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Deep Learning - Based Handwritten Signature Verification System

Omkar Reddy Polu

Department of Technology and Innovation, City National Bank, Los Angeles CA
Email: *omkar122516[at]gmail.com*

Abstract: ***The signature verification is the most important in biometric authentication, document validation and fraud prevention. Signature verification techniques from the previous generation are based on handcrafted features and statistical model, suffer from intra user variations and capable of forgeries made by skilled forgers. In this research we propose a deep learning based handwritten signature verification system that takes advantage of methodologies which have recently been developed in order to assure a level of accuracy, robustness and real time of signature verification. By integrating a Siamese Neural Network and a hybrid CNN - Transformer architecture, we learn to mimic both spatial as well as contextual dependencies in signatures. We also improve the model verification to be more accurate with the help of multi scale feature extraction, attention mechanisms and contrastive learning to distinguish the real ones from the forged ones. We further consider the use of GAN - based data augmentation to generate synthetic signatures that are more realistic and thus better lead to generalization of the model. A system that is designed to deployed on edge AI using TensorFlow Lite and both ONNX optimizations while being suitable for mobile and embedded devices. We also bring forth integration with blockchain for maintaining secure and tamper proof storage of verified signatures.***

Keywords: Handwritten Signature Verification, Deep Learning, Siamese Network, Contrastive Learning, Blockchain, CNN - Transformer, Edge AI, Biometric Authentication, GAN - based Data Augmentation, Secure Digital Signatures

1. Introduction

Written signature verification has been widely used across the biometric authentication techniques for banking, legal document, financial transaction and access control. But unlike passwords or PINs, signature is a unique thing possessed by each individual that can be used as a non repudiable authentication method. Nevertheless, handcrafted feature extraction along with the use of rule based classifiers are not ideal in traditional signature verification methods due to intra user variations, skilled forgeries and other environmental factors like ink quality, pen pressure etc.

However, with the progress of deep learning, Convolutional Neural Network (CNNs) and Transformer based architectures have brought positive changes in biometric verification by performing automatic feature extraction and a high accuracy of classification. In this work, we propose a deep learning based handwritten signature verification system using a hybrid CNN - Transformer model together with the Siamese Network on top of it, and furthermore enable it to learn in one shot using a few initialization tags. It thus enables the system to distinguish genuine signatures from forgeries despite limited training data.

To further improve the verification accuracy, our system contains GAN based data augmentation, contrastive learning, and multi scale feature extraction. In addition, we employ blockchain technology to store authenticated signatures in the secure, tamper proof manner and run the model on edge devices for real time verification. The goal of the proposed method is to deliver a scalable, secure, and high-performance solution to the modern biometric authentication challenges.

We present this paper that explores the challenges, methods, testing and practical results of our novel deep learning signature verification methodology.

2. Literature Survey

Roughly, the problem of handwritten signature verification has been studied by both traditional and machine learning based approaches. Secondly, earlier methods used handcrafted feature extraction such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG) and Scale Invariant Feature Transform (SIFT). However, these methods were effective, but they were limited by intra - class variability and prone to skilled forgeries, so they had high false acceptance and rejection rates.

As the use of machine learning begins to grow, research came into feature classification eg: Support Vector Machines (SVMs), Hidden Markov Models (HMMs), Random Forests. Although it improved accuracy, these models were heavily feature engineered and were sensitive to variations of signature style.

Signature verification has seen recently advancements in the deep learning. To extract features, CNN based architectures such as VGGNet, ResNet and EfficientNet were used and they turned out to be more robust against forgeries. The concept of metric learning was built on top of Siamese Networks and Triplet Networks, which improved similarity-based verification. In addition, Transformers and self-attention mechanisms were used for contextual understanding of signature pattern.

In order to face the data scarcity, the Generative Adversarial Networks (GANs) are used to generate realistic signature samples, which leads to better model generalization. Additionally, studies of applying blockchain to have secure signature storage and edge AI deployment have also been studied for practical, real-time authentication.

Thus, the presented innovation in our research is based on these advancements that propose a hybrid CNN - Transformer

model with contrastive learning, GAN - based augmentation, and blockchain integration into a secure, high performance signature verification system.

a) Traditional Handcrafted Feature - Based Signature Verification

Early work on handwritten signature verification made use of handcrafted feature extraction techniques, where designer had designed features which able to represent the characteristics of signature. Many methods were used including local binary patterns (LBP), Scale Invariant Feature Transform (SIFT), Histograms of Oriented Gradients (HOG) and Zernike moments. From these signature images, geometric, structural and statistics features were extracted using these techniques.

One of the major difficulties of handcrafted methods was their sensitivity to handwritten style, ink thickness, pressure, and so on. Misclassification due to handwriting inconsistencies, that is variations in signing conditions, was common. Skilled forgeries were also hard to detect since these methods did not have the capability to learn adaptively. On datasets of smaller scale, these techniques worked well yet as they are tested on real-world large-scale datasets, the accuracy of these techniques decreased.

In order to reduce the limitations mentioned above, researchers used rule-based classifiers such as k - nearest neighbors (k - NN), support vector machine (SVM), and decision trees for classification. Despite that, these models exhibited their bias towards feature selection and intra class variations. Better performance was enabled by the transition from feature-based methods to machine learning, which is signature verification.

We build on top of existing techniques by not requiring the manual selection of features, but as opposed to traditional methods, using deep learning-based models which use the signature data to learn robust features automatically.

b) Machine Learning - Based Signature Verification

Early work on handwritten signature verification made use of handcrafted feature extraction techniques, where designer had designed features which able to represent the characteristics of signature. Many methods were used including local binary patterns (LBP), Scale Invariant Feature Transform (SIFT), Histograms of Oriented Gradients (HOG) and Zernike moments. From these signature images, geometric, structural and statistics features were extracted using these techniques.

The most important problem in handcrafted methods was their vulnerability to slight differences in the writing style, ink thickness and pressure. Misclassification due to handwriting inconsistencies, that is variations in signing conditions, was common. Skilled forgeries were also hard to detect since these methods did not have the capability to learn adaptively. These techniques were studied to have worked well on the simpler datasets, but their accuracy dropped when used on large-scale, real-world datasets.

To remedy this limitation, researchers deploys rule based classifier such like k Nearest Neighbors (k NN), Support Vector Machines (SVM), and Decision Tree for classification. Despite that, these models exhibited their bias towards feature selection and intra class variations. Better performance was enabled by the transition from feature-based methods to machine learning, which is signature verification.

We have pushed forward from traditional methods owing to the fact that we do not need to select any features manually and rather use deep learning models that will automatically learn good features from signature data.

c) Deep Learning for Signature Verification

Signature Verification has been revolutionized by deep learning in that it has automated feature extraction as well as improve the classification accuracy. However, Convolutional Neural Networks (CNNs) have been the most successful architecture that learns hierarchical spatial features from signature images. The signature recognition tasks are modeled with state-of-the-art models like VGGNet, ResNet, EfficientNet and MobileNet.

But Siamese Networks and Triplet Networks brought a great improvement in verification accuracy. These architectures employ metric learning whereby model learns a similarity function between two signatures instead of learning how to classify individual signatures. It is particularly suitable for the cases with the limited training data, as it provides the means for one - shot learning.

In recent times, Transformers and Self-Attention Mechanisms have been applied for signature verification. In some cases, Vision Transformers (ViTs) exceed usage of CNNs by modeling the long-range dependencies and contextual relationships within signatures.

The hybrid CNN - Transformer model that we use is of a local spatial feature extraction (CNNs) and global contextual understanding (Transformers). By combining these features, a very robust and forgery resistant signature verification system is achieved.

d) Data Augmentation and Generative Models for Signature Verification

Among the issues in deep learning-based signature verification, lack of proper quality training data used to be one of the biggest. Signature datasets are usually small and imbalanced compared to face recognition datasets with million images.

For this reason, to tackle this issue, researchers have investigated data augmentation techniques including rotation, scaling, affine transformations, elastic distortions to artificially enlarge dataset size. Nevertheless, such traditional augmentations may not always adequately incorporate the indeterminate variations of real signatures.

It was using Generative Adversarial Networks (GANs) that a breakthrough was made in signature verification. Synthetic signatures generated by GANs achieve better model generalization due to their capability of generating synthetic ones similar to real ones. It has been studied that GAN generated samples can assist deep learning models to better learn within user variations and overfitting.

In our research, we combine GAN based data augmentation to generate realistic variations of real signatures that are 3 orders of magnitude better at inspiring trustworthy models than those of skilled and at random forgeries. With this approach, we guarantee that our verification system remains effective even in cases where there is limited amount of actual world training available.

e) Blockchain and Edge AI for Secure and Real - Time Signature Verification

With the rise of this signature verification systems, there is a demand of such systems to be deployed securely and efficiently. Traditional cloud-based model are plagued by risks of data privacy, tampering, as well as latency. Thus, in order to address these challenges, researchers have investigated blockchain as well as edge AI solutions.

Signature authentication records are stored in tamper proof way using blockchain technology. All offers are stored on a decentralized ledger and are unalterable and verifiable. It prevents fraudulent alteration thereby making sure there's no room for shenanigans and making necessary for use in applications such as legal documentation and financial transactions.

Real time signature verification is made possible on mobile devices and embedded computers not having to be connected to the internet all the time. The deployment of lightweight models on smartphones, line power hardware can easily be done using TensorFlow Lite, ONNX and pruning and quantization techniques.

To achieve security, real time, and scalability, our proposed system for edge AI enabled blockchain integrated signature verification is a new work. This is a good approach specifically for cases where offline authentication is required, as in offline banking, offline or remote contracts, and identity verification in remote places.

3. Materials and Methods

The handwritten signature verification system based on deep learning is effective only if high quality and diversity datasets are used for training from the dataset. For the research in this manuscript, we have used publicly available signature datasets like CEDAR, MCYT, GPDS and SigComp which contain mixtures of genuine and forged signatures. In real world applications, it is typically the case that signature samples per user are limited, therefore we employ data augmentation techniques as elastic distortions, affine transformations, Gaussian noise and contrast normalization. We also use Generative Adversarial Networks (GANs) to generated true for realistic variations in the signature that gives the model the ability to generalize and become more robust at times to the skills of the forger. Grayscale conversion is used so that preprocessing pipeline focuses on structural features, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance contrast, Gaussian filtering is done to reduce noise and standard resizing of the image to 128×128 or 256×256 pixels to make input images uniform.

We propose a hybrid deep learning architecture with Convvolutional Neural Networks (CNN) and Vision Transformers (ViT) for feature extraction as input and classification. Using CNNs, spatial patterns such as stroke thickness, curvature or local texture variations are efficiently captured that are key for distinguishing a genuine from a forged signature. Since EfficientNet B3 backbone is rather small and captures good feature from the image, we choose to adopt it as the CNN backbone. This is complemented by Vision Transformers as they learn the global dependencies as well as the sequential stroke relationships that are critical for analyzing varying handwriting. Unlike CNNs, Transformers with self-attention mechanisms enable the system to model intra user variations as well as highly skilled forgeries.

We adopt Siamese Neural Network (SNN) architecture in order to provide high accuracy verification. SNNs compare two signature images and classifies their similarity instead of classfying individual signatrues. The network is formed as two subnetworks for each signature, each of which processes the signature separately and shares its weights, so both signatures are passed through with identical feature extraction.

An L2 distance metric is used to compare output feature embeddings to compute similarity score. The model is trained using contrastive loss and triplet loss functions, i. e., forged signature pairs will have relatively large distance in feature space compared to genuine signature pairs. The system allows for one - shot learning, achieving high accuracy of verifying signatures even with very little training samples using such an approach to metric learning.

PyTorch and TensorFlow are used to train the model and AdamW and learning rate learning are used for stable convergence. We thus add dropout regularization (0.3), batch normalization and L2 weight decay in order to prevent overfitting. Acceleration of the training is achieved using an NVIDIA RTX 3090 GPU and distributed training of multiple GPUs for efficient computation. Specifically, data augmentation techniques, including GAN based synthetic signatures, further help training with limited data in generalization purpose by providing extra training samples.

After training, the pipeline of the verification system follows the order of: upon windowing a scanned or digital signature, the user’s signature is preprocessed to remove noise and normalize. The feature embeddings are extracted by hybrid CNN - Transformer model and the similarity score is computed with respect to stored genuine signatures using Siamese Network. The signature is classified genuine and if the similarity is above a predefined threshold, or rejected if not. The accuracy and false rejection rates are balanced by this thresholding mechanism.

The model is optimized for edge AI, such that it works in real time and securely. Model size and latency are reduced through quantization and pruning techniques so that they can be efficiently executed on mobile devices, embedded systems, as well as Edge TPU hardware like NVIDIA Jetson, Google Coral. Low latency verification that is suitable for legal, forensic and banking applications is ensured. To achieve security by preventing tampering, we integrate

blockchain technology in storing verified signatures. The trick of the blockchain is that everyone on the ledger can see precisely what is being authenticated, meaning no one can change a signature once its been authenticated. As an integration, this will offer a scalable and fraud - proof way of verifying high security signatures for applications.

As a result of our proposed system being composed of hybrid deep learning architectures, contrastive learning, GAN based data augmentation, edge AI optimizations, and blockchain backed storage, our system achieves state of the art performance in the handwriting signature verification task. The methodology guarantees high accuracy, does not require skilled forgery, real time processing and tamper proof authentication, making it — in fact — an adequate solution for modern digital signature verification systems.

4. Results and Discussion

In order to test the effectiveness of proposed deep learning based handwritten signature verification system over the multiple benchmark datasets on CEDAR, MCYT, GPDS and SigComp. Experimental results show that the verification accuracies of the hybrid CNN - Transformer architecture with a Siamese Neural Network is much higher than that of traditional methods. The system achieves an accuracy of 98.2% on CEDAR, 97.5 and 96.8 on MCYT and GPDS, respectively, outperforming CNN based conventional models and classical ML. This high accuracy demonstrates that the model is able to handle the intra - user variations that lead to robustness against skilled and random forgeries.

We find that the hybrid CNN - Transformer approach has one the most significant results. Although CNNs are efficient at extracting local spatial features like stroke thickness and the curvature, Transformers facilitate the understanding of global contextual information derived from serial stroke relationships. It improves verification performance, and especially in the case where a forged signature intends to mimic this individual strokes but reproduces to the overall structural flow of the signature. Although CNN - based models are limited because they cannot focus on fine grained details, Self attention mechanisms in the model helps it focus on what is differentiating the genuine signature from a forgery.

By learning useful similarity relationships between the signature pairs, the Siamese Network with contrastive loss was proven to be highly effective. The proof of sign verification task by learning the distance metric in the Siamese architecture, it means that the true signature embeddings are close to each other while forged signatures are far away from each other in the features space. The use of contrastive loss function allowed FAR and FRR to be reduced to 1.2% and 1.5% respectively which made the system fairly reliable for real world authentication.

In order to deal with the case of limited training data, the data augmentation based on GAN was useful to achieve generalization of models. GANs provided additional training with generated realistic synthetic signatures to help the model learn the intra user changes more effectively. In addition to elastic distortions, affine transformations, and Gaussian noise augmentation to help reduce overfitting, the model was proved to well handle unseen samples.

Critical aspects that were also analyzed in the study were computational efficiency. Finally, the optimized deep learning model was deployed using TensorFlow Lite and ONNX Runtime for real time verification for edge device such as NVIDIA Jetson Nano, Google Coral TPU and mobile processors. The model, with quantization and pruning, could achieve inference time of 12 ms per signature comparison, which is enough for instant verification applications including banking transactions and legal documentations.

The main innovation of this research is making the blockchain used to store signatures secure. Once blockchain has verified and stored a signature, this is immutable—that's by design—and cannot be forged. This approach makes security important, especially in high stake application such as financial transaction and document authentication. Finally, verification signatures were successfully stored and retrieved with a minimal amount of overhead within the blockchain, proving the scalability and tampering - proof aspect of the verification system implemented on the blockchain.

It also mentioned some limitations. The model performs very well on publicly available datasets but unblocked real world scenarios may violate, for example, acquisition variations of signature (digital, scanned or photographed signature). The future work includes expanding the dataset to have more diverse signature samples through federated learning to achieve privacy preserving authentication and multi modal biometric integration (e. g., signatures and handwriting dynamics, signatures and fingerprints, etc).

Overall, the results indicate that, the proposed hybrid deep learning method performs well in terms of the accuracy, real time and security needed in the handwritten signature verification. This system is a next generation in biometric authentication using CNN Transformer architectures, metric learning, GAN based augmentation, edge AI optimizations and blockchain security together which is suitable for banking, legal, and digital identity verification applications.

5. Conclusion and Future Enhancement

The design of a deep learning based handwritten signature verification system is a significant contribution to the biometrics authentication as the system employs a higher degree of security, robustness, and real time verification feature. A hybrid CNN - Transformer architecture with Siamese Neural Network to solve the classification of the signatures sample was proposed. Transformer self-attention mechanisms alongside convolutional layers for feature extraction at each frame have resulted in a very good combination that enables a more robust verification process to intra user variations and less robust to skilled forgeries. We experimentally show that this approach can attain state of the art across several benchmark datasets matching the performance of the state of the art in both traditional machine learning as well as standalone CNN architectures. Additionally, the use of contrastive learning in a Siamese Network has permitted the model to learn robust relationship between similarities, thus reducing the false acceptance and

false rejection rates, the key issues in real world biometric application.

In order to generalize even further, data augmentation techniques like GAN generated synthetic signatures and elastic distortions and affine transformations has been used. With this augmentation strategy, the limitations of data scarcity are mitigated so that the model can overcome data gap between individuals and acquisition conditions. Finally, we optimize the model's deployment using TensorFlow Lite and ONNX Runtime to support real time execution at the edge, on mobile CPUs, NVIDIA Jetson Nano, and Google Coral TPU. With an optimized inference time of 12 milliseconds per signature comparison, the system is processed fast enough to seamlessly integrate in high-speed authentication workflows like bank transactions, legal documentations and forensic investigations.

This research has focused on security and thus integrated blockchain technology to allow storage of verified signatures in tamper proof servers. The system uses a decentralized ledger in which, once authenticated and stored, a signature is immutable, cannot be altered and is protected from the unauthorized person. This technique will be useful to strengthen with high level of trust and non-repudiation in the applications. This is why blockchain based storage system has been designed to efficiently support large scale deployment with minimal computational overhead and hence is a good option for securing financial, legal and the governmental signature verification.

Despite its high performance, the system still faces certain limitations that present opportunities for future enhancements. Variability in signature acquisition methods is one of the main challenges for recognition of signatures collected via varied mediums, e. g., scanned documents, touchscreen devices or paper-based captures. Future work will involve developing an adaptively preprocessed pipeline for inputs verifiably obtained from different signal sources such that verification accuracy is not compromised. Furthermore, multi modal biometric authentication, that is the addition of signatures and handwriting dynamics, keystroke analysis or fingerprint recognition, can increase security and decrease the likelihood of forgery. A second promising direction is to include federated learning which would bring model training with privacy preserving across decentralized data sources and hence permitting the organizations to boost verification accuracy without sharing sensitive signature data. The integration of such methods of explainable AI (XAI) could also contribute to increasing the level of transparency in the decision-making process of the verification system, enabling to understand why a verifier authenticated a person or not. Future research may also explore energy efficient AI models for signature verification, so that the signature verification can be more power efficient in mobile and IoT based authentication systems. With the continuously improved and extended capability set of this verification system, this can be presented as the next generation solution for secure, realtime scalable biometric authentication.

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