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CNN Based Handwritten Signature Recognition and Verification

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A B S T R A C T

Handwritten signatures have become a controversial bio-metric, widely used in government, finance, litigation and security. During the past decade, researchers have actively explored the application of handwritten signature analysis and processing in various fields. This paper systematically reviews the literature on offline handwritten signatures with an emphasis on verification methods based on deep learning. The aim is to provide an overview of the most promising advances and outline possible future research directions in this area. Often, companies receive many scanned or photographed documents from customers, which requires automatic signature detection and authentication. The challenge becomes more difficult when signatures overlap with stamps, which affects the performance of object recognition models trained on pure signature images. To fix this, a new dataset is created by combining fake stamps with clean signatures for model training. A later developed image processing system successfully removes the stamps, demonstrating the ability of image processing techniques to handle the complex task of cleaning stamped signature images.

Keywords: Biometric Controversy, Litigation and Legal Processes, Deep Learning, Overlapping Signatures and Image Processing Techniques.

Introduction

Handwritten signature detection plays a key role in document forensics and authentication. Signatures, which are unique, are the primary means of verifying documents. Two main methods of signature verification are needed to improve security.

1. Online Authentication:

- Capture dynamic information in real time during signature acquisition with digital devices typically used with a pen. - Records spatial coordinates, pressure, azimuth, tilt and pen up/down movements to analyze and predict signature and authorship. - Also known as dynamic signature detection.

2. Offline identification:

- Includes writing a signature on paper, digitizing it with a scanner or camera, and identifying unique features for authentication. - Also known as static signature detection.

These methods are widely used in various fields:

- Finance: Financial institutions use sample signatures to verify the authenticity of documents. - Health:The UK's National Health Service collects doctors' signatures on patient records for authentication. - Features: Paperless contracts in the US allow you to sign with a pen on tablets or PDAs.

In the field of global security systems, bio-metrics, especially handwritten signatures, are an integral part of banking, government and financial applications. Signature processing systems process signatures in two ways: online and offline. Processing offline handwritten signatures is a greater challenge due to limited data compared to online cases. Handwritten signature verification systems (HSV) deal with three types of forgery: casual, simple, and professional. One uses writing-independent (general learning) or writing-dependent (specific learning). Although author-dependent learning gives good results, it increases the complexity and cost of the system.

Each HSV system consists of three main steps: preprocessing, feature extraction, and classification. Feature extraction can be achieved using manual methods or by learning the feature representation. The advent of convolutional neural networks (CNN) and deep learning revolutionized automatic processing systems, especially in representing learning features directly from raw data.

Transfer learning, a prominent technique, uses CNN models of source tasks to overcome data limitations or time constraints. This paper reviews signature verification/recognition methods based on CNNs and evaluates the performance of deep CNNs (SigNet, SigNet-F, VGG16, VGG19, InceptionV3 and ResNet50) for offline HSV using transfer learning. The organization of the paper includes a brief overview of CNN models and deep transfer learning, a comprehensive literature review, HSV methodology based on transfer learning with current CNN models, detailed experiments and conclusions on future perspectives.

2. Methodology

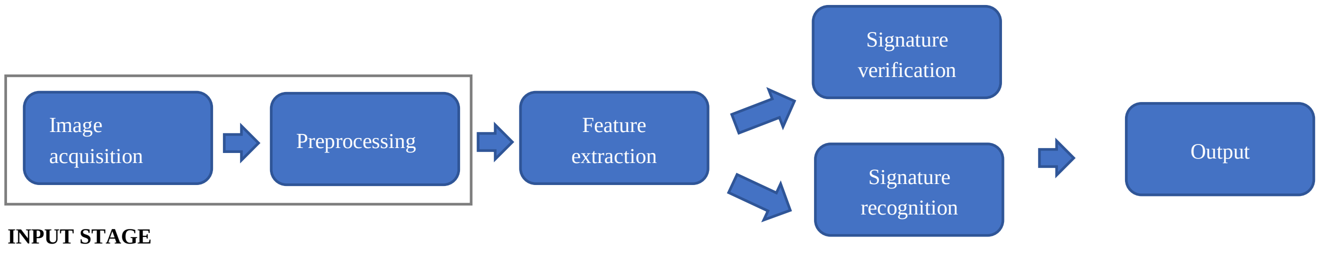

Fig.1 -Methodology Flow

Although much of the research on automatic signature verification is based on private datasets, creating problems when comparing similar work due to potential biases, publicly available signature datasets have emerged over the past decade that address this limitation. The process of obtaining signature images is similar for most public datasets. Authentic signatures are collected during one or more sessions where users submit multiple samples of forms that contain cells designed to fit common scenarios such as bank checks and credit card coupons. Fakes are collected differently; users imitate genuine signatures after receiving samples. In particular, counterfeit suppliers are not experts in counterfeit production. Once collected, the forms are scanned (often at 300 or 600 dpi) and pre-processed.

A step-by-step process for developing and implementing an offline handwritten signature recognition and validation model. It includes the following main steps:

1. Collection and preparation of data:

Ensuring the availability of data suitable for training and evaluation, including collection of signature images, pre-processing and organization of a versatile dataset.

2. Model selection and transfer learning:

Selecting and adapting a suitable pre-trained model to a specific task, signature analysis, exploiting the information already contained in the model.

3. Functional Disassembly:

Using a pre-trained model, meaningful features are extracted from signature images and important features that distinguish individual signatures and authenticity are stored.

4. Classification layer design:

Adaptation of the model and printing layer according to the desired task, either by distinguishing genuine and forged signatures (verification) or identifying the signer (identification).

5. Model training:

Refinement of the model and parameters through an iterative process using features extracted from the dataset and corresponding identifiers to guide the model's learning and decision making.

6. Evaluation:

Accurate evaluation of the model and performance in a particular set of tests to ensure its effectiveness and reliability, providing insight into its strengths and limitations.

7. Commission:

Integrating the trained model into the application or system in use, enabling real-world interaction with users and practical implementation of its functions.

8. Continuous improvement:

Recognizing the continuous nature of model development and opportunities for improvement, including data collection, fine-tuning the model and architecture, and exploring alternative techniques to optimize performance and adaptability. Essentially, the method provides a structured plan to guide a project from initial data collection to final implementation, ensuring a systematic and well-documented approach to achieving the desired results.

3. Comparison table

1. Deep learning based offline handwritten signature authentication research by Yusnur Muhtar, Wenxiong Kang, AliyaRexit, Mahpirat and Kurban Ubul included extensive analysis. The researchers used a variety of data sources, focusing on offline handwritten signature databases. Their selection criteria included different materials to ensure the generality of the proposed models. Evaluation metrics such as accuracy, precision, and recall have been used to

evaluate the performance of deep learning-based signature verification methods. One major challenge was image segmentation, which highlighted the need to separate signatures from background noise for effective authentication.

2. Şeymanur Aktı and Hazım Kemal Ekenel study signature image processing for detection and authentication. Their approach involved automatically identifying signatures on documents and matching them with customer signatures in the system for verification purposes. A notable challenge addressed in their work was the difficulty of duplicate signatures and stamps, which can complicate the identification and authentication process.

3. Krishnaditya Kancharla, Varun Kamble and Mohit Kapoor adopted a Convolutional Neural Network (CNN) approach for handwritten signature recognition. They used several image processing techniques to preprocess the images, separating signature pixels from background and noise pixels. However, one drawback highlighted was the significant memory consumption and higher time complexity associated with their approach.

4. Luiz G. Hafemann, Robert Sabourin and Luiz S. Oliveira conducted a literature review on offline handwritten signature verification. They focused on scanned signature images where no dynamic information about the signature process was available. They found that noisy images were a challenge because they were not easily recognized, highlighting the limitations associated with the lack of dynamic information in a scanned signature.

SL No.	Title	Authors	Advantages	Disadvantages	Accuracy
1.	A Survey of Offline Handwritten Signature Verification Based on Deep Learning	Yusnur Muhtar, Wenxiong Kang, AliyaRexit,Mahpirat and Kurban Ubul	Details on how the survey was conducted,including data sources, selection criteria, and evaluation metrics.	Problem of Image segmentation to separate signatures from background.	99%
2.	Pre-processing of Signature Images for Detection and Verification	Şeymanur Aktı and Hazım Kemal Ekenel	Automatically detect the signatures on the document and then match them with the customer's signature in the system for verification.	Overlapping signature and stamp makes it harder to solve the problem.	96%
3.	Handwritten Signature Recognition:A Convolutional Neural Network Approach	Krishnaditya Kancharla,Varun Kamble and Mohit Kapoor	Images are preprocessed to isolate the signature pixels from the background/noise pixels using a series of image processing techniques.	Takes up a lot of memory and has a higher time complexity.	95%
4.	Offline handwritten signature verification — Literature review	LuizG. Hafemann,Robert Sabourin and Luiz S. Oliveira	Ituses images of scanned signatures ,where the dynamic information about the signing process is not available.	Noisy images are not recognizable.	90%

4. Conclusion

During the last decade, researchers have adopted various methods for offline signature verification, witnessing significant advances mainly due to deep learning applications. Recent contributions in this area focus on different categories, including advanced extractions such as texture (LBP variants), point of interest matching (SIFT, SURF), and orientation functions (HOG), all of which improve offline accuracy. Signature control systems. Researchers have also addressed the limited number of samples per user by exploring author-independent solutions and difference-based metric learning methods. To improve classification accuracy and solution reliability, the creation of synthetic signatures for growing data and the study of both static and dynamic model ensembles were investigated. This trend is expected to continue in future research, with continued emphasis on refining feature representations, particularly through deep learning methods, and developing strategies to improve classification performance with limited samples. Furthermore, the study of single-class classification models that better fit the problem statement is still an unexplored area.

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Offline handwritten signature verification — Literature review. Luiz G. Hafemann,Robert Sabourin and Luiz S. Oliveira. https://ieeexplore.ieee.org/document/8310112