A Survey of Offline Handwritten Signature Verification Based on Deep Learning

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***Abstract*—Handwritten signatures are biometrics and a point of contention in the scientific community, the process used to verify whether a person's signature is genuine. In the past ten years, the application of handwritten signature technology in the fields of administration, finance, handling legal disputes, and security has been greatly developed, and many researchers have focused on applying systems based on handwritten signature analysis and processing to new fields on the possibility. After several years of disorderly development in this field of research, it is time to assess the applicability of its current developments to formulate a structured path forward. In this paper, we provide a systematic review of the literature on offline handwritten signatures over the past 10 years, focusing on the most prominent and promising deep learning-based signature verification methods, and attempt to elicit possible future research directions on this topic.**

Keywords—offline handwritten signature verification, neural network (NN), deep learning (DL)

I. Introduction

The field of handwritten signature verification has been extensively studied over the past few decades but is still an open research problem. The purpose of a signature verification system is to distinguish whether a given signature is genuine (made by a purported individual) or forge (made by impostors) [1]. According to the different collection methods of handwritten signature image data, the authenticity verification of handwritten signatures is divided into online signature verification and offline signature verification. Compared with online signature verification, offline signature verification does not consider the dynamic information generated during the writing process, so the accuracy rate is lower and verification is more difficult. However, offline signature verification does not require special sample input devices and has a wider application range and greater use-value.

Forgeries in signature verification systems are classified into three types [2]:

- Unskilled Forgeries are signatures in which the forger signs without any information about the signature.
- Random Forgeries are signatures in which the forger knows the signer's name without any prior examples.
- Skilled Forgeries are signatures in which the forger knows the name and form of the original signature.

Two types of learning may be used in a Handwritten Signature Verification (HSV) system: Writer-Independent (WI) or Writer-Dependent (WD). In the case of WI, learning is done based on a large population of signature samples related to all persons in the dataset, whereas in the case of WD, learning is conducted based on the signature samples from each person, separately. Although WD learning achieves good results, a classifier must be conducted for each user added to the system, and therefore the complexity and the cost of the system increase [3]. A more practical and user-friendly approach is the writer-independent (WI) approach, which requires only one global classifier for all users. The WI system can be used by providing a single signature sample, which makes this method more popular than the WD method.

Traditional machine learning methods are trained based on handcrafted features, and the accuracy of classification is directly related to these features. This dependency is considered a major weakness of the traditional model. In the past 5-10 years, many advances have been proposed in the literature, most notably the application of deep learning methods to learn feature representations from feature images. Deep learning(DL) and CNN have drawn the attention of bioinformatics researchers. Compared with hand-crafted features, the reported results of DL and CNN-based signature verification systems are significantly improved. Therefore, it can be expected that with the development and advancement of

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technology, signature authentication technology will gain an increasingly important position in the field of identity authentication. The research on authenticity verification of handwritten signatures will also make this topic even more important in practice. In view of this, this paper mainly focuses on the research technology of DL-based offline handwritten signature authenticity verification at home and abroad in recent years. The main content is expounded on the basic concepts, commonly used public datasets, preprocessing methods, and modern mainstream and cutting-edge offline signature authentication methods, and discusses the research progress and development direction in this field.

II. RELATED WORKS

The different working modes of handwritten signature classification and decision-making can be divided into handwritten signature recognition and handwritten signature verification. Offline handwritten signature recognition is a process of identifying user identities, and it is multi-classified, so the data in the offline handwritten signature data set are the real signature samples of each user. The offline handwritten signature verification is a means of identifying the authenticity of the user, and it performs two classifications. Therefore, offline handwritten signature verification requires the use of the signer's forged signature, especially the skilled forgery signature, in order to improve the system's verification capabilities. Usually, not only are there different degrees of difference between authentic and forge signatures, but there will also be certain differences between the real signatures of the same person, and even the signatures at the same time and in the same environment are not the same. Therefore, there will be two misjudgments when authenticating: False Acceptance Rate (FAR) and False Rejection Rate (FRR). At the same time, the Overall Right Rate (ORR) is introduced for evaluation. The higher the ORR, the better the processing ability of the proposed algorithm for true signatures and forged signatures. Among them, FAR refers to determining a forged signature as a real signature, and FRR refers to determining a real signature as a forged signature. In this paper, two types of error rates, FRR and FAR, are selected as evaluation indicators: FRR=(number of true signatures falsely rejected /N)×100%, FAR=(the number of false signatures falsely accepted /N)×100%, ORR=(1-(FRR+FAR)/2)×100% where N is the overall sample set for each signature.

Neural Networks Approach, this method is widely used in signature verification systems, and its powerful functions, usability, learning, and promotion capabilities are the main reasons for using this method. When using this method, we have to construct a neural network (NN) by removing features from the signer samples and learning the relationship between the signatures and their classes. Therefore, the signature verification process runs in parallel with this learning mechanism [2].

A deep neural network (DNN) is a multi-layer feedforward neural network consisting of two or more hidden layers between the input layer and the output layer. DNNs need to be properly configured and trained to obtain the desired performance. By increasing the number of hidden layers, the generalization efficiency of DNN can be improved. However, additional layers also require more data instances to prevent the network model from overfitting. Overfitting is a design error that occurs when the model learns details and noises in the training data that adversely affect the model's performance on new data. Hidden layer optimization and hyperparameter training are critical for large DNNs. DNNs are classified into three main categories, namely de novo trained models, pre-trained models, and ensemble models. CNN, a DL-based DNN model, is the most adopted ML-based validation model in selected studies. In selected studies, the researchers applied CNNs to all three forms of DNNs. A CNN model that is created and trained from scratch is called a "de novo model". CNN models that utilize previously trained networks such as AlexNet, VGGNet, GoogLeNet, and ResNet are called "pre-trained models".

In recent years, with the continuous development and application of artificial intelligence and neural networks, experimental methods of deep learning have also played a positive role in the study of handwritten signatures. Figure 1 shows the current flow chart based on these two experimental methods.

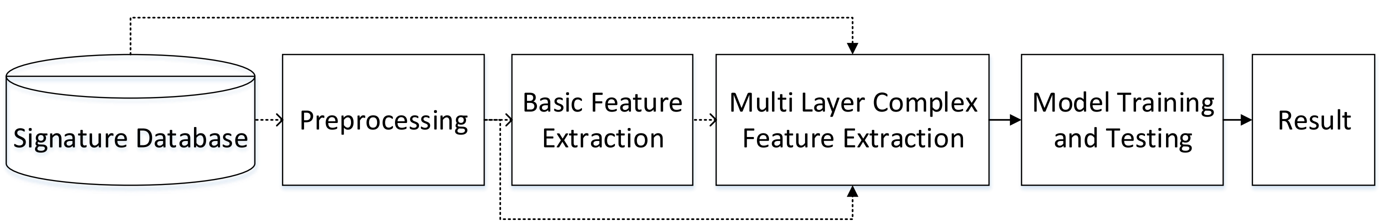

Fig. 1. Offline handwritten signature verification system (deep learning).

According to the description in Figure 1, the experimental steps of handwritten signature research based on deep learning algorithms generally include data collection, (data preprocessing, basic feature extraction), multi-layer complex feature extraction, and classification decision-making. Among them, data preprocessing and basic feature extraction are optional steps. The process of multi-layer complex feature extraction has low interpretability and is difficult to understand, but its experimental process is simple, does not require too much human intervention, and has high verification accuracy.

III. DATASETS

At present, most of the commonly used and public offline handwritten signature datasets abroad are in Western languages (Latin, mainly English). As shown in Table I, this article lists the existing common public datasets:

TABLE I. COMMONLY USED SIGNATURE DATASETS

Dataset Name	Language	explain	Data volume
CEDAR	Western	300 dpi, BMP	55 people, 24 true and 24 false
GPDS synthetic Off-Line Signature	Western	Original acquisition and electronic synthesis	4000 people, 24 true and 30 true
MCYT-75	Western	many types	75 people, 15 true and 15 false
4NsigComp2010	Western	300 dpi, BMP	2 people, 113 true,194 skilled, and 27 false
4NsigComp2012	Western	300 dpi, BMP	3 people, 113 true, 273 skilled, and 64 false
SigWIcomp2015	Italian	many types	50 people, 479 true and 249 false
	Bengali		10 people, 240 true and 300 false
UTSig	Persian	300 dpi, tiff	100 people, 1000 true and 200 false
Brazilian (PUB-PR)	Western		168 people, 6720 true and 2280 false
BHSig260	Bengali		100 people, 2400 true and 3000 false
	Sanskrit		160 people, 3840 true and 4800 false

In the table, "true" represents a real signature sample, and "false" represents a forged signature sample, which can be divided into skilled forgery (trained and learned to imitate and write signatures of forged signers) and random forgery (impersonate and write the signature of the person being forged without training). From the content of the above table, we can easily see that there are almost no offline handwritten signature datasets of Chinese characters and minority languages. Moreover, for these offline handwritten signature datasets in Western languages, even if some offline handwritten signature data in Central Asia are mostly from the same language family-Indo-European language family, although these languages are not similar in writing at present, however, for researchers, In other words, conducting such monolingual or monolingual data research, in the long run, will limit the practicability and applicability of its experimental methods, and eventually, lead to biased experimental results. Therefore, the challenge for offline handwritten signature verification is not only to improve the current state-of-the-art experimental methods and experimental results but also to take into account the research on offline handwritten signature verification in a multilingual hybrid mode in reality.

IV. PREPROCESSING

The main purpose of image preprocessing is to eliminate irrelevant information in the image and recover useful real information. The preprocessing of the signature image is the first step in the offline handwritten signature verification research process. Intra-class dissimilarity and inter-class similarity of signature image data.

As shown in Table II, this paper lists some commonly used image preprocessing methods. In addition to the data preprocessing methods shown in Table II, some image transformation methods can also be regarded as a process of image preprocessing on image data, such as Wavelet Transform, Ridgelet Transform, Contourlet Transform, Shearlet Transform, etc. These transformations separate the original data information into multiple band images containing different information content by stripping the feature information of the original image and then analyzing and studying these original images or transform coefficients.

TABLE II. COMMON PREPROCESSING METHODS

preprocessing	implementation algorithm
Grayscale	Component, maximum, average, weighted avera ge method, etc.
Binarization	OTSU, One-Dimensional Maximum Entropy, Tor que Preservation Method, Kittler, Bersen, Niblac k, VFCM, NFCM, Shanbhag, Fixed Threshold, Glo bal Threshold, Dynamic Threshold, Adaptive Thr eshold, etc.
Smooth noise Reduction	Mean filter, Gaussian filter, median filter, bilater al filter, Unger algorithm, etc.
Geometric Transformation	mage flip, image rotation, center crop, image inv ersion (translate, transpose, mirror, zoom), etc.
Normalization	Nearest neighbor interpolation, bilinear interpol ation, cubic interpolation, Lanczos interpolation.
Refinement	Iterative and non-iterative algorithms (serial an d parallel computing).
Gradient Calculation	Sobel operator, Scharr operator, Laplacian opera tor, etc.

V. LITERATURE REVIEW

A. Neural Networks and Deep Learning

1) CNN: The development of deep learning is gradually becoming mainstream. Offline handwritten signature verification algorithms based on convolutional neural networks (CNN) have always been the focus of attention. There are many network models with simple structures and high operating efficiency, which make these algorithms can be widely used CNN for Persian signature verification, which is the first reported use of CNNs in the signature verification literature [20]. Hafemann et al. used CNN for offline signature verification and obtained a 1.72% error rate for GPDS-160. Das S D et al. [25] proposed an ensemble model independent of the authors' offline handwritten signature verification task, using two Convolutional Neural Networks (CNN) for feature extraction, followed by a regularized gradient boosting tree (Regularized Gradient Boosting Tree, RGBT) for classification and stacking to generate the final prediction vector, and finally obtained a good discrimination effect. Zheng et al. [24] proposed that a convolutional neural network (CNN) has the potential to extract these micro-deformations through maximum pooling. The micro-deformation can be determined by observing the position coordinates of the maximum value of the pooling window of max-pooling, using the information as the new feature of the micro-deformation, and the convolution feature. The data uses four public data GPDS, CEDAR, UTSIG, and BHSIG260.

2) VGGNet: VGGNet, one of the well-known models submitted to ILSVRC2014, was the runner-up in the image classification task and won the ILSVRC 2014 localization task. VGG16 consists of 16 convolutional layers (3× 3 convolutions) with a very uniform architecture (using a large number of filters) that yields attractive results in many applications. Bonde et al. [7] proposed a new signature feature computation method, which is divided into two parts: an author-independent method, and an author-dependent method. The VGG16 Convolutional Neural Network (CNN) is fine-tuned using a writer-independent approach. In writer-dependent methods, this fine-tuned CNN is used to extract features from signatures. The signature is passed through this fine-tuned CNN, and the vector obtained from the first fully connected layer (after the last convolutional layer) is used as the feature vector. The curve angle is an important property of the shape pixel, so the GWBTA algorithm is used to replace the feature pixel, and both the author-independent and author-related methods use Gaussian weighting-based tangent angle (gwt) to replace the pixels of the sparse signature image. The features obtained based on the author's correlation method are input into a support vector machine (SVM) classifier to classify the authenticity of the signature.

Contributions of VGG16:

- This paper proposes a new offline signature feature calculation method.
- Replace the feature pixels with the curve angle GWBTA.
- Fine-tune VGG16 with the new method.
- Use the fine-tuned VGG16 to calculate the feature vector of the offline handwritten signature. Furthermore, the method uses an SVM classifier and is tested on three different databases.

3) LS2Net: A new large-scale signature network (LS2Net) is specially designed for the GPDS-4000 dataset with batch normalization, which overcomes the large-scale issues in the number of signatures and signers [19]. Among them, the class center-based classifier (C3) algorithm relies on the 1-nearest neighbor (1-NN) classification task, using the class centers of feature embeddings obtained from fully connected layers. In addition to this, a new network structure called LS2Net\Uv2 was created by replacing the activation function Rectifier Linear Unit (ReLU) with a leaky ReLU, which gives very good training data the result of. Batch normalization and the C3 algorithm contribute significantly to performance.

4) SigNet: Different from the above classification-based studies, Dey et al. [22] proposed a representative Siamese convolutional network model SigNet for signature discrimination. SigNet feature vectors are composed of 2048 dimensions. The model receives two signature images as output and outputs a scalar value after being processed by two parallel convolutional networks to measure the direct similarity of the input signatures. Experiments on multiple public datasets show that SigNet has better robustness than other classification-based verification models, and this design structure has become the mainstream structure of the current intelligent handwritten signature verification system. Unfortunately, due to a large number of network parameters, the model is more prone to overfitting during training due to the insufficient number of signature samples. In order to overcome this problem, Souza et al. [23] proposed The feature selection technology of the particle swarm algorithm can effectively filter redundant information in different representation spaces of handwritten signature samples, so that the model can learn more effectively features, thereby reducing the possibility of overfitting.

5) CapsNet: Deep Convolutional Neural Networks (DCNNs) have strong feature extraction capabilities. Although these networks have important advantages, they cannot identify the spatial properties of each feature in the signature. Also, max-pooling layers often remove some features that are critical for forgery detection. Parcham et al. [18] proposed a composite backbone structure (CBCapsNet) signature verification model that combines CNN and capsule neural network (CapsNet). A new training mechanism is designed in which a single network is simultaneously trained by two images of the same level, thus reducing the training parameters by half. This mechanism does not require two separate networks to learn features. The evaluation results show that the proposed model can improve the accuracy and outperform the popular signature verification methods in the community.

Contributions of CapsNet:

- CapsNet replaces the pooling layer in CNN, and the capsule retains all image features.
- Make up for the deficiencies of convolutional networks in detecting and distinguishing component spatial changes and identifying image component transformations and changes.
- It can improve the accuracy of feature extraction and make the feature extraction backbone more effective.

B. Data Augmentation

One of the main challenges in building an automated signature verification system is the small number of samples per user used for training. To solve this problem, many researchers have proposed several new methods to artificially increase the number of offline signature images. A ground-truth augmentation method (by adding random control noise to reflect actual changes in handwriting) is used to generate new training signatures from existing ground-truth signatures [6]. Similarly, generates synthetic offline signatures using a deep CNN-based approach under the supervised training perspective. Promising results are shown through methodological developments, where dynamic information is generated by providing a unified synthetic synthesizer for offline signature synthesis [8]. An offline synthetic signature generation method based on human neural motion is proposed, which utilizes the ink deposition model to generate realistic synthetic signatures [9]. Likewise, addresses the limited number of signatures by replicating offline signatures using a cognitively inspired algorithm [10]. M Diaz et al. [11] proposed a signature replication procedure based on neurocognitive distortions. All of these researchers are trying to fill this gap by adding signatures, but there is still a need to develop robust algorithms for HSV systems, so more attention from researchers is required.

C. Transfer Learning

Specifically, for most reasonable image classification tasks, the first few layers of the network learn about the same low-level features regardless of the dataset. This means that we can initialize our neural network with parameter values learned from different datasets and expect the values of the first layer of the network to work well without training. This process is called transfer learning. The necessity of large datasets is considered to be the most important deficiency in the application of CNN models [26]. To overcome this deficiency, two concepts of transfer learning and fine-tuning are proposed. Learning feature representations attempts to learn good feature representations directly from raw data, which was successfully implemented using deep CNN and censored in seconds. One of the most successful techniques in the field of CNN models is transfer learning or knowledge transfer [3]. Transfer learning enables us to transfer the potential of a CNN model from a source task to another task that is limited by massive data or lack of time. Models based on transfer learning can reduce training time and improve performance accuracy, especially when training samples are few. Some researchers have used these methods in their HSV systems. More recently, transfer learning based on dichotomous transformation in the context of HSV systems to verify signatures in other datasets (a scenario based on transfer learning between datasets) [12, 13]. Similarly, Hafemann et al. [14] proposed a meta-learning-based transfer learning solution to distinguish between real and forge offline signatures. To improve the accuracy performance of HSV systems, this research area still needs more attention from researchers.

VI. Research Trends

A. Unresolved Issues

1) Creating large public datasets: To our knowledge, there are no large standard public datasets available for developing robust HSV models. GPDS Synthesis has the most offline signatures of 4000 users. Furthermore, the available public datasets follow different signature acquisition protocols, as there is no specific standard protocol for acquiring offline signatures. Few public datasets collect offline signatures in one instance, while others give time intervals between different offline signature sample collection sessions. For different languages, such as Western, Persian, Hindi, etc., standard public datasets and standard signature acquisition protocols are urgently needed. This is necessary as it will enable researchers to compare their results on standard public datasets with accepted standard acquisition protocols. It has been observed that most HSV systems are developed for specific datasets and not tested on other datasets with different image acquisition protocols, different numbers of images per capita, etc. Therefore, there is an urgent need for such a robust HSV system, which can be better generalized. In other words, HSV systems can produce similar results on various public datasets. Few literature researchers have attempted to address this question.

2) Signature size normalization: This study explores the problem of offline signature image size normalization for DL-based HSV systems. DL-based HSV systems require fixed-size offline signature images to drastically improve performance. Hafemann et al. [15] proposed that Fine-tuning (fixed image size) representations help to adapt representations to new conditions, thereby improving the performance of CNN-based HSV systems. Furthermore, they found that fine-tuning notation also works well in multi-script scenarios. To improve the accuracy performance of DL-based HSV systems, this research area still needs more attention from researchers.

3) Improve the scalability of the system: Scalability means that the HSV system has a learning algorithm or classifier that can handle any number of signatures, be it a single sample or multiple samples. The literature shows that mixed writer-independent writers rely on the HSV system to combine the advantages of both WI and WD classifiers. A hybrid WI-WD system in which a general WI classifier was designed with a development database [16]. As long as enough samples are collected for a particular user, there is an option to switch to a safer, simpler, and more accurate model of WD operation. The performance of the initial universal (WI) validation mode is comparable to state-of-the-art offline SV systems. Similarly, A hybrid WI–WD classifier showed better accuracy performance. During WI training, there is still a need to improve the accuracy of HSV systems with hybrid WI-WD by using additional features and learning from independent forgery [17].

In addition, deep learning methods require a large number of datasets, high hardware, and software environments, and take a long time to do experiments. It is difficult to extract effective features and the intra-class variability between true signatures and forged signatures, and the discrimination rate is low. Finally, for the multi-language hybrid offline handwritten signature verification problem, the traditional machine learning algorithm or deep learning algorithm starts from each stage of the experiment, in the process of performing multi-dimensional signature image preprocessing, feature extraction, and multistage classification research methods, it is prone to problems such as high inter-class similarity and intra-class difference of signature images, sparse features that are difficult to extract, weak feature representation and low discrimination rate.

B. Challenges

HSV typically model the properties of signatures found in a particular signature database, which limits their applicability. This effect can lead to biased results because not all human behaviors are considered in the dataset. Therefore, the challenge is not only to improve the state-of-the-art results using existing databases but also to develop incremental signature data. The above studies found that the performance of most HSV models suffers from the insufficient number of signature images per user. Each user needs a sufficient number of image samples to train the model without facing overfitting and underfitting problems. Compared with traditional ML-based models, DL-based models have higher offline signature verification accuracy. Nonetheless, at the same time, these DL-based models require a large number of training samples to build a general model. Therefore, it is necessary to develop robust algorithms for HSV using a limited number of images.

Another important challenge for training an automated signature verification system is the presence of partial knowledge during training. In a realistic scenario, during training, we only have access to genuine signatures for the users enrolled in the system. However, we want the system not only to be able to accept genuine signatures but also to reject forgeries. This is a challenging task since during training a classifier has no information to learn what exactly distinguishes a genuine signature and a forgery for the users enrolled in the system. Lastly, the amount of data available for each user is often very limited in real applications. During the enrollment phase, users are often required to supply only a few samples of their signatures. In other words, even if there is a large number of users enrolled in the system, a classifier needs to perform well for a new user, for whom only a small set of samples are available.

Leveraging the advantages of technology, trends, geography, humanities, policies, etc., handwritten signature verification and verification technology have become the focus of our research. In particular, most minority languages in my country's Xinjiang region belong to the same language family as the languages of many countries in Central Asia and have many things. The study of multi-language handwritten signatures has a positive effect on promoting exchanges between my country and Central Asian countries, as well as promoting the development of my country's Xinjiang region. With the advancement of my country's Belt and Road Initiative, the system can be applied to Arabic scripts, namely Arabic, Persian, and Urdu, as well as Chinese and Xinjiang's ethnic minorities (Uyghur, Kazakh, Kirgiz) handwriting Signature verification has broad application value. Verification has broad application value. For online and offline signature research in small languages, the academic world is still a wasteland. The impact of different languages on the verification effect and the impact of different languages on writing style still needs to be explored and verified that the technology has great potential to be explored in the future. Therefore, in the next stage of research, in addition to making breakthroughs in the main goal of handwritten signature verification accuracy, on the basis of ensuring the reliability of the system, it can also provide necessary information for application departments such as public security criminal investigation departments and judicial verification agencies. Process-based on reference. In addition, the application scope of the relevant verification system will also be further expanded. In addition to being able to detect human-forged signatures, it will gradually have the ability to detect forged signatures based on artificial intelligence technology.

VII. Conclusion

Before writing this review, I read in detail the references of related research directions at home and abroad in the past ten years, compared and summarized the proposed algorithms, and analyzed the current classic and cutting-edge methods in the field of handwritten signature verification based on deep learning from multiple perspectives. This paper provides an overview of the offline handwritten signature verification problem and lists commonly used public offline signature datasets that can be used to evaluate such systems. Then, the techniques used in each process of offline handwritten signature verification are described: preprocessing, network model, and model training, and finally, recent progress and potential areas for future research are summarized.

In the past decade, researchers have proposed a variety of offline signature verification methods. While distinguishing between genuine signatures and skilled forgery is still a challenging task, the error rate has dropped substantially over the past few years, mainly due to advances in deep learning applied to this task. It can be seen that a variety of deep learning-based models have achieved good results in offline handwritten signature verification tasks, which can effectively make up for the efficiency and cost problems of traditional manual auditing methods. When the experimental data is very small, the traditional method has the advantages of being intuitive and easy to understand, using less training data, requiring less experimental environment, and being less time-consuming for the experiment; while the neural network has the advantages of high discrimination accuracy, little or no intermediate processing process (end- End-to-end) and other advantages, can truly realize the intelligence of research such as biometric verification.

Therefore, in the next study, in addition to the breakthrough in the accuracy of handwritten signature verification, on the basis of ensuring the reliability of the system, it can also provide the necessary basis for application departments such as public security criminal investigation departments and judicial verification agencies. In addition, the application scope of the relevant verification system will also be further expanded. In addition to being able to detect human-forged signatures, it will gradually have the ability to detect forged signatures based on artificial intelligence technology. This review reveals many emerging research problems that require extensive efforts to improve the performance of offline signature verification systems. We believe that this review will provide researchers with a deep understanding of DL-based offline signature verification and provide valuable insights for researchers in this field.

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