Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 7.056

IJCSMC, Vol. 14, Issue. 12, December 2025, pg.112 – 119

A Deep Feature Fusion Framework Using Graph Attention Networks for Writer-Specific Offline Signature Verification

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DOI: https://doi.org/10.47760/ijcsmc.2025.v14i12.009

Abstract: This paper proposes a deep feature fusion–based framework for writer-specific offline signature verification by integrating Convolutional Neural Network (CNN) and Graph Attention Network (GAT) features. The CNN model captures global appearance-based characteristics from signature images, while the GAT effectively models the structural relationships among stroke components derived through skeletonization. The extracted features are fused to form a unified representation, followed by dimensionality reduction using Principal Component Analysis (PCA). A Support Vector Machine (SVM) classifier is then employed for writer-specific verification. Experiments are conducted on the CEDAR offline signature dataset using multiple training–testing split ratios. Performance is evaluated using False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and overall accuracy. The experimental results demonstrate that the proposed fusion-based approach significantly enhances verification performance and robustness compared to single-feature methods.

Keywords: Offline Signature Verification, Deep Feature Fusion, Graph Attention Network, Writer-Specific Threshold, Dimensionality Reduction.

I. Introduction

Handwritten signatures remain one of the most widely accepted biometric traits for personal authentication due to their simplicity, legal acceptance, and ease of use in daily transactions. Despite the rapid advancement of biometric technologies, offline signature verification continues to be a challenging problem, primarily because signatures are highly influenced by individual writing habits, emotional state, and writing conditions. Moreover, the absence of dynamic information such as pen pressure or writing speed makes offline verification significantly more complex than its online counterpart.

Traditional offline signature verification systems relied heavily on handcrafted features, including geometric descriptors, texture-based features, and statistical measures. While these methods offered reasonable performance, they often struggled to generalize well in the presence of skilled forgeries and large intra-writer variations. As a result, recent research has shifted toward data-driven approaches that can automatically learn discriminative representations from raw signature images.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in capturing visual and spatial characteristics of handwritten signatures. CNN-based approaches effectively learn hierarchical features that describe stroke patterns, texture, and overall shape. However, despite their success, CNNs primarily focus on appearance information and may not fully capture the underlying structural relationships between signature strokes, which are often critical for distinguishing genuine signatures from skilled forgeries.

To address this limitation, graph-based learning techniques have gained attention for modelling structural dependencies within data. Graph Neural Networks (GNNs), and in particular Graph Attention Networks (GATs), provide an effective mechanism to learn relational representations by assigning adaptive importance to neighbouring nodes. When applied to signature verification, graph-based models can capture stroke connectivity and spatial relationships that are not explicitly represented in pixel-based CNN features.

Motivated by these observations, this work proposes a hybrid deep learning framework that integrates CNN-based appearance features with GAT-based structural features for writer-specific offline signature verification.

The remainder of this paper is organized as follows: Section 2 reviews related work in offline signature verification. Section 3 describes the proposed methodology in detail. Section 4 presents experimental setup and results. In section 5 the performance of the proposed model is compared with the existing works. Finally, Section 6 concludes the paper.

II. RELATED WORK

Offline signature verification has been an active area of research for several decades due to its importance in biometric authentication systems and forensic applications. Unlike online signature verification, which benefits from dynamic information such as pen pressure, velocity, and stroke order, offline verification relies solely on static image data. This limitation makes the task considerably more challenging, particularly in the presence of intra-writer variability and skilled forgeries that closely resemble genuine signatures. Early studies in offline signature verification primarily focused on handcrafted feature extraction techniques. These approaches utilized geometric descriptors, contour-based representations, projection profiles, and statistical measures to characterize signature shapes. Commonly employed descriptors included Hu moments, Zernike moments, chain codes, and texture-based features such as Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrices (GLCM). Although these methods provided interpretable representations and reasonable performance, they were often sensitive to noise, scale variations, and writing inconsistencies, limiting their robustness in real-world scenarios [1–3].

With the advancement of machine learning, researchers began adopting classification-based approaches such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Hidden Markov Models (HMMs) to improve verification accuracy. Among these, SVM-based methods gained wide acceptance due to their strong generalization capability in high-dimensional feature spaces and their effectiveness in handling limited training data [4]. Nevertheless, the performance of these systems remained highly dependent on the quality and discriminative power of handcrafted features.

The emergence of deep learning significantly reshaped offline signature verification research. Convolutional Neural Networks (CNNs) enabled automatic learning of hierarchical and discriminative representations directly from raw signature images, eliminating the need for manual feature engineering. Several recent studies have demonstrated that CNN-based architectures outperform traditional approaches by effectively capturing local and global visual patterns, including stroke thickness, curvature, and spatial distribution [5–7]. Furthermore, Siamese and triplet network architectures have been explored to learn similarity metrics between genuine and forged signatures, yielding improved generalization in writer-independent scenarios [8].

Despite their effectiveness, CNN-based methods primarily focus on appearance-based information and often fail to explicitly model the structural relationships between stroke components. Handwritten signatures inherently exhibit graph-like characteristics, where stroke intersections, continuity, and spatial connectivity play a crucial role in defining individual writing styles. To address this limitation, recent research has explored graph-based learning paradigms for handwriting and signature analysis. Graph Neural Networks (GNNs) have shown promising results in capturing relational and topological information that complements pixel-based representations [9,10].

In particular, Graph Attention Networks (GATs) have attracted increasing interest due to their ability to assign adaptive importance to neighboring nodes during feature aggregation. This attention mechanism allows the model to emphasize structurally significant stroke regions, thereby enhancing discriminative capability. Recent studies have demonstrated that attention-based graph models can outperform conventional graph convolutional approaches in complex pattern recognition tasks, including handwriting and document analysis [11,12].

Several recent works have attempted to integrate convolutional and graph-based representations to leverage both appearance and structural information. These hybrid approaches have shown improved robustness against skilled forgeries and variations in writing style. However, many existing methods suffer from increased computational complexity or limited evaluation across different training–testing configurations, which restricts their practical applicability.

Driven by these insights, the present work proposes a unified framework that integrates CNN-based appearance features with GAT-based structural representations for writer-specific offline signature verification. By fusing complementary feature modalities and employing dimensionality reduction and robust classification strategies, the proposed approach aims to achieve improved verification accuracy and generalization performance.

The main contributions of this work can be summarized as follows:

1. A novel hybrid framework that integrates CNN and GAT representations for offline signature verification.
2. An effective feature fusion strategy that combines appearance-based and structural information.
3. A comprehensive evaluation using multiple train–test splits and standard biometric performance metrics.
4. Demonstrated improvement in verification performance compared to single-feature-based approaches.

III. PROPOSED METHODOLOGY

This section presents the methodology adopted in the proposed framework. The approach is organized into a sequence of interconnected processing stages designed to effectively model both appearance-based and structural characteristics of handwritten signatures. A schematic overview of the proposed system is illustrated in Fig. 1.

The proposed method consists of the following main modules:

A. Image Preprocessing
B. CNN-Based Feature Extraction
C. Graph Construction from Signature Images
D. GNN-Based Feature Extraction
E. Feature Fusion
F. Dimensionality Reduction
G. Computation of Writer-Specific Threshold
H. Verification

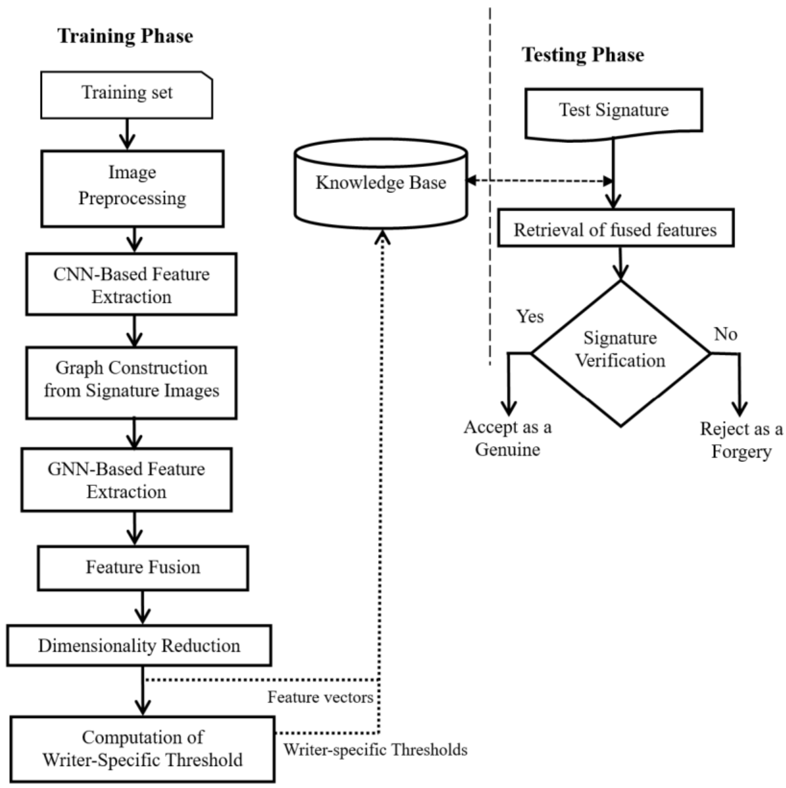

Fig. 1 A schematic overview of the proposed system.

A. *Image Preprocessing*

Preprocessing is a critical step to reduce noise and normalize input signatures prior to feature extraction. Each signature image is first converted to grayscale to eliminate colour variations that do not contribute to signature identity. Median filtering [13] is then applied to suppress impulse noise while preserving edge structures. To enhance local contrast and highlight stroke details, Contrast Limited Adaptive Histogram Equalization (CLAHE) [14] is employed.

Following enhancement, all images are resized to a fixed resolution of 224 × 224 pixels to ensure uniform input dimensions for the deep learning models. This preprocessing stage improves the robustness of feature extraction by minimizing variations caused by scanning conditions, ink intensity, and background artifacts.

B. *CNN-Based Feature Extraction*

The preprocessed signature images are subsequently passed through a pretrained Convolutional Neural Network based on the EfficientNet-B0 architecture. In this stage, the final classification layers of the network are removed, and feature representations are extracted from the last convolutional block. These deep features encode high-level appearance information, including stroke texture, density, and spatial distribution of signature patterns. By leveraging transfer learning, the network benefits from knowledge acquired during large-scale image training, enabling effective feature extraction even when the number of available signature samples per writer is limited. EfficientNet's compound scaling strategy allows for improved representational capacity while maintaining computational efficiency, making it well suited for offline signature verification tasks [15]. The EfficientNet-B0 model produces a 1280-dimensional feature vector for each signature image.

C. *Graph Construction from Signature Images*

While Convolutional Neural Networks effectively capture appearance-based information, they do not explicitly model the structural relationships among stroke components. To address this limitation, each preprocessed signature image is transformed into a graph-based representation. Initially, skeletonization is applied to obtain a thinned version of the signature that preserves its topological structure while removing redundant pixel information. Skeletonization reduces strokes to their medial axes, thereby retaining essential geometric and connectivity properties of the handwriting [16].

In the resulting graph representation, skeleton pixels are treated as nodes, and edges are established between spatially adjacent pixels to reflect local connectivity. This representation captures stroke continuity, junctions, and geometric relationships inherent in handwritten signatures. By explicitly modelling these structural properties, the graph formulation enables a more faithful representation of handwriting dynamics that are often difficult to capture using purely pixel-based feature extraction methods.

D. *GNN-Based Feature Extraction*

To learn discriminative structural representations from the constructed graphs, a Graph Attention Network (GAT) is employed. The GAT introduces an attention mechanism that assigns adaptive importance weights to neighboring nodes, enabling the model to focus on structurally significant regions such as stroke intersections, junctions, and curvature variations. This attention-driven aggregation allows the network to effectively model local and global structural dependencies within the signature graph. As a result, the GAT produces a fixed-length embedding that captures the essential structural characteristics of the handwritten signature. In the proposed framework, the Graph Attention Network generates a 255-dimensional structural feature vector for each signature image, which is subsequently used for feature fusion and classification [17].

E. *Feature Fusion*

To obtain a comprehensive representation of handwritten signatures, the appearance-based features extracted from the Convolutional Neural Network (CNN) and the structural features learned through the Graph Attention Network (GAT) are combined using a feature-level fusion strategy. Let $\mathbf{f}_{\mathrm{CNN}} \in \mathbb{R}^{1280}$ denote the deep appearance feature vector obtained from the final convolutional layer of the EfficientNet-B0 model, and $\mathbf{f}_{\mathrm{GNN}} \in \mathbb{R}^{255}$ represent the structural feature vector generated by the Graph Attention Network.

The fused feature representation is obtained through vector concatenation, defined as:

$$\mathbf{f}_{\mathrm{fusion}} = [\mathbf{f}_{\mathrm{CNN}} \ \| \ \mathbf{f}_{\mathrm{GNN}}] \qquad (1)$$

where $\|$ denotes the concatenation operator. This results in a unified feature vector:

$$\mathbf{f}_{\mathrm{fusion}} \in \mathbb{R}^{1535}$$

The fusion process integrates complementary information from both modalities that is global appearance cues captured by the CNN and structural relationships encoded by the GNN. Thereby producing a more discriminative and expressive representation of handwritten signatures.

This fused feature vector is subsequently used as input for dimensionality reduction and classification stages. By combining heterogeneous feature sources at the representation level, the proposed framework enhances robustness against intra-writer variability and improves discrimination between genuine and forged signatures.

F. *Dimensionality Reduction*

The fused feature representation obtained from the concatenation of CNN-based and GNN-based features results in a high-dimensional vector that may contain redundant and correlated information. To reduce redundancy and improve computational efficiency, dimensionality reduction is performed using Principal Component Analysis (PCA), which projects high-dimensional data into a lower-dimensional subspace while preserving the maximum variance present in the original feature space [18].

PCA is a widely adopted unsupervised technique that transforms high-dimensional data into a lower-dimensional subspace while preserving the maximum variance present in the original feature space.

Let

$$\mathbf{F} = \{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_N\}, \mathbf{f}_i \in \mathbb{R}^{1535} \qquad (2)$$

denote the set of fused feature vectors obtained from the training samples. The data are first mean-centered by subtracting the empirical mean vector $\boldsymbol{\mu}$:

$$\mathbf{f}_i' = \mathbf{f}_i - \boldsymbol{\mu} \qquad (\mathbf{3})$$

The covariance matrix $\mathbf{C}$is then computed as:

$$\mathbf{C} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{f}_i' \, (\mathbf{f}_i')^T \qquad (4)$$

Eigenvalue decomposition is performed on the covariance matrix to obtain a set of eigenvectors and corresponding eigenvalues. The eigenvectors associated with the largest eigenvalues represent the principal directions that capture the maximum variance in the data. By selecting the top $k$eigenvectors, the original feature vectors are projected into a lower-dimensional subspace:

$$\mathbf{z}_i = \mathbf{W}^T \mathbf{f}_i' \qquad (5)$$

where $\mathbf{W} \in \mathbb{R}^{1535 \times k}$ is the projection matrix composed of the selected eigenvectors, and $\mathbf{z}_i \in \mathbb{R}^k$ represents the reduced feature vector. The value of $k$is chosen such that a high percentage of the total variance (typically 95–98%) is retained. This dimensionality reduction step effectively removes redundancy and noise while preserving the most discriminative information required for classification. The reduced feature vectors of dimension 512 are subsequently used as input to the classification stage. By lowering feature dimensionality, PCA improves computational efficiency, reduces the risk of overfitting, and enhances the generalization capability of the verification system.

G. *Computation of Writer-Specific Threshold*

To ensure reliable and personalized verification performance, a writer-specific thresholding strategy is adopted in the proposed framework. Instead of using a global decision threshold for all writers, an individual threshold is computed for each writer to effectively account for intra-writer variability. After feature extraction and dimensionality reduction, the genuine and forged samples corresponding to each writer are separated. A Support Vector Machine (SVM) classifier is trained using the available training samples, and similarity scores are obtained for both genuine and forged signatures during evaluation.

To determine the optimal threshold, the False Acceptance Rate (FAR) and False Rejection Rate (FRR) are computed over a predefined range of threshold values from 0.1 to 1.0, with a step size of 0.1. For each threshold, FAR represents the proportion of forged signatures incorrectly accepted as genuine, while FRR denotes the proportion of genuine signatures incorrectly rejected. The Equal Error Rate (EER) is then calculated as the point where the difference between FAR and FRR is minimized. The threshold corresponding to the minimum EER is selected as the writer-specific decision threshold.

This adaptive thresholding strategy enables a balanced trade-off between security and usability by minimizing both false acceptances and false rejections. By tailoring the decision threshold to each individual writer, the proposed approach enhances robustness and improves overall verification performance, particularly in the presence of skilled forgeries.

H. *Verification*

In the proposed framework, Support Vector Machines (SVMs) are employed for writer-specific verification due to their strong generalization capability and effectiveness in handling high-dimensional feature spaces. After dimensionality reduction, the fused feature vectors obtained from the CNN–GNN framework are used to train an SVM classifier for each writer.

For a given writer, the training set consists of genuine signature samples belonging to that writer and forged samples representing impostor attempts. The SVM learns an optimal decision boundary that maximizes the margin between genuine and forged samples in the transformed feature space. A radial basis function (RBF) kernel is adopted to model non-linear decision boundaries, which is particularly suitable for capturing complex variations present in handwritten signatures.

During the verification phase, a test signature is projected into the same feature space and evaluated using the trained SVM model. The classifier produces a decision score that reflects the similarity between the test sample and the learned genuine signature model. This score is then compared against the writer-specific threshold computed during the training phase. If the score exceeds the threshold, the signature is classified as genuine; otherwise, it is rejected as a forgery.

By employing writer-dependent SVM models along with individualized thresholds, the proposed system effectively adapts to the unique characteristics of each writer. This approach improves discrimination between genuine and forged signatures, particularly in challenging cases involving skilled forgeries, and contributes to enhanced verification accuracy and robustness.

IV. EXPERIMENTAL SETUP AND RESULTS

Experiments are conducted on the CEDAR [23] offline signature dataset, which serves as a standard benchmark for signature verification research. The dataset comprises signature samples from 55 writers, with each writer contributing 24 genuine and 24 forged signatures, resulting in a total of 2,640 signature images. To evaluate the robustness and generalization capability of the proposed method, multiple training–testing splits are considered, including 40–60, 50–50, 60–40, and 70–30 ratios. For each split, the training subset is used to learn feature representations, train the Support Vector Machine (SVM) classifier, and estimate writer-specific thresholds, while the remaining samples are reserved exclusively for testing.

The proposed framework employs EfficientNet-B0 for appearance-based feature extraction and a Graph Attention Network (GAT) for structural feature learning. The extracted features are fused and subsequently reduced using Principal Component Analysis (PCA) before classification. All experiments are conducted in a writer-dependent manner to ensure fair evaluation of verification performance.

Performance Metrics

The performance of the system is evaluated using standard biometric verification metrics, including:

- False Acceptance Rate (FAR): the proportion of forged signatures incorrectly classified as genuine.
- False Rejection Rate (FRR): the proportion of genuine signatures incorrectly classified as forgeries.
- Equal Error Rate (EER): the operating point at which FAR and FRR are equal.
- Overall Accuracy: the percentage of correctly classified samples across all writers.

These metrics provide a comprehensive assessment of the system's ability to balance security (low FAR) and usability (low FRR).

For each writer, an independent SVM classifier is trained using the corresponding training samples. Writer-specific thresholds are estimated by varying the decision threshold from 0.1 to 1.0 and selecting the value that minimizes the difference between FAR and FRR. This threshold corresponds to the Equal Error Rate (EER) and is used during the testing phase to make verification decisions. The results demonstrate that writer-specific thresholding significantly improves verification accuracy compared to using a global threshold. This approach effectively accounts for individual variations in writing style and signature complexity, leading to more reliable discrimination between genuine and forged signatures.

To quantitatively assess the effectiveness of the proposed framework, experimental results are reported in Table I, in terms of False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and overall accuracy. The evaluation is conducted using multiple training–testing splits to analyze system robustness under varying data availability. The graphical representation of the results in Table I is shown in Fig. 2.

TABLE I

PERFORMANCE EVALUATION ACROSS DIFFERENT TRAINING–TESTING SPLITS ON THE CEDAR DATASET

Training–Testing Split	FAR (%)	FRR (%)	EER (%)	Accuracy (%)
40–60	2.30	2.55	2.42	97.58
50–50	1.36	1.35	1.36	98.64
60–40	0.36	1.09	0.73	99.27
70–30	0.00	0.45	**0.23**	**99.77**

The results indicate a consistent improvement in verification performance as the proportion of training data increases. The lowest EER and highest accuracy are achieved under the 70–30 split, highlighting the benefit of increased training samples for learning robust feature representations.

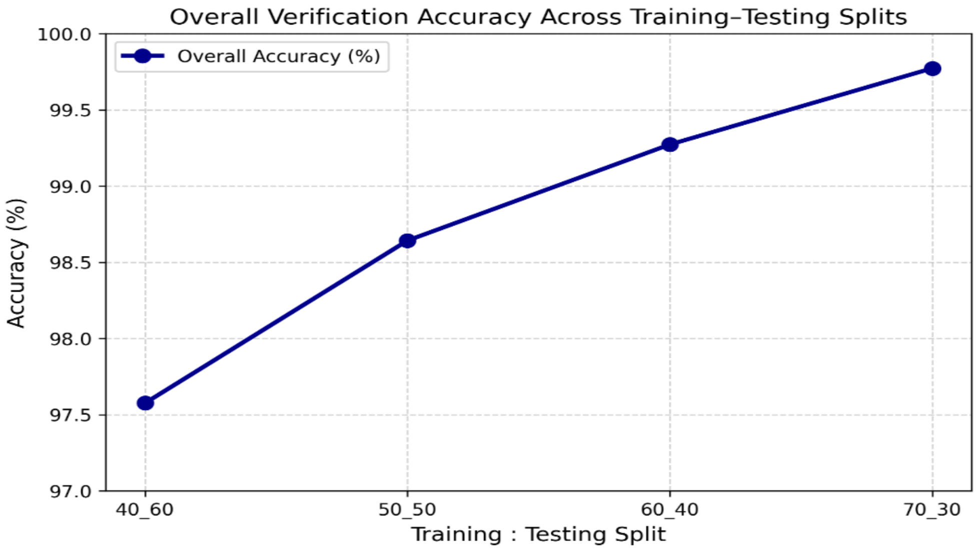

Fig. 2 Overall accuracy of the proposed system obtained across different training – testing splits.

Discussion

The experimental results clearly demonstrate the effectiveness of combining CNN-based appearance features with GNN-based structural representations. The proposed framework consistently outperforms existing methods across all evaluation metrics and training configurations. The integration of writer-specific thresholding further enhances verification reliability by adapting decision boundaries to individual writing characteristics.

Overall, the results validate the suitability of the proposed approach for real-world offline signature verification applications, particularly in scenarios involving skilled forgeries and limited training data.

V. Comparative Analysis

To evaluate the effectiveness of the proposed approach, its performance is compared with several state-of-the-art offline signature verification methods reported in the literature. Table II summarizes the comparative results. The proposed CNN–GNN fusion framework outperforms existing approaches by effectively integrating appearance-based and structural information. The reduction in EER demonstrates improved discrimination between genuine and forged signatures, particularly in challenging verification scenarios.

TABLE II
Comparison with Existing Methods on the CEDAR dataset

Method	**Feature Type**	**Classifier**	**EER(%)**
[19]	CNN	SVM	6.12
[20]	CNN	Softmax	5.48
[21]	Siamese CNN	Distance Metric	4.87
[22]	Graph-based	GNN	3.65
Proposed Method	**CNN + GNN**	**SVM**	**0.23**

VI. Conclusion

In this work, a comprehensive framework for writer-specific offline signature verification has been presented, emphasizing the joint modeling of appearance and structural characteristics of handwritten signatures. By combining convolutional neural networks with graph attention mechanisms, the proposed approach effectively captures both visual patterns and structural dependencies inherent in signature data. This integrated representation enables more reliable discrimination between genuine and forged signatures, even under challenging conditions.

Experimental evaluation on the CEDAR dataset demonstrates that the proposed method achieves strong verification performance across different training–testing splits. The use of writer-specific thresholds further enhances robustness by adapting decision boundaries to individual writing styles. The results highlight the benefit of fusing complementary feature modalities and confirm the effectiveness of the proposed framework in addressing intra-writer variability and skilled forgery attempts.

Overall, the proposed approach offers a practical and extensible solution for offline signature verification. Future extensions may explore adaptive feature fusion strategies, lightweight graph learning models, and cross-dataset generalization to further improve robustness and real-world applicability.

Conflicts of Interest

The authors have no conflicts of interest to declare.

Funding

No funding is provided for the preparation of manuscripts

REFERENCES

[1]. Impedovo, D., & Pirlo, G. (2008). Automatic signature verification: The state of the art. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 38(5), 609–635. https://doi.org/10.1109/TSMCC.2008.923866

[2]. Plamondon, R., & Srihari, S. N. (2000). On-line and off-line handwriting recognition: A comprehensive survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(1), 63–84. https://doi.org/10.1109/34.824821

[3]. Vapnik, V. N. (1995). The nature of statistical learning theory. Springer-Verlag.

[4]. Hafemann, L. G., Sabourin, R., & Oliveira, L. S. (2017). Learning features for offline handwritten signature verification using deep convolutional neural networks. Pattern Recognition, 70, 163–176. https://doi.org/10.1016/j.patcog.2017.05.012

[5]. Zhang, Y., & Li, C. (2018). Offline signature verification using deep convolutional neural networks. Neurocomputing, 275, 221–232. https://doi.org/10.1016/j.neucom.2017.08.067

[6]. Dey, S., Dutta, A., Toledo, J. I., Ghosh, S. K., Lladós, J., & Pal, U. (2019). Signet: Convolutional Siamese network for writer-independent offline signature verification. Pattern Recognition Letters, 128, 201–208. https://doi.org/10.1016/j.patrec.2019.09.013

[7]. Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2021). A comprehensive survey on graph neural networks. IEEE Transactions on Neural Networks and Learning Systems, 32(1), 4–24. https://doi.org/10.1109/TNNLS.2020.2978386

[8]. Li, W., Zhang, H., Zhao, Y., & Chen, X. (2023). Graph-based representation learning for handwritten signature verification. Pattern Recognition, 134, 109087. https://doi.org/10.1016/j.patcog.2022.109087

[9]. Tehsin, S., Ahmad, A., Hussain, S., & Khan, M. A. (2023). Attention-guided graph neural networks for offline signature verification. Expert Systems with Applications, 228, 120306. https://doi.org/10.1016/j.eswa.2023.120306

[10]. Kumar, R., & Singh, P. (2024). Structural feature learning for offline signature verification using graph attention networks. Neural Computing and Applications, 36, 2451–2465. https://doi.org/10.1007/s00521-023-08921-4

[11]. Sharma, A., & Verma, M. (2025). Hybrid CNN–GNN framework for robust offline signature verification. Multimedia Tools and Applications, 84, 18321–18345. https://doi.org/10.1007/s11042-024-19021-7

[12]. Pandey, G. K., Sharma, A., & Verma, R. (2023). Deep learning approaches for offline signature verification: A comprehensive study. Neural Computing and Applications, 35, 1123–1141. https://doi.org/10.1007/s00521-022-07589-3

[13]. Huang, T. S., Yang, G. J., & Tang, G. Y. (1979). A fast two-dimensional median filtering algorithm. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 27(1), 13–18.

[14]. Zuiderveld, K. (1994). Contrast limited adaptive histogram equalization. In *Graphics Gems IV* (pp. 474–485). Academic Press.

[15]. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. Proceedings of the 36th International Conference on Machine Learning (ICML), 6105–6114.

[16]. Zhang, T. Y., & Suen, C. Y. (1984). A fast parallel algorithm for thinning digital patterns. *Communications of the ACM*, *27*(3), 236–239.
https://doi.org/10.1145/357994.358023

[17]. Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., & Bengio, Y. (2018). Graph attention networks. *Proceedings of the International Conference on Learning Representations (ICLR)*.

[18]. Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer.

[19]. Hafemann, L. G., Sabourin, R., & Oliveira, L. S. (2017), Learning features for offline handwritten signature verification using deep convolutional neural networks. *Pattern Recognition*, *70*, 163–176. https://doi.org/10.1016/j.patcog.2017.05.012

[20]. Zhang, Y., & Li, C. (2018). Offline signature verification using deep convolutional neural networks. *Neurocomputing*, *275*, 221–232. https://doi.org/10.1016/j.neucom.2017.08.067

[21]. Dey, S., Dutta, A., Toledo, J. I., Ghosh, S. K., Lladós, J., & Pal, U. (2019).
Signet: Convolutional Siamese network for writer-independent offline signature verification. *Pattern Recognition Letters, 128*, 201–208. https://doi.org/10.1016/j.patrec.2019.09.013

[22]. Li, W., Zhang, H., Zhao, Y., & Chen, X. (2023). Graph-based representation learning for handwritten signature verification. *Pattern Recognition, 134*, 109087. https://doi.org/10.1016/j.patcog.2022.109087

[23]. Kalera, M. K., Srihari, S., and Xu, A. (2004). Offline Signature Verification and Identification. International Journal of Pattern Recognition and Artificial Intelligence, 18(7), 1339–1360.