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A Survey of Offline Handwriting Signature Verification

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Keywords: Offline Handwritten Signature, Traditional Methods, Machine Learning, Deep Learning.

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Abstract:

Each individual possesses a unique signature that is primarily employed to verify personal identity and authenticate legally binding documents or facilitate significant transactions, a method commonly utilized for verifying their identity. The utilization of this technology is restricted to the authentication of biometric recognition in a range of financial, legal, banking, insurance, and various other business documents. Techniques for recognizing signatures are employed to determine the specific user associated with a particular signature. In recent years, a significant number of researchers have focused on the implementation of novel approaches in this area, with a notable increase in the prevalence of deep learning techniques. To enhance the understanding of the evolution of offline handwritten signature recognition among researchers, this manuscript adopts a structured methodology to categorize this research, drawing primarily from studies found in set major databases. This study assesses methodologies for offline handwritten signature recognition by implementing predetermined inclusion and exclusion criteria. It explores various aspects, such as feature extraction and challenges in classification. In recent years, there have been noticeable advances and new developments. The paper accentuates the dominance of deep learning research directions in this specific domain. Differing from existing surveys, this paper does not confine itself to a particular research phase but meticulously outlines each stage, aspiring to guide future researchers in their investigations.

Keywords: Offline Handwritten Signature, Traditional Methods, Machine Learning, Deep Learning.

مسح استقصائي للتحقق من التوقيع بخط اليد دون الاتصال بالإنترنت

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الخلاصة:

يمتلك كل فرد توقيعًا فريدًا يستخدم في المقام الأول للتحقق من الهوية الشخصية وتوثيق المستندات الملزمة قانونًا أو تسهيل المعاملات المهمة، وهي طريقة شائعة الاستخدام للتحقق من هويتهم، ويتم استخدام هذه التقنية على التحقق من الهوية البيومترية في مجموعة من الأعمال المالية والقانونية والمصرفية والتأمينية ومختلف الأعمال الأخرى. يتم استخدام تقنيات التعرف على التوقيعات لتحديد المستخدم المحدد المرتبط بتوقيع معين. شهدت السنوات الأخيرة تركيز عدد كبير من الباحثين على تطبيق مناهج جديدة في هذا المجال، مع زيادة ملحوظة في انتشار تقنيات التعلم العميق. لتعزيز فهم تطور التعرف على التوقيعات المكتوبة بخط اليد دون الاتصال بالإنترنت بين الباحثين، تتبنى هذه المخطوطة منهجية منظمة لتصنيف هذا البحث، مستمدة في المقام الأول من الدراسات الموجودة في مجموعة قواعد البيانات الرئيسية. تقوم هذه الدراسة بتقييم منهجيات التعرف على التوقيع المكتوب بخط اليد دون الاتصال بالإنترنت من خلال تطبيق معايير التضمين والاستبعاد المحددة مسبقًا. ويستكشف جوانب مختلفة مثل استخراج الميزات والتحديات في التصنيف. وفي السنوات الأخيرة، كانت هناك تطورات ملحوظة وتطورات جديدة. تبرز الورقة هيمنة اتجاهات بحث التعلم العميق في هذا المجال المحدد. تختلف هذه الورقة عن الدراسات الاستقصائية الحالية، ولا تقتصر على مرحلة بحثية معينة، ولكنها تحدد بدقة كل مرحلة، وتطمح إلى توجيه الباحثين المستقبليين في تحقيقاتهم.

الكلمات المفتاحية: التوقيع المكتوب بخط اليد دون اتصال، الطرق التقليدية، تعلم الالة، التعلم العميق.

1- Introduction

Handwritten signatures are widely utilized as a form of biometric identification in various commercial documents for daily activities [1]. The offline signature is a distinctive handwritten representation of a person's name, or a mark utilized as proof of identity on various legal documents, including bank cheques, loans, and properties. It serves as a biometric measure, capturing detailed information about an individual's body, such as eye color patterns and handwriting recognition. Verifying an offline signature is a critical process traditionally conducted by analyzing the fluency of the signature pattern or visually comparing it with previously collected samples. However, manually verifying a large number of documents is time-consuming and relies on human vigilance, experience, and expertise to detect potential signature forgeries. The verification process for offline signatures can be executed online or offline based on the image acquisition technique. The online method, known as dynamic signature verification, involves capturing signatures using devices like tablets or pressure-sensitive pens, while the offline method, referred to as static signature verification, involves scanning the signature to convert it into a digital image [2]. At present, offline signatures are limited to distinguishing themselves by utilizing static characteristics such as shape, outline, and position, followed by their classification for recognition [3],[4]. Hence, the authentication of pen-on-paper handwritten signatures poses greater difficulty compared to digital signatures, and a multitude of scholars have recently devoted their efforts to exploring novel approaches to enhance this field [5]. Offline signature recognition can be partitioned into two distinct stages, in alignment with the progression of the development process: the conventional approach to recognition [3],[4] is used in the first stage . and the deep learning methodology [6], is employed in the subsequent context. The physical attributes of the signature itself are primarily utilized in traditional feature extraction methodologies. In contrast, deep learning methodologies can derive optimal features from vast datasets. In recent times, an array of advanced deep learning methods has been developed by scholars to facilitate the recognition of signatures, leading to predominantly favorable outcomes. This serves as the fundamental premise of the discourse. It is anticipated that through the examination, discussion, and comparison of both traditional methodologies and deep learning techniques, upcoming scholars will attain a more comprehensive comprehension of signature recognition [5]. The main purpose of this research is to review and classify different techniques used to organize and improve the quality of offline signature images, which helps in better verifying signatures, Additionally, the study seeks to provide a comprehensive overview of the datasets, preprocessing techniques, feature extraction methods, and machine learning models used in offline signature verification systems.

Table1: A list of the most important abbreviations

Abbreviations	description	Abbreviations	description
ANN	Artificial Neural Network	GLCM	Gray-Level Co-occurrence Matrix
ACC	Accuracy	HOG	Histogram of Oriented Gradients
CNNs	Convolutional Neural Networks	PCA	Principal Component Analysis
DL	Deep Learning	ResNet	Residual Network
DWT	Discrete Wavelet Transform	SIFT	Scale-Invariant Feature Transform
DAG-CNN	Directed Acyclic Graph-CNN	SURF	Speeded Up Robust Features
FFT	Fast Fourier Transform	SVM	Support Vector Machine
FHDNN	Fully Homomorphic Deep Neural Network	VGG	Visual Geometry Group

2- Datasets

Table 2 shows the most important and common data sets chosen because they are publicly available and can be easily downloaded from websites, either for free or with some payment, making them convenient for researchers to use.

Table 2: Description of publicly available datasets [2],[5],[7]

Dataset	Script	W	S	GS	FS
GPDS	Western	4000	216000	96000	120000
CEDAR [8]	Western	55	2624	1320	1320
UTSig [9]	persian	115	8280	3105	3175
BHSig260 [10]	Bengali Hindi	260	14040	6240	2280
MCYT-75	western	75	2250	1125	1125
SigComp2011	Dutch	10	3620	2390	1230
PHBC	persian	100	1200	1000	200

]W: Writers S: Signature samples GS: Genuine Signature FS: Forged Signature]

3- Literature Review

Currently, the field of image recognition has widely employed deep learning [DL] techniques. Various scholars are also exploring diverse DL approaches in this domain, yielding notable outcomes. Before conducting this survey, numerous researchers had additionally consolidated their findings on offline signature recognition. **[Hashim et al, 2024]** An offline signature verification model was created with 100% accuracy through the utilization of FHDNN. Principal Component Analysis [PCA], and Gray-Level Co-occurrence Matrix [GLCM], the Fast Fourier Transform algorithm are widely used methods in signal processing, and data analysis [FFT] features were employed to construct a hybrid feature vector depending on the SigComp2011 dataset, and the CEDAR dataset **[11]. [Suttedy et al, 2024]** The study examines writer identification in offline handwriting by employing a Siamese network with the Xception framework, resulting in impressive accuracy rates of 99.81% for IAM and 99.88% for CVL datasets **[12]**. **]Ibrahim et al, 2023]** The scholarly article centers on Offline Kurdish Character Handwritten Recognition [OKCHR] through the application of Convolutional Neural Networks [CNN] alongside a range of preprocessing methodologies aimed at improving recognition precision. The paper underscores the significance of preprocessing procedures in attaining elevated levels of accuracy in character identification assignments achieving high accuracy rates of 99.2% for training, 97% for testing, and 97.2% for validation after 35 iterations **[13]**. **[Al-banhawy et al, 2023**] The paper introduces a [CNN] model that has been developed specifically for conducting offline signature verification, demonstrating a significant degree of accuracy. A thorough examination was undertaken on three separate CNN models, yielding a notable accuracy percentage of 94.73 upon evaluation using the CEDAR dataset. The main emphasis of this research is centered on the procedures involved in feature extraction and classification as they relate to authentic and fraudulent signatures. [**Mitchel et al, 2023]** Offline verification of signatures through the utilization of transfer learning and data augmentation techniques on an imbalanced dataset. The study tested four different methods and found that using a pre-trained VGG16 model with enhanced data gave the best results, making it easier to tell real signatures from fake ones **[14]**. **[chang et al, 2023]** We crafted a signature recognition model with notable precision by leveraging modest sample sizes. Employed pen pressure and brush stroke characteristics for the purpose of signature authentication **[15]**. **[muslih, et al, 2023]** A genetic algorithm is utilized to optimize Convolutional Neural Network]CNN] architectures for the purpose of offline signature verification. This approach has demonstrated notable levels of accuracy when applied to datasets such as BHSig260 and CEDAR **[16]. [Lopes, et al, 2022]** An investigation was carried out on the utilization of deep neural networks in offline signature verification to authenticate attendance records, resulting in the attainment of precision and recall rates exceeding 85%, facilitated by the utilization of data augmentation **[17]. [Sharma , et al,2022]** The study centers on offline signature authentication through the utilization of a deep neural network. It introduces a refined Inception V3 architecture that surpasses the performance of existing pre-trained models such as VGG 16, VGG 19, ResNet 50, ResNet 101, MobileNet, and EfficientNet in both accuracy and performance assessments. With a success rate of 88%, the suggested model effectively discerns between authentic and counterfeit signatures **[18]** **[E. A. Soelistio et al, 2021].** The research indicates that offline signatures are predominantly identified through the utilization of a convolutional neural network, whereas online signatures are predominantly identified through the utilization of recurrent neural networks and other architectural designs **[19]. [jose et al, 2021]** The study centers on Offline Cursive Handwriting Recognition through the utilization of Convolutional Neural Networks for the English language. It attains an accuracy rate of 92.6% by employing the CNN model on the IAM database **[20]**. **[Zhao et al, 2020]** A complex Convolutional Neural Network [CNN] structure was formulated to specifically address the task of differentiating calligraphy imitation [CI]. The primary objective of the CNN revolves around the identification of distinct attributes and trends associated with CI as observed in handwritten signatures. Findings indicate that the suggested CNN design improves verification precision by 96.8% and boosts overall system effectiveness. Nonetheless, CNN-based approaches necessitate a substantial number of handwritten samples from the individual producing the signatures [21].]**Navid et al, 2019]** The objective of the research was to employ convolutional neural networks [CNN] for the automation of signature verification. The particular framework utilized in this study was developed based on the structure of VGG-19, an established convolutional neural network [22].

4- Feature Extraction Methods

Feature extraction occurs in the phase that directly follows preprocessing. The processed images serve as the main source for identifying specific traits that differentiate one signature from another. The subsequent section presents an elaborate examination of modern methodologies for feature extraction in signature identification, employing both traditional methods and Deep Learning [DL].

4-1 Traditional Methods: This section introduces the concept of feature extraction in signature images using traditional methods, and a set of sources has been collected for the period from 2013 to 2022, which helps researchers explore the methods used in these studies. As shown in **Table 3**.

Table 3:Extraction of features through conventional methodologies is the focus of this study

Technique	YEAR	Datasets	Ref.ID	ACC %
HOG & LOMO	2022	Self-built	[23]	98.4
Profile projection [pp]	2022	Self-built [12*20a]	[24]	79
Loci features	2022	Self-built [12*20a]	[24]	93
HOG & FMMC	2021	Self-built [12*20]	[24]	96
HOG	2019	Self-built	[25]	98.33
HOG	2018	Devanagari	[26]	97.06
[oBIFs] & SVM	2018	QUWI Database	[27]	76
CT & OC-PCA	2017	CEDAR GPDS	[28]	97.99
HOG	2017	Self-built [20*12]	[29]	96.875
HOG	2017	Self-Built [15*40]	[30]	98.33
PCA& DWT	2015	Self-built	[30]	
HOG	2015	SigWiCom P2009	[31]	99.27
SIFT	2015	Self-built [30*145]	[32]	71.72
Pixel matching technique [PMT]	2013	personal dataset created	[33]	94

*[The interpretation of the mathematical expression x*y can be described as follows: where x represents the number of individuals who have signed, and y denotes the average number of signatures contributed by each individual].*

4-2 Deep Learning Methods: A convolutional neural network [CNN] is a type of deep learning network that has demonstrated cutting-edge performance in various domains of computer vision, including image classification, pattern recognition, and object detection. Generally, a CNN is comprised of three primary components: convolutional layer, pooling layer, and fully-connected layer **[34]**. Convolutional neural networks [CNNs] are the most successful model. CNN can learn and extract image features automatically and performs great in machine translation **[35]**. CNNs essentially operate as mappings from input to output. The network is capable of learning a diverse range of mapping relationships without a precise mathematical formulation linking the input and output. Through training on recognized patterns, the convolutional network can effectively establish mappings between input and output pairs. In the wake of the remarkable advancements in deep learning, numerous researchers have shifted their focus toward developing signature recognition models based on CNNs. These existing models for signature recognition are characterized by their simplicity in structure, efficiency, and promising prospects for widespread applications, Hereafter follows a table of several renowned network models **[5]** :

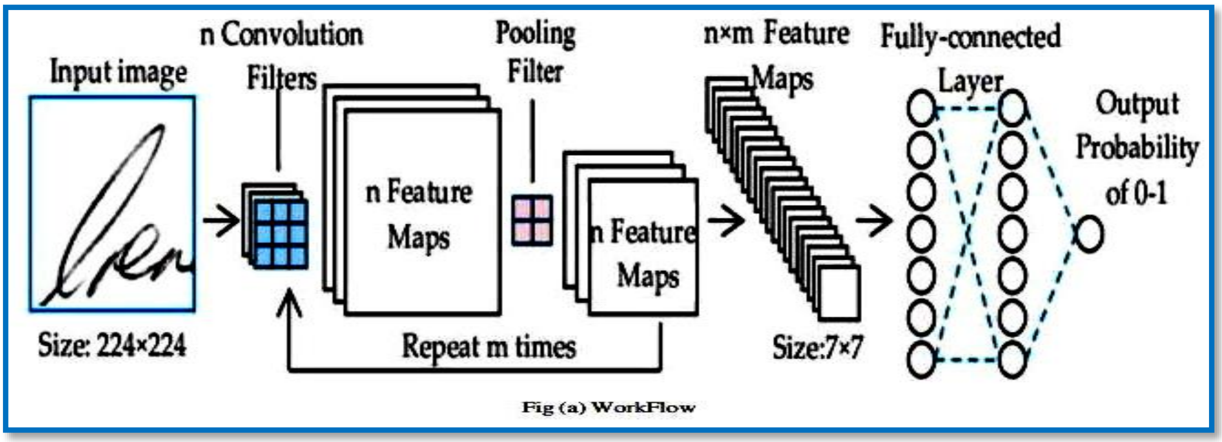

Figure 1: The Fundamental Structure of Convolutional Neural Networks]CNN] is Employed in the Task of Recognizing Signatures [34]

Table 4: The most commonly used algorithms and their details [37]

Model	***Total parameters***	***FE parameters***	***Released year***	***Trainable layers***
CAPSNET	6.86 million	5.39 million	2017	3
RESNET50	25.6 million	23.5 million	2015	51
AlexNet	62.3 million	3.7 million	2012	8
VGG16	138 million	14.7 million	2014	16
GoogleNet	5.3 million	5.3 million	2014	22

The table below shows feature extraction methods using convolutional neural networks for the period from 2019 to 2024.

Table 5: Methods of Feature Extraction for Convolutional Neural Networks [CNN]

Year	Ref ID	Feature extraction	Datasets	ACC[%]
2024	[12]	Siamese Neural Network [SNN]	IAM dataset	99.81
2023	[37]	CNN	CEDAR	94.73
2023	[[38]	MobileNetV2	Offline Handwriting Signature	97.7
2023	[39]	CNN	GPDS Synthetic Signature	82
2023	[40]	CNN	Private Signature Dataset	88.89
2022	[41]	OHS-Net	Multi-lingual	99.20
2022	[42]	- CNN-GC - CNN-HDR - SCN	CEDAR	98.03 85.38 97.82
2022	[18]	Vgg16, vgg19,EfficientNet B2, ResNet50, Resnet101 , MobileNet, Inception V3	GPDS	80 , 81 , 74 , 77, 73 , 71 , 88
2022	[43]	DCNN	-UTSig -ICDAR -MCYT	98.94 87.57 98.9 90
2021	[20]	CNN	IAM	92.6
2021	[44]	ANN	SigComp 2011	82.5
2020	[45]	CapsNet	CEDAR GPDS-100 MCYT	97 94 95
2020	[46]	Siamese neural network	Self-built	84
2019	[47]	Inception-v1 Inception-v3	GPDS	83 75
2019	[48]	DAG-CNN	building databases of genuine signatures and forgeries	99.4
2019	[49]	CapsNet	CEDAR	98.8

5. Conclusion

This study analyzes the development of offline signature recognition techniques over the past few years, taking into account all the traditional techniques aimed at obtaining greater expression features in signature samples that are still in common use. While deep learning-based methods focus on reconstructing CNNs, researchers are gradually using more network models for signature recognition tasks. These models range from simple modifications to CNNs to the use of other deep learning networks such as LS2Net, GoogLeNet, CapsNet, VGG, and other models. We conclude from this work that new readers and researchers can benefit from this study and the references mentioned in the research on the topic of offline signature verification. There is still potential for further work in this area using other classes of deep learning algorithms because current technologies still fall short of meeting the needs of society in the real world.

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