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CNN-BILSTM Architectures for Handwritten Signature Verification: Insights and Innovations

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Abstract

Verifying handwritten signatures is essential for identity authentication to guard against fraud and guarantee security across a range of platforms. The approaches and developments in handwritten signature verification are examined in this review, with an emphasis on both offline and online techniques. While online methods use dynamic information like stroke order and speed, collected by specialized devices, offline verification uses scanned photographs of signatures. Even if technology is moving toward online approaches more and more, offline systems are still needed, especially in settings where paper is used extensively. The difficulties of offline signature verification are discussed in the study, with a focus on the difficulties of feature extraction in the absence of dynamic data inputs. It also examines the development of handwritten text recognition, emphasizing the function of recurrent and convolutional neural networks, as well as its uses in optical character recognition (OCR). We evaluate and analyze various deep learning methods for handwritten document recognition, including advantages and disadvantages. Offline Handwritten Text Recognition (OHTR) has a comprehensive framework that includes phases for feature extraction, classification, and preprocessing. Lastly, a review of current developments and their consequences is given regarding the integration of CNNs and LSTMs in handwriting recognition.

Keywords: Handwritten signature verification, offline signature verification, online signature verification, convolutional neural networks (CNNs), recurrent neural networks (RNNs), optical character recognition (OCR)

INTRODUCTION

In order to address challenges of fraud and authentication, handwritten signature verification has garnered a great lot of attention in recent study. Verifying a signature is necessary to validate a person's identity. Verifying handwritten signatures is essential to preventing forgery issues that could have negative consequences. Online verification (dynamic) and offline verification (static) methods are the two types of handwritten signature verification and recognition techniques [1]. An electronic signature based on certain equipment, such as digitizers, smart pens, and pressure-sensing mobile phones, is used in an online signature verification process. Online techniques make use of the dynamic elements of a handwritten signature, like pressure, duration, speed, and striking sequence. In contrast, systems for offline verification of signatures and recognition work by having a person sign a piece of paper with a pen. The signature image is then scanned and sent into a classifier,

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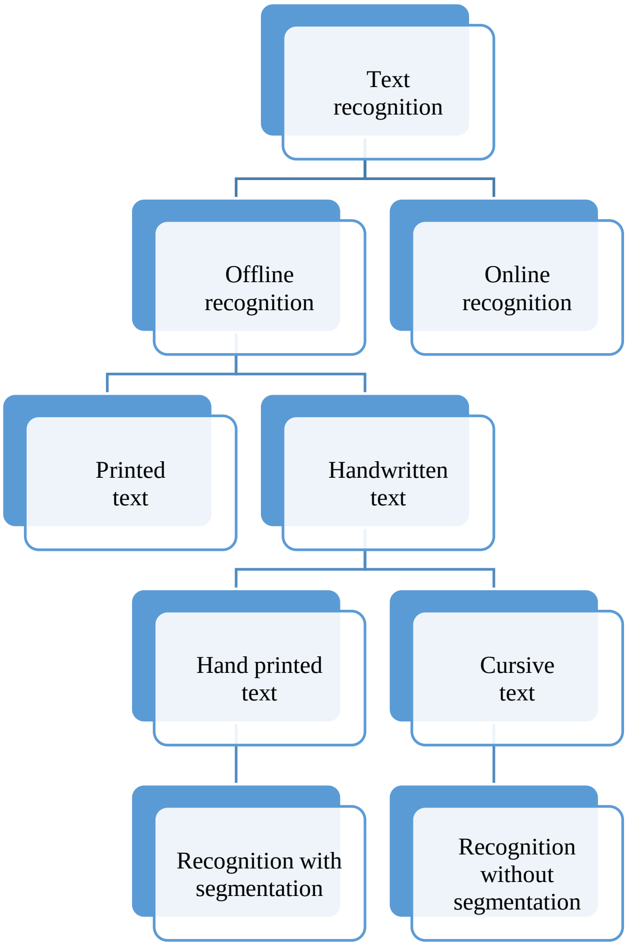

Figure 1. Classification of handwritten text recognition systems.

which verifies the signature. Even with the recent advancements in technology, many nations that still rely heavily on paper transactions still require an offline verification of signatures mechanism. Verifying an offline signature can be challenging because it lacks the dynamic elements of an online signature, which are derived from sensing devices. It is difficult to extract complex features for offline verification of signatures [2].

One of the most important areas of pattern recognition study nowadays is the recognition of handwritten text. Numerous scholars put forth methods to make it easier to transcribe historical archives, prescription drugs, general forms, and any other current document using an offline or online spatial and temporal procedure. The text recognition systems' classification is displayed in Figure 1. The process of transcription entails automatically converting handwritten text from a source into machine text within a digital image. In this sector, optical character recognition (OCR) is the fundamental method. There are two primary stages to it: first, text detection by small-pattern segmentation. The second step involves identifying the contents of the patches so that they may be converted into machine-coded text. The first and most basic OCR was created to recognize Latin numerals [3].

This method is best shown by Convolutional Neural Networks (CNNs), which use a hierarchical learning process. While the last layers extract global features that represent high-level semantic elements, the earliest layers extract local features from visual data. To improve sequence learning accuracy for action recognition, researchers have recently been investigating a few strategies, such as Transformers, transfer learning, and CNN-based approaches. Notably, on the UCF11 dataset, BT-LSTM, as used by Wang *et al.*, attained an accuracy of 85.3% [4]. For the UCF11 dataset, the accuracy rates obtained by KFDI, Dilated CNN + BiLSTM + RB, local-global features + QSVM, the dynamic human activity recognition work, 3DCNN, and deep autoencoder + CNN approaches were 79.40, 89.00, 82.60, 85.20, 96.20, and 92.40%, respectively. Even with these improvements, current methods are unable to obtain adequate accuracy for the JHMDB and UCF Sport benchmark datasets [5]. The absence of spatiotemporal information necessary for a more thorough comprehension is the main cause of the poor performance achieved by these benchmark action recognition datasets.

DIFFERENT DEEP LEARNING APPROACHES BASED HANDWRITTEN METHODS

Some of the deep learning's important approaches are given below.

Convolutional Neural Network (CNN)

The specific type of neural network model is meant to be used to image data. Among its many uses, CNN is widely employed in face recognition, recognizing objects, image recognition, and picture classification. A sequence of convolutional, pooling, and fully connected layers are applied to the input image in CNN before producing an output that may be as simple as a class or as likely to be the class that best characterizes the image. Through the application of various approaches, CNN is able to learn many layers of feature representations for an image. Using a series of convolutional layers, a computer looks for low-level characteristics such as edges and curves in order to construct a more abstract concept for image categorization. Due to its unique features, which include parameter sharing and local networking, CNN performs better and offers more accuracy [6].

Recurrent Neural Network (RNN)

When the next word in a sequence needs to be guessed, and if we are trying to use this kind of data whenever the sequence matches, then a network that can access some prior information about the data is necessary. Using this strategy, the output of the previous step feeds the input of the current phase. The input layer, the hidden layer, and the output layer are the three layers that comprise the RNN architecture. The hidden layer holds onto information pertaining to sequence. Every piece of computation-related data is stored in the storage device of the RNN model. Some of the application areas of RNN include sequence creation (e.g., machine translation); sequence labeling (e.g., picture captioning and identified entry recognition); and sequence classification (e.g., sentiment identification and video classification). Recurrent neural networks are flexible enough to handle a wide range of data types and are helpful for predicting time series [7].

Long Short-Term Memory (LSTM)

LSTMs are a type of RNN designed to overcome the vanishing gradient problem in vanilla RNNs, limiting their capability for learning long-term dependencies. LSTMs, introduced by Hochreiter and Schmidhuber in 1997, are highly competent in handling sequential data because they can retain information from earlier steps to predict future results. This is achieved using a memory pool and two basic states: short-term or the state at the current time-step output, and long-term or retained information across time [8]. LSTMs employ three gates: forget, input, and output gates, to control the flow of information so that there is proper handling of what to remember, forget, or output at each step. These gates, coupled with the dynamic interaction between cell states and hidden states, make LSTMs surpass other RNNs and classic methods in speech recognition as well as machine fault prediction applications, thus becoming indispensable for applications requiring long-term dependency learning [9].

VARIOUS ASPECTS OF A HANDWRITTEN DOCUMENT

When it comes to documents written by hand, figuring out how to read them requires identifying more than just the text, like Figure 2. Accurately recognizing each of these traits is difficult due to their intricacy. Thus, this research explores the various methods used for handwritten document recognition. It examines how different recognition methods have developed, evaluating the advantages and disadvantages of each. The study pays special attention to explaining the most recent developments in this area and how they might be used in various industries. It seeks to demonstrate how these methods

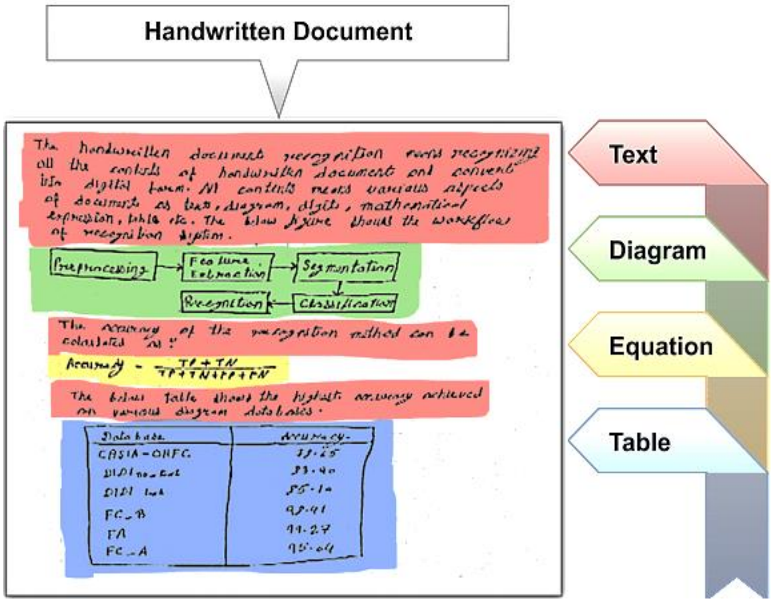

Figure 2. Various aspects of a handwritten document.

can efficiently handle the difficulties involved in processing handwritten documents and increase their usefulness in real-world situations by examining recent advancements [10]. The following factors must be considered for thorough comprehension and efficient handling of these documents:

- *Textual content:* The text is, obviously, the most important component of a handwritten document. This encompasses not only the printed words but also their alignment, formatting, and spatial organization.
- *Spatial layout:* Documents written by hand frequently have a variety of spatial layouts. Knowing how material is arranged on a page, whether it be in lists, paragraphs, or another format, can help you understand the hierarchy and structure of the document.
- *Graphical elements:* Annotations, diagrams, drawings, and sketches are examples of graphical elements that can be found in handwritten manuscripts. These components can provide context or other information in addition to the text's content.
- *Multilingualism and script variations:* Handwritten manuscripts frequently demonstrate the intricacy of having more than one language or script in one composition. Because of this variability, effectively transcribing and translating the text calls is a sophisticated strategy. Deciphering various writing systems, comprehending linguistic quirks, and guaranteeing accuracy in expressing the original meaning over linguistic barriers are all necessary to identify these variances. This kind of understanding is essential for maintaining cultural legacy, performing precise historical research, and promoting efficient communication amongst various linguistic communities.
- *Digitization and recognition:* Digitizing handwritten materials entails transforming them into formats that are readable by machines. This frequently calls for optical character recognition (OCR) software designed specifically for handwritten writing, which has different difficulties than text that is printed [10].

FRAMEWORK OF OFFLINE HANDWRITTEN TEXT RECOGNITION

Generally speaking, OHTR is the process by which a recognition system converts text picture data into the corresponding character representation, processes it, and stores it as ASCII text. The three primary components of an OHTR system are typically features extraction, classification, and pre-processing [11]. The flowchart for offline recognition of handwritten text is shown in Figure 3. To prepare for the appropriate analysis that follows, we can enhance and optimize the offline text written by hand image quality throughout the stage of preprocessing. It should be emphasized that it can be

Figure 3. Flowchart of the offline handwritten text recognition.

divided into a variety of smaller tasks, such as paragraph authentication, text-line segmentation, word/character, the process of segmentation, picture normalization, and so on. During the step of feature extraction, to make sure that these characteristics may be employed to obtain the excellent accuracy of the classification system, we extract representative features from text images.

Both the automatic learning feature-based method and the hand-crafted feature-based methods are included, depending on whether the representative features are relevant to the classification tasks without retraining. Due to their requirement for prior knowledge regarding the position and importance of the features, the former are severely constrained. These methods are obviously susceptible to variations in handwriting styles, background colors, and other non-uniform text image issues. As two examples of the latter, CNNs and RNNs make full use of the deep neural network learning architecture to automatically acquire representative features and resolve translation, scaling, and distortion issues to become among the most reliable systems. Automatic learning feature-based approaches have a general limitation in that they require greater processing power during the training phase in order to obtain representative features. A trained classifier that can predict the character or word class is fed with the representative features during the classification step. Numerous methods have been used to identify text images, and they can be broadly classified into two categories: segmentation-based and segmentation-free [12, 13]. The conventional method known as the segmentation-based approach explicitly segments a text-line image into numerous distinct characters before using a trained classifier to identify each character's class. It is important to remember that the effectiveness of these methods strongly correlates with word/character segmentation performance, and that any segmentation error will accrue and have a direct impact on the recognition accuracy of the classifier. On the other hand, the segmentation-free method, which uses an image of a word, line, or many lines as input data, recognizes the document image without the need for explicit segmentation. These methods appear to be the most widely utilized, particularly in situations when it is difficult to distinguish between lines or characters, such as in complicated backgrounds, touching text lines, or overlapping characters. These techniques, which combine CNNs and RNNs with connectionist temporal classification (CTC) or the hidden Markov model (HMM), are frequently utilized. As text recognition research continues to advance, it is thought that text recognition algorithms would perform better when they have access to contextual information. Contextual information is the result of calculations made at each time step that consider the past and future context of linked characters or phrases [14].

INTEGRATION OF CNNS AND LSTMS IN HANDWRITING RECOGNITION

It has been shown that DL approaches yield relevant feature representations and enhance sketch-based recognition. DL can be applied to the categorization or recognizing sketches and can produce more distinctive features from photos of sketches. In order to recognize sketches, deep features were originally used by Agrawal *et al.*, who created a unique neural network model [15]. However, these deep learning-based strategies outperform the traditional approaches in terms of efficiency. In this research, we propose a deep learning technique-based approach to improve drawing recognition. Specifically, we used an LSTM network for classification and a CNN to extract meaningful features from the sketches, which is a major departure from the typical feature-based techniques. Our input into the field of recognition of sketches can be summed up as listed below [16]:

- *Integration of DL:* To extract notable characteristics from freehand sketches, we leverage the capability of DL, specifically a CNN. This makes it possible for us to capture the distinct and abstract aspects of sketching, which set them apart from traditional natural photos.
- *Sequential analysis with LSTM:* To enhance our model's capacity to identify intricate drawings, we employed an LSTM network to examine the extracted sequence and stroke progression in a sketch.

- *QuickDraw dataset evaluation:* The QuickDraw dataset, one of the largest and most complete resources for sketch-recognition research, has a wide variety of sketch classes, which we used to extensively analyze our suggested method. This guarantees the suggested approach's robustness. Our approach integrates CNN, LSTM, and deep learning capabilities to enhance sketch identification accuracy. It may be a viable solution to the problems posed by freestyle sketching's abstract and symbolism character. The results of this investigation show that the proposed approach works well and outperforms other state-of-the-art methods like CNN and LSTM [17].

This study presents the results of experiments on recognizing handwritten signatures using four signature databases: BHSig260-Bengali, BHSig260-Hindi, CEDAR, and TUIT. Signatures were resized to four dimensions: 200×120, 250×150, 300×150, and 400×200 pixels, and these images were input into the proposed network architecture. The best classification accuracy was achieved with images resized to 250×150 pixels, yielding results of 94.38% on the CEDAR database, 95.63% on BHSig260-Hindi, 97.50% on BHSig260-Bengali, and 90.04% on the TUIT database [18]. These findings demonstrate the effectiveness of the proposed approach for signature recognition across various datasets.

This study deals with the challenge of white-box false positive adversarial attacks on contrastive loss-based offline handwritten signature verification models. We propose a novel attack method that conceptualizes the attack as a style transfer between closely related yet different handwriting styles. We have introduced two novel loss functions towards guiding the generation of the deceptive signatures: one changes Euclidean distance between embedding vectors of original and synthesized samples for an increase in attack success while the other minimizes perturbations to preserve similarity to the original image. Our approach achieves state-of-the-art performance in white-box attacks on contrastive loss-based models, as demonstrated by experimental results [19]: Novel false positive attack method, two specifically proposed loss functions, effective handwriting style transfer, and superior performance over existing white-box attack methods.

Signature verification from handwritten signatures is an active challenge in biometrics, and document authenticity. Its applications are seen in finance, law, and security sectors. This study presented an approach consisting of four stages to enhance the accuracy in verification. Altogether, 12,600 images from 420 people contributed and 30 genuine signatures were collected. Applying the MobileNetV2 deep learning model, features were extracted, and three different techniques for feature selection: NCA, Chi2, and mutual information (MI), were applied to select feature vectors of different sizes (200, 300, 400, 500 features). Machine learning classifiers, including SVM with RBF, poly, and linear kernels, KNN, Decision Trees, Linear Discriminant Analysis, and Naïve Bayes, were used for classification [20]. Without feature selection, the model achieved an accuracy of 91.3%, while NCA, with 300 features improved accuracy to 97.7%. The proposed approach yields high accuracy as well as a self-organized framework suitable for optimizing feature selection towards robust signature verification.

Handwritten signatures are one of the most common methods for biometric identification in financial, legal, and business environments. This study reviews the developments in offline handwritten signature recognition of the last 15 years to further highlight approaches, architectures, challenges, and trends, particularly the emergence and boom in deep learning. Drawing on studies from four of the major databases, it applies inclusion and exclusion criteria that go on to analyze the key stages involved in the process such as extraction of features and classification, offering insights into the current challenges and opportunities [21]. Unlike other surveys, this work provides a comprehensive overview of all phases and aims to guide future researchers in advancing the field.

Handwriting is a complex task, involving motor, visuospatial, and cognitive skills. For individuals with Alzheimer's disease (AD), it is significantly affected. This systematic review of 91 studies underscores impairments across the motor-cognitive hierarchy, with better preservation of signatures compared to text. The visuospatial and linguistic aspects are specially affected with solidified motor

Table 1. Overview of studies on handwritten signature recognition and handwriting analysis.

Reference	Key Findings	Parameters	Outcomes
[1]	Handwritten signature recognition experiments using four databases with resizing to different dimensions.	Databases: BHSig260-Bengali, BHSig260-Hindi, CEDAR, TUIT; Resized dimensions: 200×120, 250×150, 300×150, 400×200 pixels.	Best accuracy at 250×150: 94.38% (CEDAR), 95.63% (Hindi), 97.50% (Bengali), 90.04% (TUIT). Demonstrates effectiveness of resizing and proposed model.
[2]	Proposed white-box adversarial attack method on contrastive loss-based models using style transfer and novel loss functions.	Novel Loss Functions: Euclidean distance perturbation and minimal image perturbation.	Achieved state-of-the-art performance in white-box attacks, effectively transferring handwriting styles and outperforming existing methods.
[3]	A four-stage signature verification approach using deep learning (MobileNetV2) and feature selection techniques.	Dataset: 12,600 images from 420 individuals; Feature selection: NCA, Chi2, MI; Classifiers: SVM, KNN, DT, LDA, Naïve Bayes.	Without feature selection: 91.3% accuracy; With NCA (300 features): 97.7%. Demonstrates robust feature selection and high verification accuracy.
[4]	Comprehensive review of offline handwritten signature recognition over 15 years, emphasizing deep learning.	Topics: Feature extraction, classification, challenges, trends; Databases: Four major databases.	Offers a detailed overview of approaches, challenges, and opportunities, aiming to guide future researchers in advancing the field of signature recognition.
[5]	Systematic review on handwriting impairments in Alzheimer's disease (AD), highlighting motor, visuospatial, and linguistic deficits.	91 studies; Features: Motor (variability, duration, fluency), Visuospatial, Linguistic.	Identifies impairments in handwriting with preserved signatures, inconsistent findings on pressure and velocity, and opportunities for clinical and forensic applications.

deficits that include greater variability, longer durations, and reduced fluency in the handwriting. However, findings on pressure, speed, size, legibility, and error patterns remain inconsistent [22]. Reviewal gaps of research on the effects of AD on signatures and variants of the disease indicate potential handwriting analysis in clinical management for early detection, monitoring, and forensic applications as shown in Table 1.

CONCLUSION

This study concludes with a thorough examination of the state of the art in handwritten signature authentication and recognition techniques. It highlights how important offline and online verification methods are to preserve safe identity authentication processes. Deep learning advances, particularly in the areas of "Convolutional Neural Networks" (CNNs) and "Recurrent Neural Networks" (RNNs), have transformed the field of handwritten text detection and Optical Character detection (OCR). The accuracy and efficacy of textual content and handwritten signature identification and authentication have been markedly enhanced by these technologies. Nevertheless, there are still issues, particularly about feature extraction for offline signature verification. Because offline verification uses static image inputs, it requires sophisticated feature extraction techniques to improve robustness and accuracy, in contrast to online systems that use dynamic data, such as stroke order and speed. Research into more dependable and flexible feature extraction methods is necessary to address these issues, particularly in situations where handwriting styles differ greatly or in complex document layouts. Researchers hope to address the growing needs of contemporary authentication requirements by significantly improving the security and dependability of handwritten signature verification systems through ongoing methodology refinement.

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