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Deep Learning Techniques for Signature`s Forgery Detection in Gurmukhi Script : Challenges & Advances

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Abstract:
Handwritten signatures serve as a cornerstone of personal and professional authentication systems. However traditional verification approaches struggle to address the complexity and variability inherent in different scripts, particularly non-Latin scripts such as Gurmukhi. This research delves into the challenges of forgery detection in Gurmukhi script and proposes an innovative solution leveraging deep learning techniques. By creating a specialized dataset and employing robust neural network architectures, this study seeks to enhance the accuracy and reliability of signature verification systems.

Keywords: Forged Signatures, Scalability, Fatigue, Deep Learning.

Introduction:

A signature is the most fundamental sensation, serving as a symbol of approval and authenticity. It acts as a personal identifier that signifies an individual's intent, consent or acknowledgement. Historically, signatures have been employed in a variety of contexts, ranging from legal documents and financial transactions to artistic works and personal correspondence. The primary function of a signature is to validate the identity of the signer and to ensure the integrity and non-repudiation of the signed document [1]. Although current paradigms of document verification procedures are likewise influenced by the demands of this fast-changing globe, offline signatures still have an important role in identifying people and verifying their credentials.

As persons with same name cannot have same signature due to different hand writing skills [2]. But the major challenge in signature verification process is forgery of signature, where someone copies another person’s signature without permission for any kind of fraud activities. There are three types of forgeries are identified in signature verification systems: (a) random forgery (b) unskilled forgery and (c) expert forgery. Random Forgeries arise when signs are created without information of signer's name and its signature style. unskilled forgeries in which the forger knows the signatory's name but has no prior sample of signatures, whereas in expert forgeries the forger knows both the signatory's identity and the style of the original signature. It has become extremely important to detect forged signatures to avoid fraudulent activities that not only impact on individuals but also the status of any organization. The integrity of a signature is paramount, as a critical means of authentication in legal and financial documents. However, forgeries undermine its trust led to severe consequentially such as financial losses, legal disputes and personal identity. To address the problem of forgery, methods of manual signature verification are developed for authenticating handwritten signatures particularly in legal, financial and administrative contexts. This conventional method is predicated on the expertise of professionals who have analysed a variety of signature attributes, including shape, size, inclination, and pressure patterns, in order to ascertain authenticity. Despite the advent of digital verification techniques, manual verification continues to be a trusted method due to its complex and detailed analysis capabilities [3]. Manual signature verification faces several challenges that impact its effectiveness and accuracy. One major issue is the inherent subjectivity involved in the process, as different experts may have varying interpretations of the same signature characteristics, leading to inconsistent results. Addition to this human fatigue and cognitive biases can further exacerbate these inconsistencies and reduce the reliability of manual verification over time. Furthermore, manual verification is often time-consuming and labour-intensive which limits its scalability and efficiency.

To enhance the accuracy and efficiency of signature verification process, automatic signature verification methods have been developed. These methods primarily utilized static and dynamic features derived from signatures; Static features consisted of geometric attributes such as the shape, size, and position of signature components, while dynamic features included factors like speed, pressure, and stroke sequence. Techniques such as template matching [4], which involved comparing an input signature to stored templates, and statistical models like Hidden Markov models (HMM) [5], that captured the sequential nature of signature strokes, were commonly employed. These features are extracted using algorithms that can detect subtle differences between genuine and forged signatures, thus providing a higher degree of accuracy than manual methods. Nevertheless, these approaches grappled with variations in individual signatures and the close resemblance between authentic and fake signatures, resulting in challenges related to accuracy and resilience. Due to absence of adaptive learning capabilities of these methods, system was unable to enhance their performance over time, thereby limiting their efficacy in practical scenarios.

To further improve the accuracy, machine learning method were developed. Large datasets are required for these methods [6]**.** But the availability of datasets specifically designed for signature verification in the Gurmukhi script is very limited. Few datasets dedicated to Gurmukhi script signature verification are available [7]**.** Some datasets available for Gurmukhi handwriting recognition, but these are not specifically for signature verification HWR-Gurmukhi_1.1, HWR-Gurmukhi_1.2, HWR-Gurmukhi_1.3, HWR-Gurmukhi_2.1, HWR-Gurmukhi_2.2, HWR-Gurmukhi_2.3, HWR-Gurmukhi_3.1[14]. Difficulties for signature verification in Gurmukhi script is lack of available data. Due to Inadequate illustrations of both genuine and forged signatures, it is challenging to train models effectively. Current datasets may not include a wide range of forgeries, such as skilled and unskilled forgeries. To address these issues comprehensive datasets would be required for advance research and improve verification accuracy for Gurmukhi signatures.

For the signature verification, many authors performed experiments with various feature extraction methods like Geometric, DCT Feature Extractions[21], Gray-Level Co-Occurrence Matrix (GLCM) for texture features, geometric features, and dynamic features [15], Local Quantized Patterns (LQP) for texture features, discrete wavelet features[16], Histogram of Oriented Gradient (HOG) for geometric features such as length distribution and entropy[17], Local Ternary Patterns (LTP) and oriented Basic Image Features texture descriptors to extract features[18] and classifiers such as Support

Vector Machines (SVMs)[6], Random Forest or Neural Networks[7].

To enhance the accuracy of these methods some authors performed experiments with deep learning methods Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), Mobile Net, ResNet50, Inceptionv3, and VGG19, in combination with YOLOv5 have been used. Compared to more conventional techniques, these models can accurately categorize signatures and automatically extract pertinent characteristics, considerably reducing error rates [19][20].

However, most existing research has predominantly focused on widely used scripts, with limited attention to scripts like Gurmukhi. Gurmukhi script presents unique challenges due to its distinct calligraphic style and cursive nature. Some authors performed experiments with statistical and machine learning models [14] like Artificial Neural Network (ANN) [7], HMM [5] for automatic verification systems. A very few authors attempt to experiments with deep learning models for Gurmukhi handwritten script like Deep Convolutional Neural Network [22], primary challenge for machine learning is the limited availability of high-quality labelled Gurmukhi signature datasets, which delays the training of robust machine learning models. Gurmukhi characters have complicated structures with various combinations of base characters, conjunct characters, and diacritics, lead to complex feature extraction and classification. Gurmukhi handwriting styles, including different fonts, sizes, and writing pressures create obstacles for training of model. Similarly Deep learning models typically require large amounts of data to achieve optimal performance but availability of in sufficient Gurmukhi data remains a constraint. This purposed research focuses on analysing and detecting forged signatures in Gurmukhi script, leveraging deep learning techniques.

Challenges:

Forgery detection in Gurmukhi script involves unique challenges due to the complexity and specificity of the script. Gurmukhi, a primary script for Punjabi, Punjabi is widely spoken language in Punjab and surrounding states. Government of Punjab focus to speak and write Punjabi which in written in Gurmukhi script. It is one of the most widely spoken native languages in the world with approximately 121 million native speakers. **Punjabi is spoken as a first language by more than 30 million people, making it the 10th most widely spoken language in the world** that poses intricate issues such as high variability in handwriting, the presence of visually similar characters, and the lack of diverse datasets for training robust deep learning models. Advances in machine learning and deep learning have led to significant strides in writer identification and forgery detection, often leveraging convolutional neural networks (CNNs), generative adversarial networks (GANs), and transfer learning approaches. Despite progress, challenges persist in dataset quality, algorithm generalization, and computational efficiency.

Over the past decade, a wide range of studies have been conducted in this field. But limited availability of high-quality labelled Gurmukhi datasets and lack of experimentation with state of art methods results in lower accuracy in the recognition of Gurmukhi signature verification. Some limitations of existing work are given as under:

- Lack of Systematic review / critical analysis of the existing methods of Gurmukhi Signature Verification.
- Non-availability of the publicly available comprehensive data sets for Gurmukhi

Signature. In past, few authors have performed experimentation on a small size data set [7][21]. Minimum number of samples in this data set will 2000 and this data set is not publicly available. To ensure fair comparisons and advancement in the field, benchmark datasets and defined evaluation criteria specific to Gurmukhi signature verification are required.

- Very few authors attempt to recognise the Gurmukhi Signature in the past [7][31]. These authors performed experiments with, DCT Feature Extractions and Neural Network methods, SVM, HMM and these experiments were performed on a very smaller data set. But no one performed experiment with modern deep learning methods on a comprehensive data set.
- In literature majority of signature verification algorithms were developed for Latin, Chinese, Thai, Devanagari etc. scripts and these algorithms cannot apply on the signatures in benchmark data set and methods for the verification of signatures in Gurmukhi script despite its use in banking, legal documents, and various forms of identification.

  With advancements in technology, the challenge of distinguishing between authentic and forged signatures has become more complex. There is a need of time to develop a comprehensive dataset and method for signature verification.

Deep Learning Architectures: Advanced neural networks, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been employed to recognize subtle variations in Gurmukhi script handwriting. These methods enhance character recognition accuracy, which is crucial for detecting forged content.

Feature Extraction Techniques: Histogram-oriented gradients and texture-based features are used to strengthen the robustness of detection models.

Summary of the approaches develop for signature verification of various scripts

Author	Language/ Script	Year	Dataset	Feature Extraction	Classification Method	Accuracy/Result
Shailendra Kumar Shrivastava [34]	Hindi	2012	3430	Energy feature	SVM	96%,
Srikanta Pal [31]	Hindi	2012	1890	gradient and Zernike moment	SVM	7.42% FRR and 4.28% FAR
K S Radhikaa et. al. [3]	Latin script	2014	715	Projection feature, Gradient feature	SVM	74.04
Ankita Wadhawan et al. [7]	Gurmukhi	2014	600	Dynamic Features	SVM	85%
Karun Verma [23]	Gurmukhi Character	2017	1750	Geometric features	SVM HMM	96.4 %
Sounak Deya [32]	Hindi/English/Bengali	2017	2640	SigNet	CNN	79:19%
Miguel A. Ferrer [35]	Bengali and Devanagari	2017	2400	Geometric features	HHM, SVM	42%
Rimpi Suman et al. [21]	Gurmukhi	2018	250	DCT	SOM, ANN	60,90%
Abhijit Das [33]	thai	2018	5,400	LBP and LDP	HMM	1.41, 1.64, and 1.34% for TS, ES, and TES,
Yiwen Zhou et al. [6]	Chinese	2021	1200	GLCM and HOG	SVM, DTW	93.33%
Prakash Ratna Prajapati et al [27]	Latin	2021	1035		CNN	83.73%
R, Anagha et al. [25]	NA	2022	60	SHIFT, OSTU	SVM, K-Means	95.83%

Neha Sharma [30]	Hindi/English/Bengali	2022	Hindi 8640, English:216000, Begali :5400		Siamese Deep CNN	78,80,92%
Abdullahi Ahmed Abdirahma et al. [19]	Handwritten Signature	2024	Kaggle, CEDAR, ICDAR, Sigcomp.		MobileNet architecture	89.80%

Conclusion:

This study addresses a critical gap in forgery detection for Gurmukhi script. By leveraging deep learning techniques and creating a comprehensive dataset, it offers a novel approach to biometric authentication in a regionally significant context. Future work may explore extending these methods to other scripts and incorporating real-time verification capabilities.

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