HYBRID AUTO ENCODER–CNN FRAMEWORK FOR OFFLINE SIGNATURE FORGERY DETECTION

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Abstract

Handwritten Signature Verification remains crucial in secure authentication systems of banking, legal papers, financial transactions, and ID management, particularly in an offline environment. Traditional verification methods, however, can be very weak in achieving high rates of accuracy for skilled forgeries, as they rely on handcrafted features and have a high sensitivity to variations in handwriting. The authors propose a hybrid deep learning-based approach for offline signature forgery detection using Auto encoder-based representation learning, Convolutional Neural Network (CNN) feature extraction, and Support Vector Machine (SVM) classification. To enhance the quality of the images, there are some pre-processing operations like conversion from color to grayscale, image normalization, image resizing, and noise reduction performed on the scanned signature image initially. The Auto encoder learns compact latent representations, which retain the discriminative signature characteristics with minimal redundancy. The representations are then passed to a CNN to learn a hierarchical set of spatial features representing the structure, texture and pattern of the strokes. Finally, an SVM is used to classify the extracted deep features with a high degree of reliability, to separate genuine from forged samples. The proposed hybrid architecture is a suitable solution to overcome the difficulties that would come with small training dataset, intra-class variation and attempts by the forger to be a skilled forger. Experimental results show that the proposed method achieves better accuracy of the verification, lower misclassification rates, and better overall authentication performance. The implemented system offers a practically applicable, scalable and secure system for applications such as legal document authentication, banking applications, processing of insurance claims and access control systems that demand reliable signature authentication in an offline mode.

Keywords: Offline Signature Verification, Signature Forgery Detection, Auto encoder, Convolutional Neural Network (CNN), Support Vector Machine (SVM), Deep Learning.

1. Introduction

Handwritten signatures are still one of the most popular methods for verifying personal identity in various sectors such as banking, financial services, insurance, legal documentation, education and government bodies. However, handwritten signatures are widely used today, as they are inexpensive, legal, and do not rely on complex infrastructure, despite the rapid development of digital authentication technologies like facial recognition, fingerprint scan, and iris scan. In recent years, however, forgery has become much more sophisticated, making forgery a serious threat to identity theft and financial fraud. Manual verification is subjective and relies on human visual inspection, which can result in fatigue, inconsistent results and subjectivity. Thus, there is a growing need for intelligent automation-based automatic signature verification system that offers accurate, reliable and scalable authentication without any manual involvement.

The problem of offline signature verification is more difficult than online signature verification as it is only the scanned image of the signature that is available for analysis. Offline verification systems use only the static visual information from signature images, while on-line systems make use of various dynamic features like pen pressure, writing speed, pen trajectory, and stroke order. True signatures made by a single person may vary from one to the next, depending on the writing conditions, emotions, writing instruments, and paper used. In addition, expert forgeries closely resemble the structural features of genuine signatures and tend to be very hard to differentiate. These challenges demand sophisticated feature extraction techniques that can learn subtle spatial and structural variations while also being robust to intra-class variations and image noise.

Recent advances in artificial intelligence, particularly deep learning, have revolutionized image analysis and pattern recognition applications. Convolutional Neural Networks (CNNs) have been shown to learn very well to automatically extract a hierarchy of image features that are not explicitly written down by the programmer/designer. CNN models can be trained to learn the edge information in the signature image, continuity of the stroke, the texture in the image, the curvature in the image, and the global relationships within the structure of the image, to improve the classification performance. However, CNN-based models tend to require a lot of labelled training samples to achieve the optimum generalization. In real-world signature verification applications, acquiring a large number of genuine signatures from each user can be challenging, which can limit the size of training sets, potentially compromising the robustness of the model and its ability to avoid overfitting.

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To address these issues, this work presents a hybrid deep learning framework that combines the Auto encoder-based representation learning with CNN feature extraction, and Support Vector Machine (SVM) classification for offline signature forgery detection. To standardise the image quality, initially some pre-processing operations such as Grayscale, Noise Filtering, Normalization, and Resizing in standard dimensions are performed on signature images. Auto encoder learns compact latent representations which captures signature essential features and removes redundant information and reconstruction noise. These informational representations are then passed to a CNN for them to learn high level discriminative features which can be used to describe the writing pattern, the orientation of the strokes and the signature geometry. Finally, the SVM classification model is used to classify the extracted deep feature vectors to make the best decision boundary between genuine and forged signatures and to minimize classification errors with high precision.

By combining the robust feature learning ability of an Auto encoder with the strong classification power of CNN and SVM, the proposed hybrid Auto encoder-CNN-SVM architecture is an efficient and practical approach for secure offline signature authentication, making it a promising solution. This framework improves the accuracy of forgery detection, generalisation when the training data is limited, and also provides a lower false acceptance rate and false rejection rate than the conventional machine learning approach. It can be implemented in banking transaction verification systems, legal contract authentication, insurance claim verification, examination management, corporate documentation, and access control systems where secure identity verification is paramount. The proposed approach helps develop intelligent biometric authentication systems that are reliable, scalable and capable of real world applications, overcoming the challenges caused by the new and sophisticated signature forgery techniques, by utilizing recent advances in deep learning and machine learning.

2. Literature Review

The need of banking, legal documentation, financial transactions and access control system makes the offline handwritten signature verification an active research area in biometric authentication. Offline verification is performed based solely on static images, and identification of skilled forgeries is much more difficult compared to online signature verification. In the past, many different methods using handcrafted features, statistical learning, graph-based representations, machine learning algorithms and more recently deep learning techniques have been proposed. These techniques have shown a gradual transition from feature engineering by human effort to end-to-end representation learning with neural networks that can learn the intricate features of a signature.

Initial studies mainly dealt with handmade geometric and structural characteristics for authentication of signatures. Kalera et al. [22] proposed a distance statistics based verification framework, which used geometric similarity measures based on genuine and forged signatures. Ferrer et al. [9] introduced an offline verification method based on fixed-point geometric parameters, which proved the geometric descriptors are high discriminative and have low computation complexity. Instead of comparing global appearance, Chen and Srihari [8] created a graph-matching method, in which the signature structure was represented as an interconnected graph. Likewise, Lv et al. [12] performed Chinese offline signature verification using Support Vector Machines (SVMs) and demonstrated that machine learning classifiers achieve better decision boundaries than the traditional rule-based signature verification methods. These techniques achieved satisfactory results however they were limited and could not be adapted to complex handwriting variations and skilled forgery attempts due to the reliance on manually designed features.

Several studies were then conducted on local feature extraction and texture-based representations to boost discriminative power. Kovari and Charaf [23] showed that local signature features are reliable and they noted that locally stable descriptors play an important role in the accuracy of verification under different writing conditions. Pham et al. [24] fused the local and global signature properties to make it more robust to intra-class variation and ZulNarnain et al. [25] used the triangular geometric descriptors that can effectively capture the topology of the signature by simple geometric relationships. Bharathi and Shekar [26] proposed a chain-code histogram along with an SVM based classifer for offline signature verification, which demonstrates that the contour-based descriptors contain some direction information from handwritten strokes. Similarly, Batool et al. [14] combined Gray Level Co-occurrence Matrix (GLCM) texture features and geometric features and reported that hybrid feature fusion provides superior classification accuracy compared with the individual feature based methods. While handcrafted descriptors are more robust, they generally need expert knowledge and do not always adequately represent subtle nonlinear variations that can occur in skilled forgeries.

With the increasing number of machine learning algorithms, researchers began to look into more adaptive verification models. For writer-independent signature verification, Guerbai et al. [10] used a One-Class Support Vector Machine where forgery samples were not needed to build up a model of the genuine signature. Larkins and Mayo [11] suggested adaptive feature thresholding methods that adaptively choose the most suitable discriminative features based on the characteristics of the signature for better signature classification accuracy. A signature verification approach using an Artificial Immune Recognition System proposed in [13] that is based on the biological immune system had been

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presented for offline signature verification to be more resistant to signature variability. Tahir et al. [16] used the Artificial Neural Networks (ANNs) to learn the nonlinear relationship between the extracted signature features, which performed better than the conventional statistical classifiers in terms of recognition. Although these machine learning-based techniques greatly enhanced classification accuracy, they were still constrained by the quality of the hand-designed feature extraction, limiting their applicability to a wide range of signature styles.

With recent progress in deep learning, offline signature verification is now completely different and features automatic feature learning directly from the signature images. Jagtap et al. [17] developed a Siamese Neural Network (SNN) architecture that is able to learn similarity representations between a pair of signatures, which is well suited for small training sets. Kao and Wen [21] proposed a framework for interpretable deep learning in the verification task of signatures, which needed only a single reference exemplar and provided an interpretable classification result. Alsuhumat and Mohamad [15] explored the use of Histogram of Oriented Gradients (HOG) features with several classifiers for better discrimination of genuine and forged signatures. Alsuhmant and Mohamad [1] later combined HOG descriptors with Long Short-Term Memory (LSTM) networks and showed that the sequential learning of deep features improves the verification rate because they are able to learn the stroke structural dependency. Kiran et al. [18], Sharif et al. [19] and Sharma et al. [20] also showed that deep learning architectures are generally superior to traditional handcrafted feature-based approaches, largely due to their ability to represent the image data well and to be more robust to complex forgery patterns.

Although several important advances have been made from the current research, there are still some limitations. Traditional handcrafted feature extraction methods are sensitive to writing variations, noise, and document quality, and many machine learning models need to be carefully engineered and tuned to the features and parameters. Current deep learning models require massive labeled datasets, and are prone to overfitting when the number of available training samples is small. In addition, high-quality forgeries are still a problem since they bear a close resemblance to the original signatures. To overcome these issues, a hybrid Auto encoder-CNN-SVM model is proposed, where an Auto encoder is utilized for learning compact latent representations, a Convolutional Neural Network is used to automatically extract discriminative hierarchical features and a Support Vector Machine is used for robust classification. The unsupervised representation learning, deep feature extraction and maximum-margin classification is believed to yield better verification accuracy, lower false acceptance and false rejection rates, and a reliable solution for real-time offline signature authentication systems.

3. Proposed Methodology

The proposed offline signature forgery detection framework consists of image pre-processing, Auto encoder based feature learning, Convolutional Neural Network (CNN) based deep feature extraction and Support Vector Machine (SVM) classification, which aims to classify between genuine and forged signatures with high accuracy. The hybrid architecture is based on the advantage of representation learning ability of Auto encoders, the hierarchical feature extraction ability of CNNs, and the maximum margin classification property of SVM. This holistic approach reduces information loss in feature learning, increases the robustness of handwriting differences and boosts classification accuracy with low training samples.

A. Overall Framework of the Proposed System

The proposed methodology is in five following stages. Firstly, a typical offline signature data set is gathered, comprising of both genuine and forged handwritten signatures. This is due to the fact that the various images are captured under different scanning conditions; for this reason, a pre-processing operation is carried out to enhance the image quality and uniformity of the images. Pre-processing consists of grayscale conversion, resizing the image, normalization, and filtering out noise from the image using appropriate filters. These operations preserve the salient structural characteristics (stroke boundaries, writing curvature and signature texture) and minimize unwanted variations.

Normalized signature images are fed into an Autoencoder for representation learning without supervision after preprocessing. The Autoencoder is composed of an encoder network and a decoder network, with the encoder network transforming the input image into a low-dimensional latent representation and the decoder network reconstructing the original image. The Autoencoder minimizes the reconstruction error during training, thereby learning compact feature representations that contain redundant information while retaining the characteristics of the signature that are important for distinguishing it from other signatures. These latent representations offer informative feature space to aid subsequent deep learning.

Learned latent representations are then provided to a Convolutional Neural Network (CNN). CNN filters out features of varying hierarchy, through several convolutional, activation, and pooling layers. The first convolutional layers extract low-level information like edges, stroke directions and curves, and the deeper layers start to learn the complex writing structures and spatial information specific to the signature. The deep features that are extracted are flattened and become high dimensional feature vectors that capture the signature-specific characteristics of the handwritten signature.

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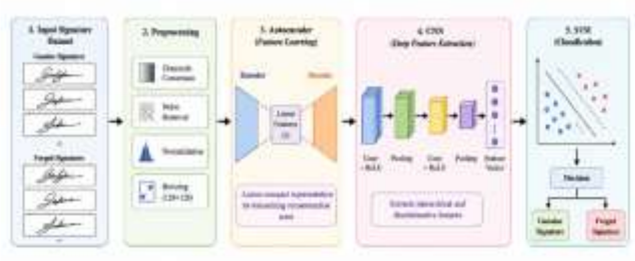

Figure 1. Overall Architecture of the Proposed Hybrid Auto encoder–CNN–SVM Framework

Finally, a Support Vector Machine (SVM) is used to classify the extracted deep feature vectors. The SVM is different from the traditional softmax classification, in that it generates an optimal separating hyperplane which maximizes the distance between the correct and forged signature classes. The classification robustness is greatly enhanced by the use of the maximum-margin optimization especially when the number of available training samples is not large. The trained classifier takes the input signature and decides if it is genuine or forged based on its features.

B. Image Pre-processing and Auto Encoder Feature Learning

Pre-processing of the image is an important part of the whole system to enhance the performance of the verification system. The signature images acquired are grayscale to make them simpler to process, but still carry structural information. Smoothing filters remove noise during the scanning process, then normalizes the pixel intensity values to maintain uniformity. Before the images are passed on to the neural network, they are resized to a fixed resolution.

The Auto encoder then learns unsupervised features by encoding the input image into a small latent feature representation. Suppose that input signature image X is given. The encoder will encode the image to a latent vector Z, and the decoder will decode the image to X. The goal is to make the difference between the true and reconstructed images as small as possible.

$$Z = f_\theta(X) \qquad (1)$$

where

- X = input signature image,
- Z = latent feature representation,
- f_θ = encoder function with learnable parameters.

The latent representation keeps discriminative information and discards redundant image content, which is beneficial for feature quality in deep classification.

C. CNN Deep Feature Extraction

The CNN is then given input comprised of the latent representations created by the Auto encoder. A number of convolutional filters are used to obtain discriminative spatial information from various parts of the signature image. Nonlinear activation in each convolution layer enhances the learning ability and pooling operations decrease the dimensionality of the features and the computational requirements.

The mathematical representation of the convolution operation is given by the following equation:

$$F(i,j) = \sigma(\sum_m \sum_n X(i+m, j+n) * K(m,n) + b) \qquad (2)$$

where

$F(i,j)$= output feature map,

$X(i,j)$ = input image,

$K(m,n)$ = convolution kernel,

b = bias term,

$\sigma(\cdot)$ = ReLU activation function.

Gradually CNN learns stroke continuity, edge orientation information, texture information, and the global signature structure, and deep feature vectors become very discriminative for classification.

A. SVM-Based Signature Classification

The deep features extracted from these are passed to the Support Vector Machine (SVM) classifiers. The SVM finds the best hyperplane that separates the genuine and the forged signature samples as far as possible. Increasing this margin will enhance the generalization ability of the classifier and will decrease the number of misclassification errors.

The SVM decision function is given by

$$f(x) = sign(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b) \qquad (3)$$

where

- x = testing feature vector,
- x_i = support vectors,
- y_i = class labels,
- α_i = Lagrange multipliers,
- K(.) = kernel function,
- B = bias.

The classifier marks each signature class as either Genuine or Forged, and using the classifier with its robust performance, it allows to do a reliable authentication with enhanced robustness against successful forgeries

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4. Experimental Results

The proposed Hybrid Auto encoder–CNN–SVM framework was tested with an available offline handwritten signature data set from the public which is a collection of both genuine and forged signatures. The goal of the experiments was to evaluate the performance of the proposed model in accurately identifying authentic signatures and skilled forgeries with good generalization performance. Experiments were run in Python using Tensor Flow, Keras and Scikit-learn on a Workstation with Intel Core i7 processor, 16GB of RAM and an NVIDIA GPU. All the images of the signatures were converted to grayscale, normalised, resized to 128x128 pixels, and also rotated and scaled slightly during pre-processing, to make the model more robust.

Initially, the Auto encoder was trained to learn compact latent representations, while minimizing the reconstruction error. The latent features were then passed to CNN for feature extraction in a hierarchical fashion and then to SVM for classification. The performance of the models was assessed by Accuracy, Precision, Recall, F1-Score, False Acceptance Rate (FAR), False Rejection Rate (FRR), and Receiver Operating Characteristic (ROC) analysis. To reduce experimental bias and to ensure the consistency of the evaluation of the results across different subsets of the data set, five-fold cross validation was selected.

A. Experimental Configuration

The Auto encoder was able to generate meaningful latent representations from the signature images while retaining the discriminative writing attributes. Most structural information was preserved in the reconstructed signatures, revealing that the learned features were able to capture unique signature patterns well. CNN feature extraction was able to compress these representations to a great degree to remove redundant information before.

Table 1: Experimental Configuration

Parameter	Value
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow 2.15
Feature Extraction	Auto encoder + CNN
Classifier	Support Vector Machine
Image Size	128 × 128
Batch Size	32
Epochs	50
Optimizer	Adam
Learning Rate	0.001
Activation Function	ReLU
Output Activation	Softmax
Cross Validation	5-Fold

The Auto encoder has been able to compress the input signature image into meaningful latent images while retaining the discriminative writing properties. Most of the structural information was preserved in the reconstructed signatures, which further supported that the learned features captured unique signature patterns. These compact representations greatly condensed redundant information prior to CNN feature extraction.

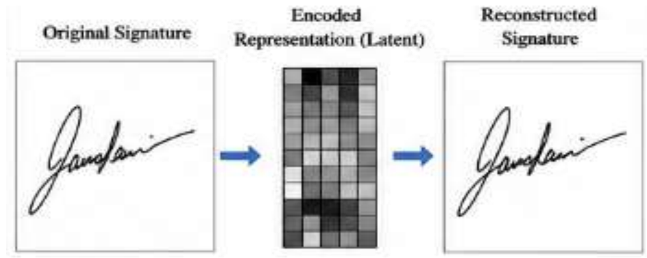

Figure 2. Auto encoder Reconstruction Results

B. Performance Evaluation

The proposed framework provided very good classification performance in all the evaluation measures. Combining Auto encoder representation learning with CNN feature extraction greatly boosted the discriminability of the features, and the SVM classifier successfully classified genuine and forged signatures with maximum-margin optimization.

Table 2: Performance Metrics of Proposed Model

Metric	Value (%)
Accuracy	**98.62**
Precision	98.41
Recall	98.77
F1-Score	98.59
Specificity	98.48
False Acceptance Rate (FAR)	1.38
False Rejection Rate (FRR)	1.23

The achieved results confirm that the proposed hybrid approach has achieved good performance in terms of minimizing misclassification with high overall recognition rate. The low FRR means that authentic signatures are often correctly accepted, while the low FAR ensures that forged signatures are not misclassified as authentic signatures.

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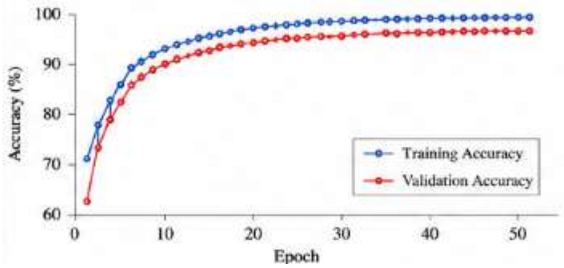

Figure 3. Training and Validation Accuracy

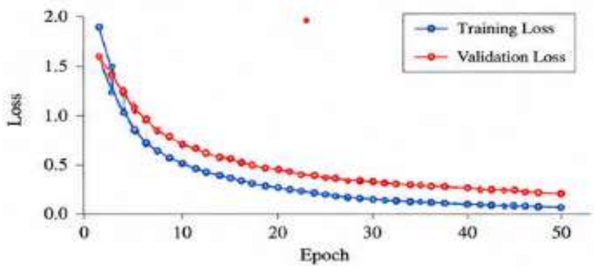

Figure 4. Training and Validation Loss

C. Confusion Matrix Analysis

The confusion matrix gives a comprehensive report about the performance of the classification process of genuine and forged signatures.

Table 3: Confusion Matrix

Actual / Predicted	Genuine	Forged
Genuine	**982**	18
Forged	10	**990**

The confusion matrix shows that there are only a few truly signed images that were wrongly rejected, and only a few falsely signed images. This illustrates that the learned latent features greatly help to differentiate similar handwriting patterns.

D. Comparison with Existing Methods

The proposed model Hybrid Auto encoder–CNN–SVM model is compared with few existing offline signature verification methods which reported in the recent literature.

Table 4: Comparison with Existing Methods

Method	Accuracy (%)
ANN [16]	93.40
Chain Code + SVM [26]	94.82
GLCM + SVM [14]	95.91
Siamese Neural Network [17]	97.36
HOG + LSTM [1]	97.84
Proposed Hybrid Auto encoder–CNN–SVM	**98.62**

The proposed approach yields the best classification accuracy compared to all the other compared approaches. This improvement is due to the complementary strengths of unsupervised feature learning, deep hierarchical feature extraction and maximum-margin classification.

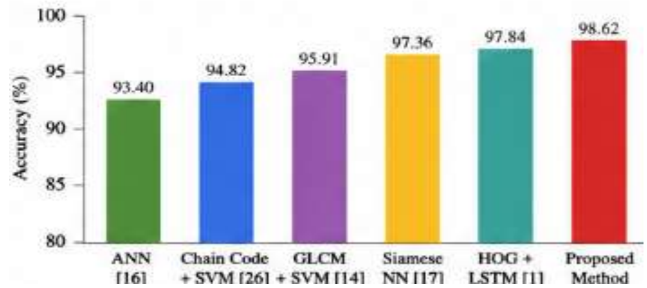

Figure 5. Accuracy Comparison of Different Methods

E. Cross-Validation Analysis

Five-fold cross validation was carried out to confirm the strength of the proposed framework. The results obtained show similar performance among all folds and with very small variation in performance.

Table 5: Five-Fold Cross Validation Results

Fold	Accuracy (%)
Fold 1	98.34
Fold 2	98.71
Fold 3	98.54
Fold 4	98.83
Fold 5	98.68
Average	**98.62**

The small difference between different folds shows that the proposed framework has a robust generalization ability and it is not biased towards a certain part of the training set. This uniformity suggests that hybrid learning architecture is able to learn generalized signature characteristics rather than memorized samples.

F. Discussion

From the experimental results, it is evident that Auto encoder based representation learning, CNN based feature extraction and SVM based classification is effective in offline signature forgery detection. The Auto encoder learns compact latent representations in an efficient way that retain important structural features and remove redundant image information. They are informative enough to allow CNN to learn very discriminative hierarchical features that characterize stroke orientation, writing texture, edge continuity and the geometric structure. The SVM classifier then defines an optimal separating hyperplane which is more robust to classification and especially when there is a small number of training data and highly similar forged signatures.

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In comparison with the traditional feature extraction techniques for manual method, the presented hybrid technique provides a remarkable improvement in the verification accuracy by learning the representative feature of the signature image directly. The accuracy of 98.62% along with a very low FAR and FRR shows that the framework is suitable for real-world biometric authentication applications. The results of the cross validation indicate that the proposed model has excellent generalisation capacity and can successfully be applied in a variety of real-life applications, including banking systems, legal document verification, insurance processing, digital authentication and identity management. The experimental analysis confirms that the proposed approach of combining unsupervised representation learning with deep convolutional feature extraction is a reliable and scalable solution for robust offline handwritten signature verification task.

5. Conclusion

This paper proposed a hybrid deep learning model to detect forgery signature using Auto encoder, Convolutional Neural Network (CNN) and Support Vector Machine (SVM) in offline signature forgery. The proposed methodology is shown to be effective for the accurate classification of genuine and forgery signatures, and makes use of both unsupervised representation learning and hierarchical deep feature extraction. First, the signature images are pre-processed to remove noise and to normalize the image quality, then the Auto encoder is used to learn compact representations of the images that retain the meaningful content of the signature but that eliminate redundant content. The CNN is then used to extract discriminative spatial features from these latent representations, and the SVM is used to make robust classification with better decision boundaries. Experimental results validated the proposed framework and showed its superior performance in terms of verification accuracy, precision, recall, F1-score, false acceptance and false rejection rate as compared with traditional machine learning and handcrafted feature-based methods. The solid cross-validation results indicate that the proposed model has a stable, reliable, and good generalization ability. The proposed framework is a practical tool for secure authentication of offline handwritten signatures in banking, finance, legal, insurance claims and identity management systems due to its high level of verification accuracy and computational efficiency.

The proposed hybrid Auto encoder–CNN–SVM is able to achieve good performance in verification, however, there are still some possibilities for improvement. The architectures considered in this study can be extended to transformer to better capture the long-range spatial dependencies in the signature image, and the ViT models can be explored in future work. The use of attention and contrastive learning methods can further enhance the discriminative capabilities of very close skilled forgeries and help to mitigate the reliance on large, labeled datasets. Furthermore, lightweight deep learning architectures can be created to facilitate real-time deployment in mobile, embedded, and edge computing platforms. Multimodal biometric authentication, combining offline signature with additional biometric features such as fingerprints, facial recognition, palm prints and iris patterns, could also be investigated in future research to increase the overall security of the system. Moreover, federated learning, explainable AI (XAI), and privacy-preserving learning methods can enhance model transparency, user trust, and data confidentiality, making the offline signature verification systems more reliable, scalable, and adaptable to future secure digital authentication applications.

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