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Deep Feature-Based Writer Constraint Modeling for Offline Signature Verification

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Abstract: Offline handwritten signature verification remains a challenging biometric authentication task due to significant intra-writer variations and the presence of skilled forgeries. This paper proposes a Deep Feature-Based Statistical Writer Constraint Model (WSCM) for offline signature verification by integrating deep feature extraction using a pretrained ResNet18 network with writer-specific statistical modeling. Deep feature representations are extracted from genuine reference signatures and used to construct feature-wise statistical constraints that characterize the expected variation of each writer. During verification, a query signature is evaluated against the learned statistical constraints, and a normalized Constraint Score is computed to determine its authenticity. The proposed approach eliminates the need for conventional classifier-based decision making while providing an interpretable verification process through feature-level constraint analysis. Experiments conducted on the CEDAR offline signature dataset under three training–testing configurations demonstrate that the proposed framework achieves a maximum verification accuracy of 84.70% with competitive False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER). The results demonstrate that writer-specific statistical constraint modeling provides an effective, computationally efficient, and explainable solution for offline signature verification.

Keywords: Deep feature extraction, Offline signature verification, ResNet18, Statistical constraint model, Writer-specific modeling.

I. Introduction

Offline handwritten signature verification is one of the most widely used biometric authentication techniques for validating an individual's identity in financial transactions, legal documentation, and administrative applications. Unlike physiological biometrics such as fingerprints or iris patterns, handwritten signatures are a behavioral biometric that naturally exhibits intra-writer variability, making automatic verification a challenging task. The presence of skilled forgeries further increases the complexity of distinguishing genuine signatures from forged ones, particularly in writer-independent verification systems [1], [2].

Traditional offline signature verification methods primarily rely on handcrafted feature extraction techniques that describe signature characteristics based on geometric, statistical, texture, or directional information. Although these methods have demonstrated reasonable performance, their effectiveness largely depends on the quality of manually designed features and often degrades when significant variations exist in genuine signatures or when confronted with skilled forgeries [1], [2].

Recent advances in deep learning have significantly improved signature verification by enabling convolutional neural networks (CNNs) to automatically learn discriminative feature representations from signature images [3], [4]. Among various deep architectures, ResNet18 has demonstrated an effective balance between feature representation capability and computational efficiency, making it suitable for offline signature verification tasks with limited training samples [4]. Nevertheless, most existing deep learning approaches rely on supervised classifiers or distance-based similarity measures, which generally require large amounts of labeled data and provide limited interpretability during the verification process [5], [6].

To address these limitations, this paper proposes a Deep Feature-Based Statistical Writer Constraint Model (WSCM) for offline signature verification. Instead of learning a decision boundary between genuine and forged signatures, the proposed framework models the statistical characteristics of genuine signature features for each writer using feature-wise statistical constraints. During verification, a query signature is evaluated against these learned constraints to determine its consistency with the claimed writer. This strategy provides a compact, computationally efficient, and interpretable verification framework while effectively accommodating natural intra-writer variations.

The main contributions of this work are summarized as follows:

- A writer-specific statistical constraint model is proposed to characterize the distribution of genuine deep signature features.

- A feature-wise constraint verification strategy is introduced to evaluate the consistency of query signatures without employing conventional classifiers.
- A normalized Constraint Score and Violation Rate are developed to support reliable and interpretable verification decisions.
- The proposed framework is validated on the CEDAR offline signature dataset, demonstrating competitive verification performance under multiple training–testing configurations.

The remainder of this paper is organized as follows. Section II reviews the related work on offline signature verification. Section III presents the proposed Deep Feature-Based Statistical Writer Constraint Model. Section IV discusses the experimental setup and verification results, while Section V concludes the paper and outlines future research directions.

II. Related Work

Offline handwritten signature verification has been extensively studied as a behavioural biometric authentication problem. Early approaches primarily relied on handcrafted feature extraction techniques, including geometric, statistical, texture, contour, and directional descriptors, combined with conventional classifiers such as Support Vector Machines (SVM), Hidden Markov Models (HMM), and Artificial Neural Networks (ANN). Although these methods achieved satisfactory performance under controlled conditions, their effectiveness was often limited by the discriminative capability of manually designed features and their sensitivity to intra-writer variations and skilled forgeries [1],[2].

With the advancement of deep learning, convolutional neural networks (CNNs) have significantly improved offline signature verification by automatically learning hierarchical feature representations from signature images. Hafemann et al. [3] demonstrated the effectiveness of deep CNNs for writer-independent signature verification using learned feature embeddings. Subsequently, transfer learning with pretrained networks such as VGGNet, AlexNet, ResNet, and DenseNet has become increasingly popular, as these models provide robust feature representations while reducing the need for large task-specific training datasets [4], [5].

Among the available architectures, ResNet18 has gained considerable attention because of its residual learning framework, which facilitates effective feature extraction while maintaining computational efficiency [7]. Several studies have reported improved verification performance by combining ResNet-based deep features with similarity measures or machine learning classifiers [6], [7]. Despite these advances, most existing methods rely on supervised classifiers or distance-based matching techniques, which often require extensive labelled training data and provide limited interpretability regarding the verification decision.

More recently, statistical and template-based verification methods have been explored to improve model interpretability and computational efficiency. Instead of learning complex decision boundaries, these approaches model the distribution of genuine signatures and determine authenticity based on statistical similarity. However, many existing statistical models rely on handcrafted features and therefore cannot fully exploit the discriminative capability of deep feature representations [2], [8].

Motivated by these observations, the present work proposes a Deep Feature-Based Statistical Writer Constraint Model (WSCM) that combines the representation power of a pretrained ResNet18 network with writer-specific statistical modeling. Rather than employing a conventional classifier, the proposed framework constructs feature-wise statistical constraints from genuine signature features and verifies query signatures by evaluating their conformity to these learned constraints. This approach provides a compact, computationally efficient, and explainable verification framework while effectively accommodating the natural variability of genuine handwritten signatures.

III. Proposed Method

This section presents the proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM) for offline handwritten signature verification. The framework integrates image preprocessing, deep feature extraction, writer-specific statistical modeling, and constraint-based verification to determine the authenticity of a query signature. Unlike conventional approaches that rely on supervised classifiers or distance-based similarity measures, the proposed method models the statistical behavior of genuine signature features for each writer and verifies a query signature by evaluating its conformity to the learned statistical constraints.

The overall framework consists of four sequential stages. First, the input signature images are preprocessed to remove noise, normalize their size, and standardize their appearance. Second, discriminative deep features are extracted using a pretrained ResNet18 convolutional neural network. Third, the extracted features from genuine reference signatures are used to construct a Writer-Specific Statistical Constraint Model (WSCM) by estimating feature-wise statistical parameters and generating acceptable constraint intervals. Finally, a query signature is verified by comparing its deep feature vector with the learned statistical constraints, and a Constraint Score is computed to determine its authenticity. The complete workflow of the proposed framework is illustrated in Fig. 1.

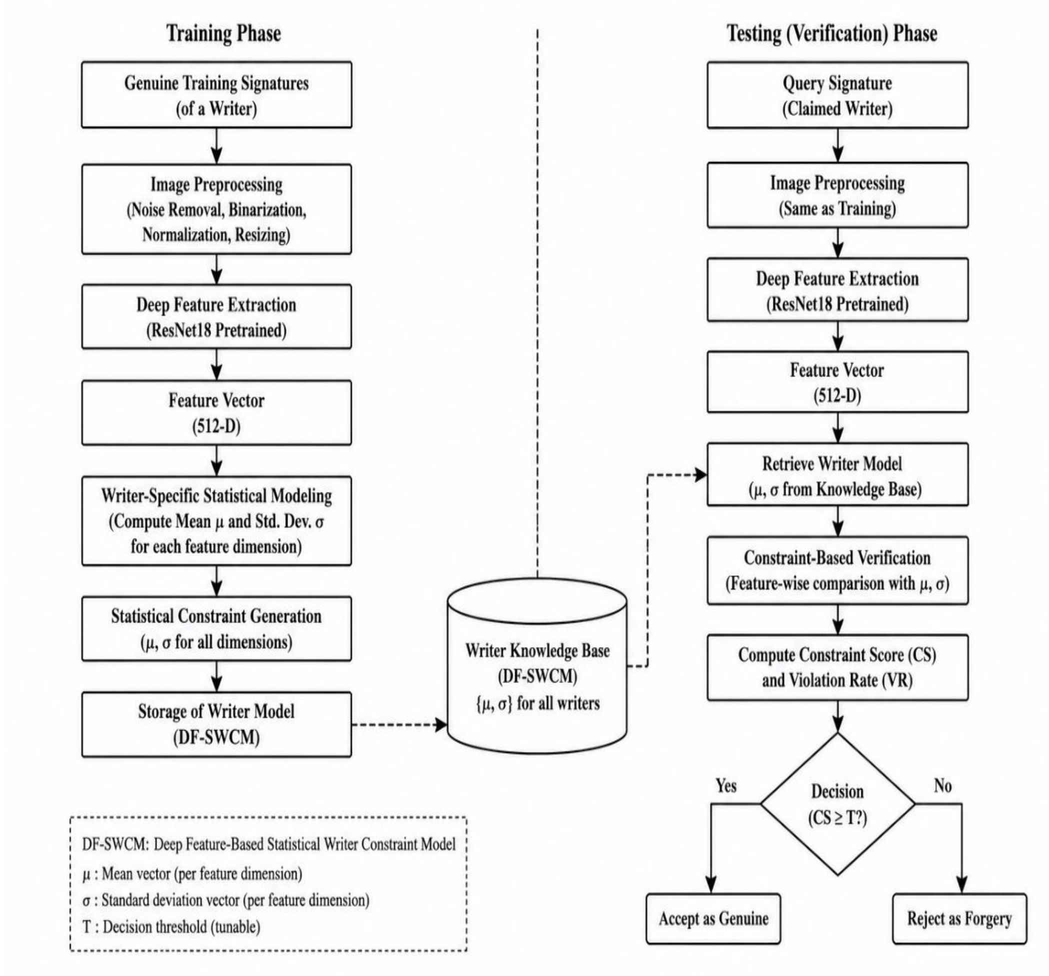

Fig. 1: Architecture of the proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM).

1. Signature Image Preprocessing

The signature images were preprocessed to generate a standardized representation for deep feature extraction. The preprocessing pipeline comprised grayscale conversion, noise removal, image binarization, signature localization, size normalization, image centering, and pixel normalization. These operations reduce image variability while preserving the structural characteristics of handwritten signatures.

Initially, each signature image was converted to grayscale, as colour information is unnecessary for offline signature verification. A median filter was subsequently applied to suppress impulsive noise while preserving the boundaries of signature strokes [9]. The filtered image was then binarized using Otsu's thresholding method, which automatically determines an optimal threshold to separate the foreground signature from the background [10].

The binarized signature was localized using its minimum bounding rectangle and cropped with a small margin to eliminate redundant background while retaining the complete signature structure. The cropped image was resized while preserving its aspect ratio to prevent geometric distortion and then centered on a fixed **224 × 224** white canvas, ensuring consistent image dimensions and spatial alignment across all samples.

Finally, the grayscale image was replicated into three channels to satisfy the input requirements of the pretrained ResNet18 network. The resulting image was normalized using the standard ImageNet mean and standard deviation values before being used for deep feature extraction in the subsequent stage.

2. Deep Feature Extraction Using a Pretrained ResNet18 Network

Following preprocessing, deep feature extraction was performed using a pretrained ResNet18 convolutional neural network. Unlike conventional handcrafted feature extraction methods, deep convolutional neural networks automatically learn hierarchical feature representations directly from image data, capturing both low-level visual characteristics and high-level structural patterns that are effective for distinguishing genuine signatures from skilled forgeries.

ResNet18 was selected as the feature extraction backbone because of its favourable balance between representational capability and computational efficiency. The network comprises an initial convolutional layer followed by four residual stages interconnected through identity shortcut connections, which facilitate effective feature propagation and alleviate the degradation problem encountered in deep neural networks [4].

The preprocessed signature images of size 224 × 224 pixels were provided as input to the pretrained ResNet18 model. Since the network expects three-channel RGB images, each grayscale signature image was replicated across three channels and normalized using the standard ImageNet preprocessing parameters to ensure compatibility with the pretrained network.

In this study, ResNet18 was employed solely as a fixed feature extractor. The final fully connected classification layer was removed, and the output of the global average pooling layer was used as the deep feature representation. Consequently, each signature image was represented by a 512-dimensional feature vector,

$$F = [f1, f2, \dots, f512]$$

Where f_i denotes the *i*th deep feature.

The extracted feature vector provides a compact and discriminative representation by encoding both local stroke characteristics and global structural information. These 512-dimensional deep feature vectors serve as the input to the proposed Writer-Specific Statistical Constraint Model (WSCM) described in the following section.

3. Writer-Specific Statistical Constraint Model (WSCM)

Following deep feature extraction, a Writer-Specific Statistical Constraint Model (WSCM) is constructed to characterize the statistical distribution of genuine signature features for each enrolled writer. Unlike conventional classifier-based approaches that learn decision boundaries between genuine and forged signatures, the proposed method models only the statistical behavior of genuine signatures in the deep feature space. By estimating feature-wise statistical characteristics from genuine reference signatures, the model effectively captures the natural intra-writer variations of signature features.

Instead of storing multiple reference feature vectors or employing complex classification models, the proposed WSCM represents each writer using a compact set of feature-wise statistical constraints. During verification, the deep feature vector extracted from a query signature is compared with these learned constraints to evaluate its consistency with the claimed writer. The final verification decision is then obtained based on the overall degree of conformity between the query signature and the writer-specific statistical model.

The proposed WSCM comprises the following four stages:

- **(i)** Construction of the writer-specific statistical model using genuine reference signatures.
- **(ii)** Generation of feature-wise statistical constraints from the estimated statistical parameters.
- **(iii)** Constraint-based verification of the query signature using the learned statistical intervals.
- **(iv)** Constraint score computation and decision making to classify the query signature as genuine or forged.

The methodology adopted in each stage is presented in the following subsections.

(i) Construction of the writer-specific statistical model using genuine reference signatures

To construct the proposed Writer-Specific Statistical Constraint Model (WSCM), the genuine signatures of each writer are divided into training and testing subsets. The training subset comprises only genuine signatures and is used to estimate the statistical characteristics of the claimed writer, whereas the testing subset consists of the remaining genuine signatures together with the corresponding skilled forgeries. This experimental protocol enables the proposed framework to be evaluated under different quantities of available reference signatures and facilitates a comprehensive assessment of its robustness and generalization capability.

Each genuine training signature is represented by a 512-dimensional deep feature vector extracted using the pretrained ResNet18 network, expressed as

$$F = [f1, f2, \dots, f512]$$

Where f_i denotes the *i*th feature component.

Let N denote the number of genuine training signatures available for a particular writer, and let f_{ij} represent the value of the *i*th feature extracted from the *j*th genuine signature. The statistical parameters of each feature dimension are estimated independently using all genuine training signatures.

The mean of the ith feature is computed as

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \qquad (1)$$

Where μ_i represents the average value of the ith feature.The corresponding standard deviation is calculated as

$$\sigma_i = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^2} \qquad (2)$$

Where σ_i measures the variation of the ith feature among the genuine reference signatures.For completeness, the minimum and maximum values of each feature dimension are also recorded as

$$L_i = \mu_i - k\sigma_i \qquad (3)$$

$$U_i = \mu_i + k\sigma_i \qquad (4)$$

These values describe the observed range of each feature and are retained for statistical analysis, although they are not directly used during the verification stage.

The estimated statistical parameters provide a compact representation of the distribution of genuine signature features and form the basis for constructing the proposed Writer-Specific Statistical Constraint Model. These parameters are subsequently used to generate the feature-wise statistical constraints described in the following subsection.

(ii) Generation of feature-wise statistical constraints from the estimated statistical parameters

The statistical parameters estimated from the genuine training signatures are subsequently used to define the acceptable variation of each feature dimension. For each deep feature, a statistical constraint interval is generated using the corresponding mean and standard deviation.

The lower and upper boundaries of the statistical interval for the ith feature are defined as

$$L_i = \mu_i - k\sigma_i \qquad (5)$$
$$U_i = \mu_i + k\sigma_i \qquad (6)$$

Where L_i and U_i denote the lower and upper bounds of the statistical interval, respectively, μ_i and $\sigma_i$represent the mean and standard deviation of the ith feature, and $k$is a scaling parameter that controls the width of the statistical interval.

The value of $k$determines the tolerance permitted for natural intra-writer variations. Smaller values of $k$produce narrower statistical intervals, resulting in stricter verification, whereas larger values allow greater variation in genuine signature features. The optimal value of $k$is determined experimentally using the validation data to achieve an appropriate balance between the False Acceptance Rate (FAR) and the False Rejection Rate (FRR).

Accordingly, the acceptable interval for the ith feature is expressed as

$$[L_i, U_i] \qquad (7)$$

A feature extracted from a query signature is considered statistically consistent with the claimed writer if$L_i \leq f_i \leq U_i$ (8)

Otherwise, the feature is regarded as a constraint violation.

Applying this procedure independently to all 512 feature dimensions yields the proposed Writer-Specific Statistical Constraint Model (WSCM), represented as

$$\mathbf{C} = \{(L_1, U_1), (L_2, U_2), \dots, (L_{512}, U_{512})\} \qquad (9)$$

Where each ordered pair (L_i, U_i)defines the acceptable statistical interval for the corresponding feature dimension. Collectively, these feature-wise statistical constraints constitute the reference model used during the subsequent constraint-based verification stage.

(iii) Constraint-based verification of the query signature using the learned statistical intervals

During the verification stage, the query signature undergoes the same preprocessing and deep feature extraction procedures as the genuine reference signatures. A 512-dimensional deep feature vector is extracted using the pretrained ResNet18 network and represented as

$$\mathbf{Q} = [q_1, q_2, \dots, q_{512}] \qquad (10)$$

Where q_i denotes the value of the ith feature extracted from the query signature.

The extracted feature vector is subsequently evaluated against the Writer-Specific Statistical Constraint Model (WSCM). Instead of comparing the entire feature vector as a single entity, the proposed framework performs feature-wise statistical verification, where each feature is independently compared with its corresponding statistical constraint interval. This enables the consistency of individual feature dimensions with the learned writer model to be assessed.

For the ith feature dimension, the extracted feature value q_i is considered statistically consistent with the claimed writer if

$$L_i \le q_i \le U_i \qquad (11)$$

Otherwise, the feature is regarded as a constraint violation.

To facilitate the verification process, a binary constraint indicator is assigned to each feature as

$$c_i = \begin{cases} 1, & \text{if } L_i \le q_i \le U_i, \\ 0, & \text{otherwise} \end{cases} \qquad (12)$$

Where $c_i = 1$ indicates that the ith feature satisfies the corresponding statistical constraint, whereas $c_i = 0$ denotes a constraint violation.

This verification procedure is repeated independently for all 512 feature dimensions, producing a binary constraint vector

$$\mathbf{C} = [c_1, c_2, \dots, c_{512}] \qquad (13)$$

Where each element of **C** represents the verification result of the corresponding feature dimension. The resulting binary constraint vector summarizes the overall consistency of the query signature with the learned writer model and forms the basis for computing the **Constraint Score** and **Violation Rate**, as described in the following subsection.

(iv) Constraint score computation and decision making to classify the query signature as genuine or forged

Following feature-wise verification, the overall consistency between the query signature and the **Writer-Specific Statistical Constraint Model (WSCM)** is quantified using the proposed **Constraint Score (CS)**. The Constraint Score represents the proportion of feature dimensions that satisfy their corresponding statistical constraints and serves as the primary criterion for signature verification.

The Constraint Score is computed as

$$CS = \frac{\sum_{i=1}^{512} c_i}{512} \qquad (14)$$

Where c_i denotes the binary constraint indicator obtained during the feature-wise verification stage. The Constraint Score is bounded by

$$0 \le CS \le 1 (15)$$

A higher Constraint Score indicates greater consistency between the query signature and the learned writer model, whereas a lower score indicates that a larger number of feature dimensions violate the statistical constraints.

To further quantify the deviation of the query signature, the **Violation Rate (VR)** is computed as

$$VR = 1 - CS \qquad (16)$$

Where

$$0 \le VR \le 1 \qquad (17)$$

The Violation Rate represents the proportion of feature dimensions that violate the learned statistical constraints. Consequently, lower values of **VR** indicate greater similarity to the claimed writer, whereas higher values indicate greater deviation from the expected characteristics of genuine signatures.

The final verification decision is obtained by comparing the computed Constraint Score with a predefined decision threshold τ, determined experimentally using the validation data,

$$\text{Decision} = \begin{cases} \text{Genuine}, & \text{if } CS \geq \tau, \\ \text{Forgery}, & \text{if } CS < \tau \end{cases} \tag{18}$$

The threshold $\tau$is selected to achieve an appropriate balance between the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). Increasing the threshold results in stricter verification by reducing the acceptance of skilled forgeries, whereas decreasing the threshold reduces false rejections at the expense of a higher probability of false acceptance.

The normalized Constraint Score provides a simple, computationally efficient, and interpretable measure of signature consistency. Since the score is bounded within the interval **[0,1]**, it facilitates consistent threshold selection while providing a reliable basis for the final verification decision.

IV. Experimental Results and Discussion

This section presents the experimental evaluation of the proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM) for offline signature verification. The experiments were conducted on the CEDAR offline signature dataset to assess the effectiveness of the proposed framework under different training–testing configurations. The evaluation focuses on the framework's ability to distinguish genuine signatures from skilled forgeries using writer-specific statistical constraints derived from deep feature representations. The experimental setup, evaluation metrics, quantitative results, and comparative analysis are presented in the following subsections.

1. Experimental Setup

The proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM) was evaluated using the CEDAR offline handwritten signature dataset, one of the most widely used benchmark datasets for offline signature verification research [12]. The dataset comprises signature samples from 55 writers, with each writer contributing 24 genuine signatures and 24 skilled forgeries, resulting in a total of 2,640 signature images. The availability of skilled forgery samples makes the dataset suitable for evaluating the robustness and discriminative capability of offline signature verification systems.

Prior to feature extraction, all signature images were preprocessed following the procedure described in Section III, which included grayscale conversion, median filtering, Otsu's thresholding, signature localization, aspect-ratio-preserving resizing, image centering, and pixel normalization. The preprocessed images were standardized to 224 × 224 pixels to satisfy the input requirements of the pretrained ResNet18 network.

Deep feature extraction was performed using a pretrained ResNet18 model. The final fully connected classification layer was removed, and the output of the global average pooling layer was used as a 512-dimensional feature representation for each signature image. These deep feature vectors served as the input for constructing the proposed Writer-Specific Statistical Constraint Model.

To investigate the influence of the number of reference signatures on verification performance, three training–testing configurations were considered: 25%–75%, 50%–50%, and 75%–25%. For each writer, only the genuine signatures in the training subset were used to estimate the writer-specific statistical parameters and generate the corresponding feature-wise constraint model. The remaining genuine signatures, together with the associated skilled forgeries, were used as query samples during the verification stage. The scaling parameter (k) and the decision threshold (τ) were determined experimentally using validation data to achieve an appropriate balance between the False Acceptance Rate (FAR) and the False Rejection Rate (FRR).

2. Performance Evaluation Metrics

The performance of the proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM) was evaluated using widely accepted biometric verification metrics, namely Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and the Area Under the Receiver Operating Characteristic Curve (AUC). These metrics collectively assess the effectiveness of the proposed framework in distinguishing genuine signatures from skilled forgeries.

- **Accuracy**

Accuracy measures the overall proportion of correctly classified signatures and is defined as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Where:

- TP (True Positive): Genuine signatures correctly classified as genuine.
- TN (True Negative): Skilled forgeries correctly classified as forgeries.
- FP (False Positive): Skilled forgeries incorrectly classified as genuine.

- FN (False Negative): Genuine signatures incorrectly classified as forgeries.
  A higher accuracy indicates better overall verification performance.

- **False Acceptance Rate (FAR)**

The False Acceptance Rate represents the percentage of forged signatures that are incorrectly accepted as genuine and is computed as

$$\mathrm{FAR} = \frac{FP}{FP + TN} \times 100$$

A lower FAR indicates a more secure verification system with a reduced likelihood of accepting forged signatures.

- **False Rejection Rate (FRR)**

The False Rejection Rate measures the percentage of genuine signatures that are incorrectly rejected and is given by

$$\mathrm{FRR} = \frac{FN}{TP + FN} \times 100$$

Lower FRR values indicate improved recognition of genuine signatures and better user convenience.

- **Equal Error Rate (EER)**

The Equal Error Rate corresponds to the operating point at which the False Acceptance Rate equals the False Rejection Rate, that is,

$$\mathrm{EER} = \mathrm{FAR} = \mathrm{FRR}$$

EER is one of the most widely used performance measures in biometric verification because it provides a threshold-independent assessment of system performance. Lower EER values indicate better discrimination between genuine signatures and skilled forgeries.

- **Area Under the Receiver Operating Characteristic Curve (AUC)**

The Area Under the Receiver Operating Characteristic (ROC) Curve evaluates the overall discriminative capability of the verification system across all possible decision thresholds. The AUC value ranges from **0** to **1**, where a value closer to **1** indicates superior discrimination between genuine signatures and skilled forgeries. Unlike accuracy, AUC is independent of a specific decision threshold and therefore provides a comprehensive measure of verification performance.

The proposed framework was evaluated using all five performance metrics under each training–testing configuration to provide a comprehensive assessment of its verification accuracy, robustness, and generalization capability.

3. Experimental Results

The performance of the proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM) was evaluated under three training–testing configurations: 25%–75%, 50%–50%, and 75%–25%. The verification results were analyzed using the performance metrics described in Section IV, including Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and Area Under the Receiver Operating Characteristic Curve (AUC). The quantitative results obtained for each experimental configuration are summarized in Table 1.

Table 1: Performance evaluation of the proposed writer constraint model under different training–testingsplits

Training –Testing Split	**Accuracy (%)**	**FAR (%)**	**FRR (%)**	**EER (%)**	**AUC**
25%–75%	75.10	8.77	41.03	24.26	0.812
50%–50%	81.71	10.61	29.82	23.83	0.809
75%–25%	**84.70**	13.33	21.21	25.59	0.792

4. Discussion

Table 1 presents the verification performance of the proposed Deep Feature-Based Statistical Writer Constraint Model (WSCM) under different training–testing configurations. The results show that increasing the number of genuine training signatures improves verification performance. The 75%–25% split achieved the highest accuracy (84.70%) and the lowest FRR (21.21%), indicating that additional reference signatures enable more reliable estimation of writer-specific statistical constraints. Although the FAR increased slightly, the relatively stable EER and AUC demonstrate that the proposed framework maintains consistent and robust verification performance across different training configurations.Figure 2 illustrates the verification accuracy of the proposed framework for the three training–testing configurations.

The verification accuracy increases with the number of genuine training signatures used to construct the writer-specific statistical model. The 75%–25% split achieved the best performance (84.70%), demonstrating that richer reference data improves the reliability of the learned statistical constraints and enhances signature verification accuracy.

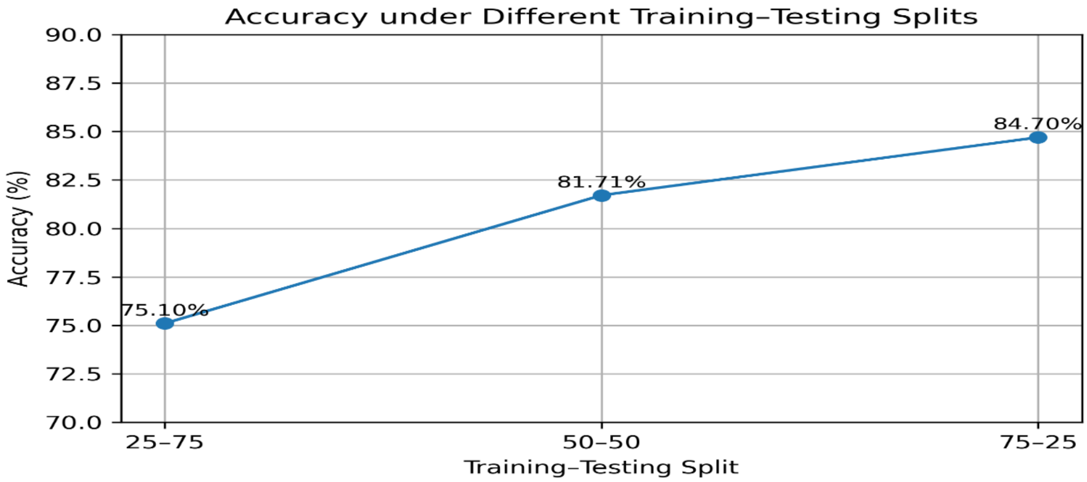

Figure 2: Comparison of the verification accuracy of the proposed model under different training–testing splits.

V. Conclusion

This paper presented a Deep Feature-Based Statistical Writer Constraint Model (WSCM) for offline signature verification by integrating deep feature extraction using a pretrained ResNet18 network with writer-specific statistical modeling. The proposed method verifies query signatures through feature-wise statistical constraints, providing a simple, computationally efficient, and interpretable alternative to conventional classifier-based approaches. Experimental evaluation on the CEDAR offline signature dataset demonstrated that the proposed framework achieved its best performance with the 75%–25% training–testing split, attaining an accuracy of 84.70% while maintaining competitive FAR, FRR, and EER values. These results confirm the effectiveness of writer-specific statistical constraint modeling for reliable offline signature verification. Future work will focus on adaptive constraint learning, feature selection, and validating the proposed framework on larger and more diverse signature datasets.

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