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SURVEY

Advances in Offline Handwritten Signature Recognition Research: A Review

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ABSTRACT A person's handwritten signature, one of the methods frequently used to confirm their identity, is used exclusively to confirm the biometric identification of different financial, legal, banking, insurance, and other business documents. Signature recognition techniques are used to identify which user someone's signature is affiliated with. In recent years, many researchers have worked on applying new methods to this work, and deep learning methods have become quite prevalent among them. In order to provide more researchers with a better comprehension of how offline handwritten signature recognition work has evolved, the existing approaches, different architectures, challenging issues, and trends within the last 15 years, this paper follows a protocol to organize this work, collects information primarily from studies published in four major databases, applies inclusion and exclusion criteria, reviews offline handwritten signature recognition methods, including issues such as feature extraction and classification, and attempts to summarize the challenges and opportunities in the field. This paper emphasizes the popularity of research directions in this research area in deep learning. In contrast to other surveys in the field, this paper is not limited to a particular phase of work but provides a detailed account of each stage with the expectation that this will help future researchers.

INDEX TERMS Offline handwritten signature recognition, deep learning, traditional methods, biometric, review.

I. INTRODUCTION

As a form of biometric identification in daily life, handwritten signatures are extensively employed in some commercial papers [1]. It signifies that the signer accepts all of the contents of the signed document, is accountable for ensuring its legitimacy, and has some legal weight. Since handwritten signatures are unique and easy to gather, identifying the signature becomes a highly crucial undertaking to determine whether a signature belongs to the original signer. Systems are required to automate the process and raise the recognition rate because manual recognition is labor-intensive and prone to recognition errors.

Among these, handwritten signature images can be separated into genuine and forged signatures. Usually, fake signatures can be either randomly or expertly generated.

-Genuine: It is the real signature of the signer.

-Random forgery: It is a name that the forger has not practiced and has forged at random or one in which the forger merely knows the signer's name.

-Skilled forgery: A signature that has been faked by someone who not only knows who the original signer is but also knows the form of the true signature and may have practiced it several times previously.

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In this work, there are two different concepts: verification [2] and recognition [3]. The former addresses the dichotomous problem and focuses primarily on determining whether a specific signature is real or fake. Recognition, on the other hand, refers to the multi-classification problem and is generally used to identify the signer.

According to the different modes of signature sample picture acquisition, online and offline handwritten signature recognition technologies can be further divided. The image obtained through an online signature is a dynamic image that incorporates dynamic features including the ink pressure and writing speed throughout the signature-writing process, that he typically obtains from devices like electronic handwriting boards or touch screens. The offline signature acquisition procedure involves writing the signature on the paper beforehand, scanning it with other tools to turn it into a photo, and then further processing it on the computer. However, it does not get important dynamic information. Because the sample lacks dynamic information that can identify handwriting activity, researchers must meticulously capture quite well data such as a signature's line and writing manner [2]. Currently, offline signatures can only seek specificity among them based on static information for instance shape, outline, and position, and then classify them for recognition [4], [5], [6]. Therefore, the recognition of offline handwritten signatures is more challenging than that of online, and in the past few years, many researchers have worked on discovering and investigating new methods to advance the work of it.

Offline signature recognition can be broken down into two phases, according to the development process: traditional recognition approach [4], [5], [6], [7], [8] is used in the first stage, and the DL approach [3], [9], [10], [11] is used in the second. The physical characteristics of the signature itself are mostly used by conventional feature extraction techniques. Deep learning techniques, in contrast, can extract the best features from enormous databases. Researchers have developed numerous cutting-edge deep learning techniques recently for recognizing signatures, with generally encouraging outcomes. This is the central concept of the piece. We expect that by studying, debating, and contrasting both conventional approaches and deep learning methods, future scholars will have a more complete understanding of signature recognition.

The abbreviations covered in this thesis are shown in Table 1.

Our contributions to this review are:

-We provide an updated and systematic overview of offline handwritten signature recognition systems: history, present and upcoming challenges.

-We provide information on five publicly available datasets that are currently in widespread use.

-We review and summarize nearly 100 papers on the task of offline handwritten signature recognition from the years 2009 to 2023, carefully analyzing the job according to specific implementation processes, with a particular focus on deep learning-based approaches, which we believe may be considered state-of-the-art.

TABLE 1. Detailed list of abbreviations.

Abbreviations	Complete description
DL	Deep learning
ACC	Accuracy
HOG	Histogram of Oriented Gradients
PCA	Principal Component Analysis
SIFT	Scale Invariant Feature Transform
SURF	Speeded UP Robust Features
DWT	Discrete Wavelet Transform
DCT	Discrete Cosine Transform
DT	Decision Tree
BPNN	Back propagation neural network
RNN	Recurrent Neural Network
ANN	Artificial Neural Network

-We compare several network models based on network architecture analysis and compare the effectiveness of their improved models for this task, we also compared the concepts of various classification techniques and their corresponding frequency of use and ended up with promising results.

-We discuss some new directions and challenges for offline handwritten signature recognition, especially in data collection and feature fusion.

The rest of the paper is organized as follows: the second section presents the related work and motivation for signature recognition. Section III describes the methodology of the review. In the fourth section of this paper, the common public datasets for offline handwritten signature recognition are shown; the preprocessing methods often used in the signature recognition process are shown in the fifth section; the study of various feature extraction techniques is mentioned in detail in the sixth section; the classification and prediction methods used for recognition are represented in the seventh; the possible future directions of the field are proposed in the section eighth; the paper concludes with a conclusion of the whole paper.

II. RELATED WORK AND MOTIVATION

A. RELATED WORK

At present, image recognition has made extensive use of deep learning (DL). Many researchers are also attempting to use different DL methods for this work with excellent results.

Before this survey, many researchers have also summarized their work on offline signature recognition. The PRISMA flowchart in [12] shows that offline signatures are mostly recognized using a convolutional neural network, while online signatures are mostly recognized using recurrent neural networks and other architectures. Foroozandeh et al. in [11] evaluate the performance of DCNN using transfer learning in recognition and verification, and by comparing VGG16, VGG19, ResNet50, and InceptionV3, the superiority of VGG16 in signature recognition was demonstrated. In [13], The authors concentrate on various methods applied to work on signature identification and verification, but

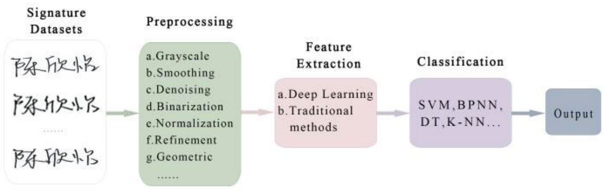

FIGURE 1. The general procedure of offline signature recognition is as follows. (A) Acquire a data set (or utilize a publicly available one). (B)Next, preprocess the image. (C)Extract features using a variety of approaches. (D)Use these features to train the model for classification output. (Example of Chinese signature in the figure: Chen Xinyi.)

there is no separate sub-module comparison for recognition or verification. The signature recognition feature extraction techniques mainly studied by Impedov et al. in [14] are thought through both global and local features and are not summarized to DL methods. Figure 1 depicts the overall workflow for offline signature recognition.

B. MOTIVATION

Since the writing dynamics stereotype [15] is based on temporary neural connections in the cerebral cortex associated with writing activities, it is both stable and variable. As an individual's age and life change, as the individual interacts with the social environment and as consciousness intervenes, the writing dynamics stereotype changes accordingly. Thereby, signature habits are not the same for every individual and there is the possibility of intraclass variation. As mentioned in Section II-A, the current research direction of the survey on signature recognition is not comprehensive, and our research aims to drive innovation in the field of signature recognition through a more comprehensive study to meet the growing demand and address the technological challenges in order to provide more secure, efficient, and reliable signature recognition solutions for the social and business sectors.

III. METHODOLOGY

This research aims to explore the methods used to implement and evaluate signature recognition systems. This research aims to evaluate the methods used through a specific and refined study of the general process of signature recognition and to propose future directions to improve the knowledge in this field. The focus of the study is to analyze how the use of traditional methods and deep learning in the literature have worked respectively, and what might be done in the future to advance research in this direction.

We used the search terms "offline signature recognition" and the semantically similar "signature identification". The four major databases we used in our research were ScienceDirect, Web of Science, Institute of Electrical and Electronics Engineers (IEEE) Xplore, and SpringerLink to organize the broader literature. We compiled a total of 104 papers from 2009 to 2023 after removing duplicates based on search terms. Papers will be excluded in the following cases:

TABLE 2. Common datasets.

Datasets	Language	Individuals	Information
GPDS synthetic [16]	Latin	4000	24 G; 30 F
CEDAR[17]	Latin	55	24 G; 24 F
MCYT-75[18]	Latin	75	15 G; 15 F
BHSig260 Hindi[19]	Devanagari	160	24 G; 30 F
BHSig260 Bengali[19]	Bengali	100	24 G; 30 F
UTSig[20]	Persian	115	27 G;42 F

1. The same literature with co-authors, we consider the latest one.
2. Work on signature verification will be excluded.
3. Work on online signature recognition will be excluded.
4. Papers published before 2009 (Only the experimental flow part of the study, i.e., feature extraction and classification).
5. Evaluating the metrics is not the accuracy of those papers.

IV. DATASETS

Currently, foreign languages make up the majority of the frequently used public datasets for this work. In this paper, we list several widely used public datasets and their attributes, as shown in Table 2.

The table's first column lists the titles of several publicly available datasets, the second lists the languages of the samples within every dataset, the third lists the number of distinct signers in each dataset, and the final line displays "G" for genuine and "F" for fake. Datasets for Chinese or other racial or ethnic minorities are scarce.

It's crucial to highlight that each dataset only has a single language. As a result, the developed system may perform exceptionally well on one dataset while producing only marginally better results on another. This represents one of the upcoming difficulties in recognition work. The usefulness of the new research approach will be somewhat constrained because there is still a significant amount of variation in how people perceive the overall writing of signature samples between languages.

In addition to the larger public datasets mentioned above, researchers take the approach of creating their datasets to fit their respective experiments as well as their purposes. For example, in [21], Keykhosravi et al. created the DANASIG Persian dataset, which contains more than six thousand signature samples from eleven left-handers and seventy-four right-handers.

A lot of local researchers have also suggested using self-built datasets for their investigations, which include samples of signature images in other minority languages in addition to Chinese. This is one of the trustworthy pillars for the direction of offline handwritten signature recognition going forward.

V. PREPROCESSING

Without expert preprocessing, there may likely be significant disparities in the experimental results when the samples from the dataset are fed directly into the network for training. These discrepancies will be caused by certain irrelevant elements in the samples. To acquire a higher recognition rate, preprocessing [22] can effectively reduce some uncontrollable noise, edge backdrop, and other influencing elements in the datasets.

The following are some frequently used preprocessing techniques:

-Grayscale: Conversion of color images to grayscale images.

-Smoothing and Denoising: Mainly to remove spurious points and noise.

-Binarization: A binary image is one in which there are only two gray levels, that is, any pixel point in the image has a gray value of 0 or 255, representing black and white, respectively.

-Normalization: mainly refers to size normalization.

-Refinement: it refers to removing the points on the edge of the side shadow layer by layer of the already binarized text while preserving the skeleton graphic of the original text.

-Geometric Transformations: flip, rotate, invert, and center crop an image (translation, transposition, mirroring, rotation, scaling), etc.

It is worthwhile to know that since a handwritten signature has a specific orientation if it is sufficiently flipped, its characteristics alter and it ceases to be a signature. Therefore, in truth, the flip operation is often not performed on the sample.

VI. FEATURE EXTRACTION TECHNIQUE RESEARCH

Feature extraction is a stage immediately after preprocessing. The preprocessed images are primarily used to extract characteristics that can tell one signature from another. The following provides a detailed discussion of recent approaches to feature extraction for signature recognition using DL and conventional techniques.

A. DEEP LEARNING

CNNs are feedforward neural networks with depth structure and convolutional computation. It is one of the deep learning algorithms that serve as a model. CNN is just an input-to-output mapping. Without a specific mathematical phrase connecting the input and the output, it can learn a vast variety of mapping relations. The convolutional network will have the ability to map between input and output pairs as long as it has been trained with recognized patterns. Following the great success of deep learning, several researchers have started to concentrate on signature recognition models using CNNs. The existing signature recognition models are simple in structure, effective, and have wide application prospects.

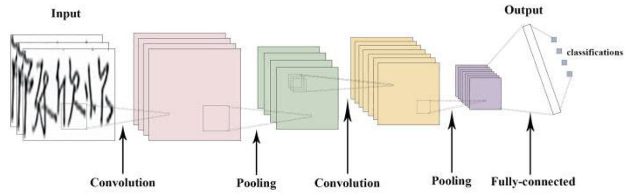

FIGURE 2. The basic CNN structure is used for signature recognition. (Example of Chinese signature in the figure: Chen Xinyi.)

In recent years, researchers have continued to combine CNNs and their various variants with offline handwritten signature recognition work and have obtained promising results. Figure 2 depicts a flowchart of offline handwritten signature recognition using basic CNN.

Existing network structures and improved architectures are gradually being used more and more in pattern recognition work because deep learning has a potent learning capability. Below is a brief description of a few well-known network models.

1) RESNET [23]

For its simplicity and viability, Residual Network was first proposed by Kaiming He et al. in 2015 and took first place in the classification task of the ImageNet competition. Since then, many methods have been developed based on it, and it is now widely used in the fields of segmentation, recognition, and other related technologies.

ResNet is advancing along with the times in a constant state of development. There are numerous ResNet18, ResNet34, ResNet50, and other variations that are currently in use.

Jampour et al. proposed an innovative and effective architecture that combines CapsNet (discussed in the next point) and ResNet18 to gain the benefits of both architectures [10]. While CapsNet enables a strong understanding of the components of the object and their locations, ResNet18 offers efficient feature extraction. ResNet18 [23] consists of eight main components: a 7*7 conv, a pooling layer, four 3*3 conv, an average pooling layer, and a linear layer. Given that the residual blocks inside the residual network use jump connections, mitigating the issue of gradient disappearance due to increasing depth, and being able to improve accuracy by increasing depth, the authors of the article use this technique to solve the problem that the capsule network does not represent complex features well for classification.

2) CAPSNET [24]

Hinton made the CapsNet proposal in [24] in October 2017. The main benefit of CapsNet is that it addresses the issue that CNN can only extract features and not information about the relationships between the features' relative sizes, positions, and other relationships. With only two conv layers and one FC layer, CapsNet is a very light network. As previously mentioned, [10] proposed the simultaneous use of ResNet18 and CapsNet. Although CapsNet can maintain the spatial location information of the signature part (black pixels) using capsules, it is only appropriate for representing shallow structures. Therefore, the authors combined CapsNet with ResNet18 and achieved good performance on several datasets.

3) ALEXNET [25]

Alex Krizhevsky's AlexNet was put forth in 2012 and won the ImageNet competition with the highest scores. AlexNet's main contributions are: first, it uses dropout to randomly ignore some neurons during training, thus effectively reducing the problem of overfitting; second, to avoid the ambiguity of average pooling, AlexNet uses max-pooling. To increase feature richness, it also allows the step size to be shorter than the kernel size. There are eight layers of transformations in AlexNet.

The authors of [26] extracted features from AlexNet's FC layer and stored them in a feature vector with a size of 4096. Finally, two classifiers—SVM and RT—were employed to predict classification.

4) VGG NET [27]

At the 2014 ILSVRC competition, Karen Simonyan and Andrew Zisserman's VGG Net came in second place for the classification task. The primary contribution of VGG is its deeper network structure, which uses smaller convolutional kernels and pooled sampling to gain more features while limiting the number of parameters, avoiding excessive computational effort and overly complex structures.

The authors in [11] used a variety of pre-trained models for experimental comparison on four datasets, confirming the efficiency of the VGG16 and SigNet models for signature verification as well as the excellence of the VGG16 in tasks requiring signature identification. Although VGG has helped CNN networks get deeper, it has its drawbacks, including a slow training speed and the tendency for training effects to fade, gradients to disappear, or gradients to explode, as networks get deeper.

5) GOOGLENET [28]

At the 2014 ILSVRC competition, Christian Szegedy's GoogLeNet project was awarded first place in the classification category. By constructing a "base neuron" structure, GoogleNet was initially intended to build a sparse, high computational performance network structure. GoogLeNet has three outputs, two of which are auxiliary classifiers, in contrast to AlexNet and VGG, which each has just one. First, the network finally switches to average pooling, which can reduce the use of parameters. Second, GoogLeNet adopts a modular structure and introduces Inception, which is simple to add and modify and improves parameter utilization. Finally, GoogLeNet uses parallelism to deepen and amplify the model structure.

The authors in [29] chose GoogLeNet as a pre-trained model because of its improved network width and a minimal number of parameters. The gradient disappearing issue can also be solved using the auxiliary classifier. The network model's structure is shown in Figure 3.

This paper gives recognition work in recent years using CNN as the base structure for feature extraction as shown in Table 3.

It is specifically noted that the experiments described in [3] were derived for ACC with training set-test set=25-75. Joshi et al. in [26] investigated the performance of signature recognition using AlexNet-based features, all studies have been investigated using the signatures of 14 people from the dataset, and DT and SVM were both used to predict classification.

Attention Mechanism is also the focus of recent research. It focuses attention on the most interesting regions in the image in a focused manner. the SE [30] consists of two key operations, squeeze and excitation, which focus on the channel level. Different from it, there is a CBAM [31] mechanism, which combines spatial (spatial) and channel (channel) modules of the attention mechanism and can achieve better results compared to SE-NET. The authors in [32] mentioned the integration of SE into Resnet networks and achieved good results.

The extraction of image features is the major hurdle in image recognition. Deep learning uses features that are automatically learned from big data, which is the biggest difference between it and traditional pattern recognition methods (described in the following subsections). Additionally, for specific tasks, like offline handwritten signature recognition, researchers can design different neural network structures for learning (as shown in Table 3). DL excels at selecting global features and contextual information from samples in work involving signature recognition due to its powerful learning capability and effective feature representation.

B. TRADITIONAL METHODS

In contrast to deep learning, this section will introduce feature extraction of signature images using traditional methods. Global and local features can be approximately distinguished from one another. Whereas local methods divide the image into several sections and then effectively gain data from them, global features are utilized to extract the entirety of the image. As indicated in Table 4. The first four in the Table belong to global features, the middle ten belong to local features, and the last one takes both into account.

In particular, it is explained that the ways used in the excellent ACC obtained in [5] on datasets cover four techniques, while ablation experiments (randomizing three of them) were also performed in this experiment, and the results were not as favorable as those obtained using all four techniques, while the classifier used for this result is BLSTM, which gives better results compared to LSTM obtained better results. In [33],in addition to using SIFT to extract features, Global Features and Grid Features were also used and if all three are taken together, an accuracy of 88.97% is achieved, which is much more effective than using only SIFT.

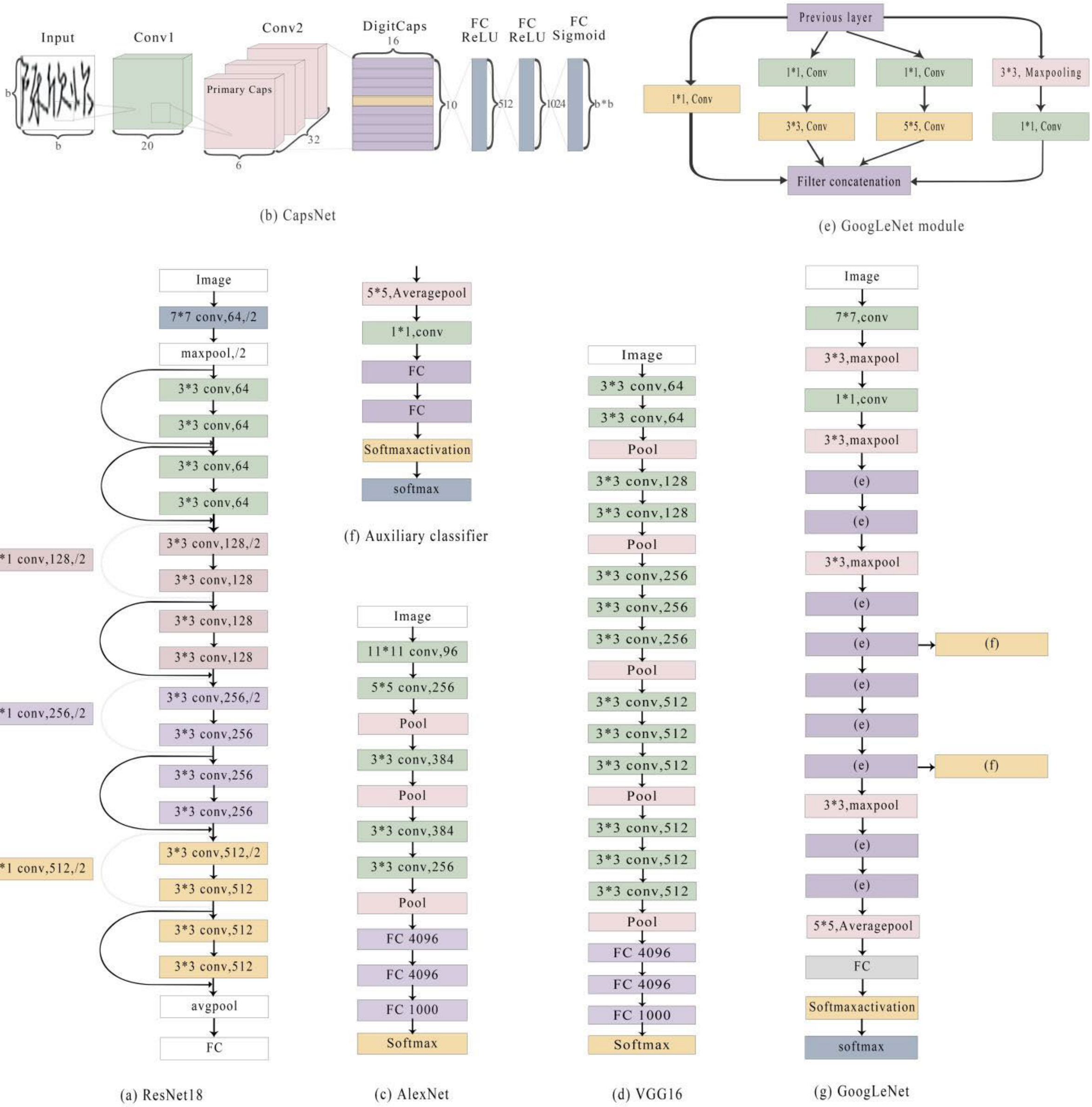

FIGURE 3. **Network model structure diagram. ((a) is Resnet18: 7∗7 conv, pooling layers, four 3∗3 conv, average pooling layers, and linear layers; (b) is CapsNet: 2 conv layers and 1 FC layer; (c) is AlexNet: 5 conv layers, 3 pooling layers, and 3 FC layers; (d) is VGG16: 13 conv layers, 5 pooling layers, and 3 FC layers; (g) is GoogLeNet: there are 3 outputs, 2 of which are auxiliary classifiers).**

In addition to this, additionally frequently used in offline signature recognition work are geometric features. For instance, the features in [57] that were used for feature extraction were kurtosis, skewness, etc. Chauhan et al. in [58] analyzed the regional characteristics of digitized feature images using eccentricity, convex area, standard deviation, entropy, and orientation. Kaur and Kumar both in [59] focused on describing the recognition technique of Gurumukhi using partitioned, diagonal, intersections, and open endpoints four methods to extract features from the sample image and optimized using AdaBoost algorithm and finally obtained 88.78% recognition accuracy.

Researchers are steadily attempting to apply deep learning to extract features from signature photos, as can be shown in Tables 3 and 4, and have had promising results. While classic methods of extracting features from global and local data are still extensively utilized, with HOG performing particularly well, CNN has a significant capacity for learning.

The current work on signature recognition is also evolving, and due to the extensive use of deep learning, researchers have progressively started experimenting with various methods to do this job. While traditional feature extraction methods also have better results, CNN-based methods have stronger learning capabilities and can better adapt to the

TABLE 3. Feature extraction ways for CNN.

Paper ID	Year	Feature extraction	Datasets	ACC (%)
[34]	2022	CNN-GC CNN-HDR SCN	CEDAR	98.03 85.38 97.82
[35]	2022	OHS-Net	multi-lingual	99.20 (Top-1)
[10]	2021	CapsNet+ResNet18（RCR）	CEDAR MCYT UTSig	100 99.66 99.38
[36]	2019	CapsNet	CEDAR	98.8
[9]	2020	CapsNet	CEDAR GPDS-100 MCYT	97 94 95
[29]	2021	GoogLeNet	Bengali Hindi GPDS-300 MCYT	94.95 92.76 99.31 98.6
[37]	2020	Crest-Trough Algorithm	1320 pics	90-94
[38]	2019	Signet and Signet-f	CEDAR Bengali Hindi	92 94 86
[3]	2019	LS2Net LS2Net_v2	CEDAR MCYT GPDS	98.30 96.41 96.91
[26]	2021	AlexNet	UTSig Bengali Hindi	96.2 100 99.1
[21]	2022	DCNN	UTSig ICDAR MCYT	98.94 87.57 98.90 90
[39]	2020	CNN	4 datasets	99 (best)
[40]	2018	CNN	Chinese Dutch UTsig	85.11 100 96.29
[41]	2017	CNN (Improved ESA)	Self-built Turkish	91.2 (best)
[42]	2020	Siamese neural network	Self-built	84
[11]	2020	VGG16	GPDS Synthetic (100) MCYT UTSig FUM-PHSD	99.79 100 98.71 100
[43]	2022	VGG16 VGG19	particular dataset	95.31(NN) 91(KNN) 93(NN) 91.96(KNN)

variability between signature samples themselves. Investigators are also proposing and experimenting with higher robustness methods.

VII. OVERVIEW OF CLASSIFICATION TECHNIQUES

This paper gives the notion and comparison of classification techniques used in recent years in offline handwritten signature recognition tasks, as shown in Table 5.

A character recognition way based on DCGAN was first proposed by Li et al. in [101]. The method's efficacy was demonstrated through a series of tests, and it makes use of traditional convolutional networks for feature extraction and improved GoogLeNet for recognition. By contrasting five classifier models with an accuracy of 92.88%, the authors of [102] were able to conclusively demonstrate the superiority of neural networks.

It is also noteworthy that Ghosh in [5] used four methods for feature extraction, and then used RNN for classification, and obtained superior results of 96.08%-99.94% on six public datasets; Angadi et al. in [7] based on Radon transform for

TABLE 4. Feature extraction for traditional ways.

Class	Name	Key concept	Advantages and Disadvantages	Paper ID	Datasets	ACC (%)
Global features	Profile projection (PP)	By counting the sample's background pixels up until the first pixel is seen, the image edges are represented by vectors.	**A:** Simple calculation, intuitive representation. **Dis:** Higher feature dimensions, higher computational effort, not applicable to the case where the image is occluded.	[44]	Self-built (12*20a)	79
	Loci features	The background pixels of the entire image is scanned, and the number of transitions in each background pixel in each of the four directions is calculated.		[44]	Self-built (12*20a)	93
	PCA	minimize information loss while reducing the feature dimension		[8]	CEDAR	97.99
				[45]	Self-built	
Local features	HOG	Any shape in an image can be easily recognized as long as the edge orientation is known, even if its precise placements are unknown.	**A:** The correlation between features is small and the detection of other features is not affected by the disappearance of some features in the case of occlusion. **Dis:** Significant change in viewpoint, may not provide enough information, computationally burdensome, limited contextual information.	[44]	Self-built (12*20)	96
				[46]	Self-built (20*12)	96.875
				[47]	SigWiComp2009	99.27
				[48]	Self-built	98.4
				[49]	Devanagari	97.06
				[50]	MCYT, DB	98.30
				[4]	Self-built (15*40)	98.33
	Change of trajectory direction	The signature block's change in orientation within each section of the divided octet image is calculated.		[5]	GPDS	96.08
	Trajectory slope	The signature block's change in the slope within each section of the divided octet image is calculated.		[5]	GPDS	98.02
	Trajectory waviness	Each piece's signature's Euclidean distance is calculated by dividing its longest edge by its Euclidean distance.		[5]	MCYT-75	99.39
	Centre-of-mass	the location of the center of mass for all the black pixels in a given area.		[5]	CEDAR Hindi Bengali	99.94 99.28 99.37
	SIFT	Locate the critical points in various scales of space and determine the direction.		[33]	Self-built (30*145)	57.93
	SURF	The use of harr features and the concept of integral images greatly speed up the running time of the program and build on top of SIFT.		[6]	Self-built	96.87
	DWT	The signal's characteristics or other acceptable criteria are typically used to determine the right number of decomposition layers.		[45]	Self-built	
				[51]	Self-built	90-100
				[52]	GPDS960 Self-built (20*15)	92.06 92.20
	DCT	It is equivalent to performing a DFT on a real even function that is roughly twice its length.		[53]	Uyghur (100*20) English (50*20)	99.5 97.5
	Curvelet Transform (CT)	High-dimensional wavelet transforms for describing images at different scales and different angles.		[8]	GPDS	94.96
				[54] (DCT)	Self-built	97.95
				[55]	GPDS-300 CEDAR MCYT	98.31 98.06 99.89
	Grid features	The area of each of the numerous rectangular segments that make up the signature image is calculated. Then		[56]	Self-built (50*20)	93.53

TABLE 4. ***(Continued.)*** **Feature extraction for traditional ways.**

Class	Name	Key concept	Advantages and Disadvantages	Paper ID	Datasets	ACC (%)
		normalize the process and take 1 for the highest number of black pixels and 0 for the opposite.				
Both	Radon Transform	Obtain along both axes the standard deviation and average of global and local features like height, width, and center of mass.	NA	[7]	Self-built	87-97

a The meaning of x*y is: x is the number of signers, and the number of signatures per signer is y.

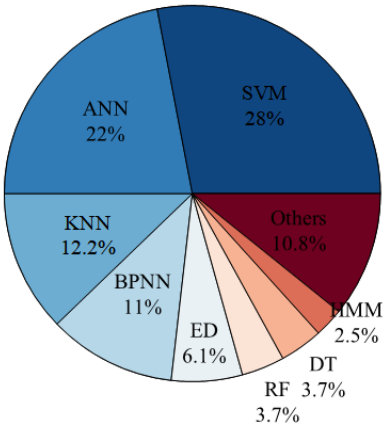

FIGURE 4. **Distribution of multiple classification techniques. ("Others" indicates that all nine remaining classification techniques were used once, with a probability of 1.2% each).**

projection feature extraction and using BPNN for classification work and finally obtained 87-97% accuracy.

Table 5 and Figure 4 indicate that SVM, KNN, BPNN, and ANN have been employed frequently recently in offline signature recognition tasks, which is evidence of their adoption by academics. Furthermore, a large number of scholars are continually attempting to suggest novel classifiers for use in their recognition tasks, which generates fresh concepts for future study.

Accurate identification of the author's identity information is necessary for signature identification like a multi-classification issue, and in real applications, an institution typically has many registrants, which places extremely high demands on the recognition system. Additionally, an institution cannot have a large enough training data set to guarantee the necessary accuracy for the subsequent classification process.

VIII. FUTURE WORKS

As the difficulty in extracting features from the samples' wide white backgrounds and sparse valid features, offline signature detection is tough. In this section, we present possible directions for future work on signature recognition, as well as possibilities for realization.

A. ACQUISITION OF DATASETS

-Diversification of sample types: The samples in the public datasets that are currently in common use are derived from scans, such as CEDAR, whereas in real-life applications the most direct way to obtain samples is to take a picture of the signature using a device such as a mobile phone, which is something that needs to be considered during the dataset acquisition process.

-Multilingualism of the sample: The currently accessible public datasets are primarily monolingual. This makes it difficult to create a powerful recognition system. It has been noted that researchers typically create a system before running experiments on various datasets to obtain various results, sometimes using self-built datasets and sometimes using publicly available datasets. There is a dearth of research on multilingual offline handwritten signatures [48], and the technique still has great potential for future development. It is urgent to investigate an offline handwritten signature recognition system with higher robustness for multilingual datasets, particularly containing some minor language texts.

-Difficulties: Similarities between different user samples. The scripts of some of the ethnic minorities (Uyghur, Kazakh, and Kirgiz) in the Xinjiang region of China share many similarities with the scripts of many Central Asian countries, which is also a great challenge for a multilingual dataset.

B. INTERNAL FACTOR

Although the current pre-processing of signature samples will include size normalization, the ratio of black pixels to white backgrounds represented by the signature itself is still very different within the same size (sparsity of effective features). The kernel of the attention mechanism is to concentrate on the most important regions of the picture, then, how to add the attention mechanism to the recognition task and get better results still needs to be further compared and explored by the researchers.

C. SELF-SUPERVISED LEARNING

The present deep learning used in signature recognition is supervised learning, and the addition of self-supervised learning to the signature verification work proposed in [2] is also a relatively great inspiration for further research on signature

TABLE 5. Classification techniques for signature recognition.

Classifier	Key concept		Advantages and Disadvantages	Paper ID
Regularized Gradient Boosting Tree	A new model is constructed in the negative of the gradient of residual reduction after each calculation is completed to reduce the residuals from the previous one.		NA	[38]
C3	Class centers using feature embeddings obtained from the FC layer, dependent on 1-NN classification tasks.		NA	[3]
SVM [60]	Creating a wire that "prime" classifies the points is the goal of an SVM to ensure that the classification remains accurate even if additional points are added later.		**A:** Excellent in high dimensional spaces, dealing with small sample datasets, nonlinear problems. **Dis:** High computational overhead, Sensitive to large number of features, not suitable for large-scale datasets.	[11],[21],[26],[29],[50],[33],[6],[54],[59],[61],[62],[63],[64],[65],[66],[67],[68],[69],[70],[71],[72],[73],[74]
DT	It represents the process of classifying instances according to features in the classification issue. Each leaf node of the tree corresponds to the value of the object represented by the path taken from the root node to that leaf node, while each fork represents the possible values and each node of the tree represents a specific object.		**A:** Strong interpretability, suitable for classification and regression, can effectively deal with mixed types of features, without the need for complex data preprocessing. **Dis:** Prone to overfitting, sensitive to noise and small changes, generated trees may be unstable, sometimes fail to capture complex relationships, not suitable for continuous outputs.	[26], [43], [72]
BPNN	It consists of two main processes: forward information propagation and error backpropagation.		**A:** Wide applicability, Weights and biases can be adjusted automatically and can be used directly for multi-class classification problems without additional modifications.	[21],[46],[7],[75],[76],[77],[78],[79],[80]
RNN	LSTM	A forward hidden layer.	**A:** Can handle variable length sequential inputs, can remember and utilize previous information, recursive structure.	[5]
	BLSTM	For handling the input sequence both forward and backward, there are two hidden layers.		
ANN	Simulating neuronal activity with mathematical models is an information processing system based on mimicking the structure and function of neural networks in the brain.		**Dis:** Requires large-scale data for training, is prone to overfitting, has high computational resource requirements, and may require additional processing for datasets with unbalanced categories.	[39],[43],[49],[4],[45],[57],[58],[81],[82],[83],[84],[85],[86],[87],[88]
	BPANN	BPANN uses multiple input layers (usually 3 layers) and each layer must be one of the following two layers: input layer; hidden layer.		[89],[90],[91]
One Class Classifier (OCC)	Lower computational costs, such as OAO and OAA.		NA	[8]
	OC-PCA	Can absorb high-size feature vectors generated by Curvelet Transform and generate a well-represented model for each signer.		
Efficient fuzzy Kohonen clustering networks (EFKCN)	The topological structure is formed by individual neurons forming a whole in different excitation states, and the formation of this topological mapping structure has a self-woven character.		NA	[92]
K-NN	The k nearest neighbor is determined by calculating the minimum length between the candidate and the storage vector, and indeed the majority is used as the prediction.		**A:** No training required, directly used for multi-class classification problems, suitable for small datasets, applicable to a variety of data types and distributions.	[22],[43],[48],[56],[59],[67],[70],[72],[93],[94],[95]
Random Forest (RF)	Consists of many decision trees. Which type of tree receives the greatest number of votes determines the model's prediction.		**A:** High accuracy, relatively good robustness to outliers and noisy data, suitable for high dimensional data, not easy to overfitting, can be trained in parallel, suitable for unbalanced data.	[43],[48],[59]

TABLE 5. ***(Continued.)*** **Classification techniques for signature recognition.**

Classifier	Key concept	Advantages and Disadvantages	Paper ID
XGBoost	The fundamental concept is the same as GBDT, but optimizations have been added, such as second-order derivatives to improve the accuracy of the loss function, regular terms to prevent overfitting of the trees, block storage for parallel computation, etc.	NA	[96]
Fuzzy Min Max Classification	Has three layers: an output layer, a hiding layer, and an output layer.	NA	[44]
Euclidean Distance	The actual separation between 2 locations in m-dimensional space, is measured in terms of the vector's true size.	**A:** Simple and intuitive, widely used, usually performs well with linear data, easy to calculate.	[51],[56],[63],[97],[98]
Probabilistic Neural Network (PNN)	There are generally four layers. Easy learning procedure and quick training speed; more precise classification and good error tolerance.	NA	[52]
Hidden Markov Model (HMM)	A Markov process with implicitly unknown parameters is described by a statistical model. Finding the implied parameters of the process from the observable parameters and using them for further analysis is difficult.	NA	[53],[99]
Conic Section Function Neural Network (CSFNN)	It combines the benefits of both RBF and MLP networks into a single framework. The CSFNN circuit structure is independent and is implemented using mixed-mode circuits.	NA	[100]

recognition in the future. Self-supervised learning is a specific type of unsupervised learning that involves using labels found in the data itself to do supervised learning. This method gets over the issue that supervised learning faces when it comes to annotating vast volumes of real-world data. For training, supervised learning often needs a lot of data, and labeling takes a long time.

Generative learning [2] and contrastive learning [103] are the two broad categories that self-supervised learning falls under. In the first case, it involves training a self-encoder to encode the input x into a vector z through the encoder and then input to the decoder for reconstructing x. It performs better when the dataset is partially masked, like with random mask masking in face recognition. It might be able to successfully recognize partial signature samples when used for the recognition of signatures. Finding positive and negative examples [104] is the challenging part of contrastive learning, which involves the search for the minimum distance between x and positive samples and the maximum distance between x and negative samples.

D. FEATURE FUSION

Feature extraction is divided into deep learning and traditional methods, and classification is roughly divided into traditional machine learning (SVM, RF, HOG, etc.) and deep learning (ANN, RNN, BPNN, etc.), each with its characteristics. Finding new techniques for signature recognition from various angles will continue to be a challenge in the future. For instance, one approach could be to feed features extracted using conventional methods into deep learning models or combine features extracted through traditional methods and deep learning techniques, followed by an effective classification of the results. This would enable researchers to better understand and improve the accuracy of signature recognition systems, thus advancing the field further.

IX. CONCLUSION

This study analyzes the growth of offline signature recognition at home and abroad over the course of the last 15 years, taking into account both conventional techniques that aim for greater expression features in the signature samples and the still-commonly employed HOG and CT. While deep learning-based methods concentrate on reconstructing CNNs, researchers are gradually using more novel and effective network models for signature recognition tasks. These models range from simple modifications to CNNs to utilizing networks like LS2Net, CapsNet, VGG, GoogLeNet, and AlexNet alone to the combination of CapsNet+ResNet18 (RCR). There is still more work to be done in the field of signature recognition since current techniques still fall short of society's needs in the actual world.

The focus of future work will continue to be on mixing deep learning with traditional learning to obtain more robust recognition, even if many other researchers have attempted to fuse conventional feature extraction techniques with deep learning.

This paper identifies several novel research issues that call for ongoing research efforts from academics to enhance the functionality of offline handwritten signature recognition systems.However, there are still shortcomings, such as the lack of a careful analysis of each traditional method for performing feature extraction and the lack of a comparison of related papers using the same classification method. This work, from our perspective, can be a useful resource for academics interested in learning more about current offline signature recognition methods.

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