symbols and approximately 14 special diacritic symbols modifying pronunciation and altering the meaning of syllables. Compared to other languages, Khmer script patterns are more complex due to the increasing number of character patterns and structure (Fig. 1), making Khmer writer identification a challenging task.

In this paper, a deep learning approach is proposed for handwriter identification by analyzing and comparing images of Khmer script, hereafter referred to as OHWI (Online Handwritten Khmer Identification). In this initial contribution, we introduce an online data collection tool designed to gather and process Khmer script handwriting samples. This tool, deployed globally and accessible through web browsers, enables users to register and upload sample images of Khmer script. The collected data includes detailed coordinate information of the handwriting strokes, demographic information of the users, and corresponding word labels. This comprehensive dataset forms the foundation of the training dataset., then propose a deep learning architecture for writer identification. This architecture comprises two convolutional neural networks (CNNs) with identical architectures and shared weights. Weights are numerical values that determine the strength and direction of connections between neurons in artificial neural networks. This symmetrical structure, where both networks share the same weights, is characteristic of Siamese neural networks. By leveraging image features extracted from sample handwriting data resized to a standardized dimension of 128 x 128 pixels, the network learns to discern unique patterns in the Khmer script associated with individual writers. This approach aims to bridge the gap between traditional handwriter identification methods and the capabilities offered by deep learning techniques, presenting a comprehensive solution for online handwriting writer identification in Khmer script. This methodology recognizes handwriter identity by analyzing handwriting subtleties such as stroke dynamics, grapheme formations, orthographic patterns, stylistic preferences, and individual idiosyncrasies.

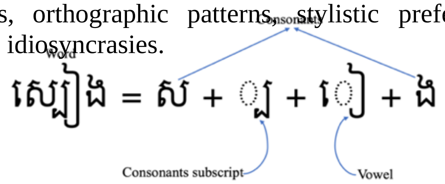

Fig . 1. An example of the Khmer script / characters constructed by combining between one or more consonant, consonantal subscript, vowel, and diacritic

2. LITERATURE REVIEW

Handwriting-based identity identification has long been a topic of study, with applications ranging from forensic analysis to document verification. A writer's handwriting is a distinctive biometric characteristic that can disclose both their identity and their psychological condition [3]. This literature review first examines language-specific research in handwriting recognition, with emphasis on diverse scripts. Following this, we explore advancements in online applications of handwriting analysis and delve into the integration of deep learning techniques to enhance the accuracy and efficiency in writer identification tasks.

Deep learning may be used for many tasks including prediction and classification., Deep learning has further transformed handwriting identification by employing CNNs to automatically learn and extract information from handwriting images. CNNs have significantly improved accuracy and robustness by being especially effective in analyzing and defining complex handwriting patterns. Research indicates that CNNs are a useful tool for identifying writers in major languages. For example, He and Tang [17] developed a CNN-based system that successfully identified Chinese handwriting with a high degree of accuracy. Language-specific writer identification techniques have been extensively studied, acknowledging the unique characteristics and challenges presented by various scripts. For instance, the complex characters in Chinese handwriting necessitate the use of sophisticated feature extraction approaches [11]. Similarly, Mridha et al. (2021) focused on Bengali handwriting, which involves intricate patterns that demand advanced deep learning techniques, much like those used for Chinese characters [8]. Their findings demonstrated that their deep learning model could accurately classify different writers, effectively capturing the unique characteristics of the Bengali script. While English handwriting may have fewer character variations, Purkayastha et al. (2017) found that the distinctive stylistic differences between individual writers still present significant challenges. Their study showed that deep learning techniques surpassed traditional methods in identifying English handwriting, proving the robustness and generalizability of CNNs in writer identification tasks [16].

Similarly, Khmer script, used in the Cambodian language, presents unique challenges due to its complexity and the number of character patterns. As noted, the contemporary Khmer script is characterized by its intricate system, which includes a rich inventory of 33 primary consonant symbols, 17 dependent vowel symbols, and approximately 14 diacritic symbols [4]. This complexity presents a significant challenge for writer identification tasks, requiring advanced deep learning models capable of capturing the subtle variations inherent in Khmer handwriting [19]. Addressing this complexity is crucial for achieving accurate and reliable results in applications such as forensic analysis, document verification, and linguistic research.

Although research on handwriting recognition for other languages has advanced, little progress has been made related to the Khmer script [14]. By presenting a deep learning method for Khmer handwriting recognition using Siamese neural networks, this work seeks to close this gap. Siamese neural networks are especially well-suited for writer identification since they can distinguish between samples of handwriting that differ slightly from one another.

Furthermore, we employ an online data collection tool to acquire examples of Khmer handwriting, which we use as training data for a Siamese neural networks architecture. Using image features obtained from handwriting data, the network can recognize distinct patterns in Khmer script linked to certain writers. By bridging the gap between conventional approaches and innovative deep learning techniques, this research aims to provide a more rigorous solution to the problem of Khmer script recognition.

3. METHODOLOGY

In this study, a comprehensive framework (Fig. 2) was designed for the collection and processing of handwriting data. The collected data was resized to a standardized dimension of 128 x 128 pixels to ensure uniformity during analysis.

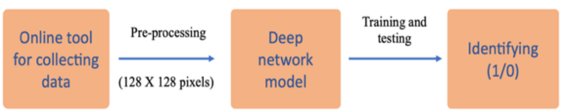

Fig . 2. Research framework for identifying Khmer script handwriters (1 indicating similarity and 0 indicating dissimilarity)

3.1 Data collection tool

To collect data, an online tool named *Online Tools for Khmer Handwriting (OTKH)* was developed, allowing users to register, create an account, and sign in to draw Khmer words. OTKH captures each user's writing style based on the (x, y) coordinates of their strokes and also collects user information. Although the appearance of words written on OTKH may differ from those written on paper due to the absence of tactile feedback and differences in pressure sensitivity and screen smoothness, the underlying writing style generally remains consistent, rooted in an individual's habitual motor patterns. However, the validity and reproducibility of handwriting captured via OTKH can be influenced by factors such as the input device used, screen size, and user familiarity with the tool. Users may experience a learning curve when adapting to the digital interface, which could introduce variability in initial handwriting samples. Over time, as users become more accustomed to the tool, their handwriting may stabilize, reducing these variations. Additionally, the frequency of data entry could impact consistency; repeated sessions might lead to greater familiarity and more uniform handwriting, although factors like fatigue could also introduce subtle changes.

The word is randomly generated (Fig. 3) from Chuon Nath dictionary (containing 17000 words).

Fig . 3. Chuon Nath dictionary user interface for drawing Khmer scripts using OTKH. The black word represents the user's handwritten input, while the blue word represents the word generated from the database (photograph by author)

To create OTKH, applied Python a popular high-level, general-purpose programming language (van Rossum, 1991) in an opensource a Python-based [21] web application framework Django [22], to reduce task repetition and simplify web development coding. The Django framework is a collection of modules which facilitates development of apps or websites with existing components and is designed for rapid deployment. Chapkovski & Kujansuu (2019), and Thakur & Jadon (2023) note that Django follows a model view template (MVT) design pattern that retrieves data from models and passes it to templates for display based on the model view controller (MVC) software design pattern as follows:

- **Model:** This component performs as a medium for saving data from the user input into the database. It is responsible for handling the logical part of the web application as well as how the data will be stored in the database.
- **Views:** Is responsible for manipulating data from databases and storing data provided by the user. In Django Framework, views are different from those in basic MVC structure.
- **Template:** This MVC component is responsible for the business logic and computations behind the web application. When a user makes a request, the controller receives the request and sends or returns the proper response.

3.2 Dataset collection and pre-processing

The OTKH tool was then used to collect data from users. Users could access the website and register by filling some required information. Once registered, they can log in to *OTKH* with their username and password to draw Khmer words and view their personal information, which would be protected for privacy purposes. The participants in this study were students of university who volunteered to contribute their handwriting samples. These students were selected depended on their willingness to attend and their familiarity with the Khmer script, ensuring a diverse representation of handwriting styles. The goal of the study, which involves utilizing the Online Tools for Khmer

Handwriting (OTKH) to analyze handwriting patterns, was explained to them. Students were allowed to log in and submit at least fifteen handwriting samples at any time after registering, enabling consistent and varied data collection. They had to draw a series of randomly selected Khmer words produced by the tool each time they logged in in order to capture different aspects of their handwriting. The students were not made aware of the specific research topic involving the use of a model for writer identification, even though they were told that the study aimed to explore the possibility of employing handwriting for identification reasons.

3.2.1 Collecting data

A total of 1,400 handwritten samples from 171 individuals were gathered; on average, each user contributed thirty words. The training and testing sets of the dataset, which had 983 and 417 words, respectively, were separated out. Coordinates, word labels, and user data were among the details that were kept in a database.

3.2.2 Data pre-processing

Before feeding the data into OWHI, we conducted normalization and cleaning procedures to enhance the quality and uniformity of the dataset. These processes involved standardizing the data to a common scale and removing noise or artifacts which could affect model performance. By normalizing and cleaning the data, we mitigated the impact of unusual or irregular samples, thereby improving the robustness of a OWHI.
The raw handwriting data, initially captured as coordinates, were converted into an image format for compatibility with deep learning architectures. These images were then stored in a data storage methodology which employed unique folders within the dataset structure (Fig. 4).

Fig . 4. The dataset converted from coordinates into images and stored in different folders. The image name is a combination of user id, word id, and word label

In this approach to keep the preprocessed handwriting data, each handwriting sample was represented as an image and organized into unique folders based on predefined categories or labels (Algorithm 1). This structured storage system facilitated efficient data management and retrieval during model training and evaluation.

Algorithm 1: Converting coordinates to image

```
DECLARE n = 1 // as folder label
DECLARE data // all data retrieve from database
DECLARE image_dir // as a main folder for storing image
FOR LOOP n in data:
    1. Filter user_id, writing_id, word, and coordinates
       from data
    2. // Create the images label
       name = str(user_id)+"_"+str(writing_id)+"_"+word
    3. Get coordinate x, y and then plot it on scatter graph
       x = coordinates[::2]
       y = coordinates[1::2]
       fig, ax = plt.subplots()
       ax.scatter(x, y)
    4. Start assigning label to folders
       i = n // n start from 1
       label_dir = os.path.join(image_dir, str(i))
    5. Creating directory and save image
       IF not exists(label_dir):
         Create a new label_dir directory
         Os.makedirs(label_dir)
       END IF
       image_path = os.path.join(label_dir, f'{name}.png')
       plt.savefig(image_path)
END FOR
```

3.3 The proposed OHWI model architecture

The proposed model architecture is based on a Siamese neural network, which was well-suited for tasks requiring similarity comparison or identification of patterns within complex data sets. In this case, the Siamese network consisted of two identical subnetworks, each accepting a resized handwriting image as input. These subnetworks share the same weights and architecture, facilitating the extraction of meaningful features from the input images.

In accordance with preprocessing procedures, the handwriting images were resized to a standardized dimension of 128 x 128 pixels before being utilized as input for the model. This resizing step was integral to enhancing the stability and performance of the system's model-training process. By ensuring uniformity in the size of input images, we aimed to mitigate potential issues related to variations in image dimensions and aspect ratios, thus promoting more consistent and effective training results. The output of each subnetwork is a vector representation (i.e., embedding) of the input image in a high-dimensional feature space. These embeddings are then compared using a contrastive loss function, which encourages similar images to have embeddings that are close together and dissimilar images to have embeddings that are further apart. Through the iterative process of model training, the network learned to distinguish between different authors' handwriting styles based on the learned embeddings. The following formula illustrates the use of a Sigmoid function in the contrastive loss function and is a common choice for mapping the similarity scores. Fig. 5. illustrates the architecture of OWHI model.

$$Z = \sigma(\sum_{k=1}^{n} w_I \left| f(x^{(i)})_k - f(x^{(j)})_k \right| + b) \qquad \text{(Eq. 1)}$$

Where,

- $x^{(i)}$ and $x^{(j)}$ are input vectors.
- n is the dimensionality of the feature embeddings $f(x^i)$and $f(x^j)$.
- w_i represents the weight connected with the $i-th$ dimension.
- b represents term of a bias.
- σ is the sigmoid activation function.
- $\sum_{k=1}^{n}$ represents the summation over all dimensions.

If a score of Z equals 1 means that both words are similar or Z equals 0 means that both words are dissimilar.

3.4 Experimental setup

Data collection, experiments, and evaluations were performed using Python 3.11 and Django Framework 4.2. OWHI were implemented utilizing the Pytorch library [23]. NumPy [15] and OpenCV [24] were used to perform mathematical operations and image processing on an individual basis. Model training and testing were conducted in a computing environment equipped with an Apple M2 Pro processor and 16 GB of RAM.

4. RESULTS AND DISCUSSION

4.1. Results

To evaluated the performance of the proposed approach on a dataset consisting of 1400 handwriting samples.

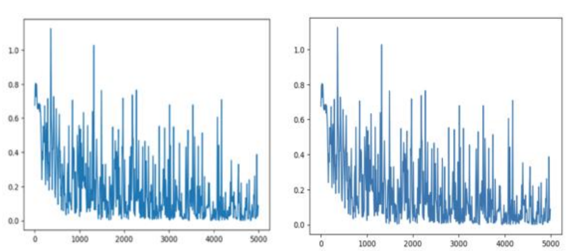

Fig . 6. a-b. Accuracies of testing and training of the proposed model over multiple epochs: accuracy on the training dataset on the 983 networks with 96 % accuracy (7a) and on the 417 networks with 94 % accuracy (7b)

Th[illegible] 3 samples used for training and 417 samples for testing. The OWHI demonstrated promising results, achieving a training set accuracy of 96% and a testing set accuracy of 94% (Fig. 6). The model architecture utilized a Siamese neural network (SNN) framework. The neural networks were trained with a learning rate (lr) of 0.001 and a dropout rate (dr) of 0.2 to improve generalization and prevent overfitting. We used the CrossEntropyLoss() function to compute the loss during training because it is well-suited for classification tasks, where it measures the performance of a classification model whose output is a probability value between 0 and 1. The concept of CrossEntropy was developed by Good(1995) in the context of rational decisions (Good, I.J., 1952). To update the model parameters, we employed the stochastic gradient descent (SGD) optimizer, which is effective in finding the minimum of the loss function efficiently.

4.2 Discussion

The possibilities and difficulties of employing Siamese neural networks for writer identification in the Khmer script are discussed. With a testing accuracy of 94% and a training accuracy of 96%, the study demonstrated the robustness and dependability of the model when applied to the Khmer script. The Siamese neural network scored much better than a single CNN model and traditional classifiers, demonstrating its efficacy in capturing fine-grained handwriting data. However, using the Adam activation function [25] led to a significant drop in accuracy to 64%, highlighting how crucial it is to use the correct activation functions.

With potential applications in forensic analysis, document verification, and linguistic research, this work represents a significant advancement in the identification of Khmer script writers. The methodology and results demonstrated here could be extended to other complex scripts, paving the way for future research into writer identification across various languages. However, the robustness and generalizability of the model may be affected by the relatively small size and limited diversity of the dataset used in this study, underscoring the need for larger and more varied datasets—potentially around 100,000 samples—to further validate and enhance the model's performance. The results of the misclassification analysis on the training and testing sets, which showed error rates of 4% and 6% respectively on existing data, indicate that the model had difficulty differentiating writers with minute variations in their handwriting. This underscores the need for strategies to address these challenging cases. To provide more detailed information about the model, future work may incorporate features such as pen pressure and writing speed. Conducting methodical evaluations of various activation functions and hyperparameters may aid in determining the best choices for tasks involving the detection of handwriting. The applicability of the results may be confirmed by cross-linguistic investigations employing the Siamese neural networks technique, which would also advance the field of writer identification studies. Overall, the work opens the door to more investigation and useful applications by showing how well Siamese neural networks identify Khmer handwriters.

5. CONCLUSIONS

The study demonstrates the effectiveness of employing carefully selected training parameters and a robust model architecture in achieving promising results on a Khmer handwriting sample dataset. These findings represent a significant contribution to the advancement of writer identification techniques, offering potential applications in various fields. However, to fully realize its potential, further experiments on various architectures and testing against other methods with the dataset are warranted. This ongoing exploration will deepen our understanding and refine the applicability of the approach in practical settings.

6. FUTURE WORK

Expanding on the results of our investigation, subsequent research may investigate several avenues to augment the efficiency and suitability of the methodology. Enhancing the OHWI's performance and generalizability would require gathering a more extensive and varied dataset that encompasses samples from a wider range of demographics. Furthermore, the model's capacity to recognize sequential and temporal connections in handwriting may be further improved by fusing a recurrent neural network (RNN) with a Siamese neural network. This could increase the OHWI's accuracy in writer identification. Larger-scale data collection and higher-quality handwriting samples could be achieved by improving data collection tools by making them responsive and allowing users to draw words from various devices. This would ensure a more user-friendly experience and better representation of diverse handwriting styles. By addressing these areas, future work can refine and expand the capabilities of the OHWI model, making it more robust, accurate, and applicable to a wider range of scenarios and languages.

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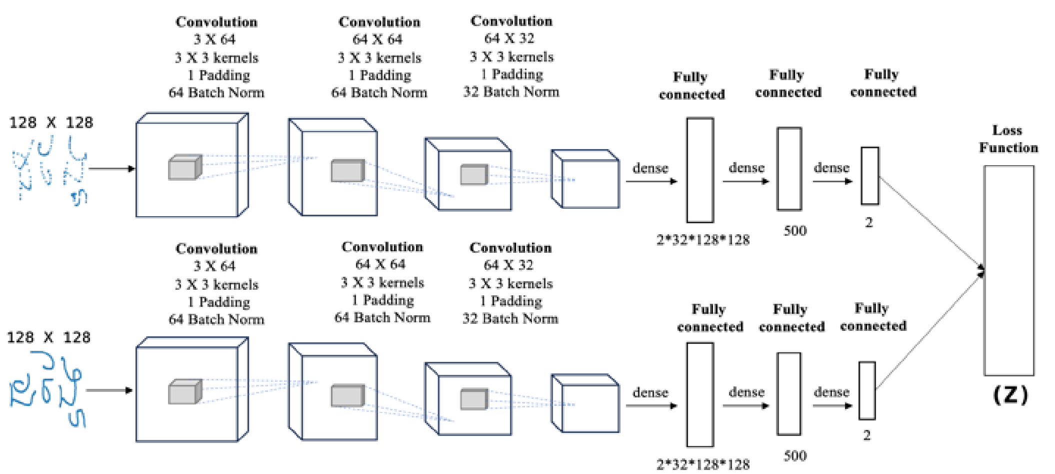

Fig. 5. The architecture of OHWI consists of two identical networks, each sharing the same channel and weight configurations. This symmetrical structure is characteristic of Siamese neural networks. Within the architecture accepts input images with dime