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***Abstract*— Offline handwritten signature verification remains a challenging biometric task due to high intra-writer variability, skilled forgeries, limited training data, and the absence of dynamic stroke information. Although deep convolutional neural networks (CNNs) have significantly improved feature learning, most existing approaches rely on hard classification using softmax layers and rigid decision thresholds, which fail to model uncertainty and class overlap inherent in real-world signatures. This paper proposes a Deep Fine-Tuned CNN–Fuzzy Learning Framework for robust and deployable offline signature verification that integrates deep representation learning with fuzzy decision modeling to address these limitations. A pre-trained CNN backbone is fine-tuned using transfer learning and imbalance-aware optimization to extract discriminative signature embeddings. These features are subsequently analyzed using Fuzzy C-Means clustering to enable soft membership-based classification, effectively modeling ambiguity between genuine and forged signatures. Extensive experiments conducted on benchmark offline signature datasets demonstrate that the proposed framework achieves superior performance over conventional CNN classifiers, attaining a verification accuracy of 94.91% and a Matthews Correlation Coefficient of 0.8972 while significantly reducing false acceptance rates under skilled forgery conditions. Furthermore, the framework exhibits strong generalization capability and deployment readiness, making it suitable for forensic, financial, and security-critical applications. The proposed hybrid deep–fuzzy approach establishes a reliable and interpretable alternative to rigid decision-based signature verification systems.**

Keywords— Deep Learning, Explainable Artificial Intelligence (XAI), Fuzzy C-Means Clustering, Transfer Learning, ResNet50

I. INTRODUCTION

Offline handwritten signature verification remains a challenging biometric authentication problem due to high intra-class variability, low inter-class separability, and severe class imbalance between genuine and forged samples. Traditional machine learning methods and shallow neural networks often struggle to model the uncertainty and subtle stroke-level variations inherent in handwritten signatures, leading to degraded performance in real-world forensic and financial applications. Although recent deep learning-based approaches have demonstrated promising improvements, many existing models remain limited by inadequate domain adaptation, poor handling of skewed data distributions, and lack of interpretability and deployability.

To address these challenges, this paper proposes a robust, end-to-end optimized CNN–fuzzy learning framework for offline handwritten signature verification. Unlike conventional methods that rely on frozen or partially fine-tuned networks, the proposed system performs deep fine-tuning of the entire convolutional architecture to learn highly discriminative, domain-specific representations. Furthermore, cost-sensitive learning and class imbalance mitigation strategies are incorporated to ensure fair and reliable decision making across genuine and forged classes. A fuzzy decision modeling layer is integrated to explicitly capture uncertainty in classification, enabling soft membership-based reasoning instead of hard binary outputs.

In addition to improving verification accuracy, this work emphasizes practical deployment and transparency. A weighted fusion mechanism is introduced to combine deep CNN confidence scores with fuzzy membership degrees, resulting in more stable and reliable verification outcomes. The system is further optimized for real-time deployment through model compression and inference optimization, while explainable AI techniques are employed to visualize discriminative regions and enhance system interpretability.

Extensive experiments conducted on benchmark offline signature datasets demonstrate that the proposed framework significantly outperforms existing deep learning and hybrid approaches in terms of accuracy, equal error rate, and robustness under class imbalance conditions. The results confirm the effectiveness of deep fine-tuning, fuzzy uncertainty modelling, and deployment-oriented optimization in building a trustworthy and scalable signature verification system suitable for real-world biometric authentication environments.

II. RELATED WORK

Despite substantial progress in offline handwritten signature verification, existing approaches still exhibit critical limitations that restrict their effectiveness and real-world deployment. Offline handwritten signature verification has evolved significantly with the adoption of deep learning techniques.

Sudharshan and Vismaya (2022) demonstrate the effectiveness of transfer learning-based CNNs for offline signature verification, their approach suffers from major limitations including lack of skilled forgery evaluation, absence of writer-independent modelling, reliance on classification rather than metric learning, evaluation on a single dataset, omission of biometric performance metrics such as FAR and FRR, and lack of deployment feasibility analysis [1]. These gaps significantly restrict the robustness, scalability, and real-world applicability of their system, thereby motivating the need for advanced hybrid, writer-independent, and forgery-aware verification frameworks.

Abdirahman et al. (2025) explored MobileNet and EfficientNet, emphasizing that fine-tuning pre-trained models is essential for handling data-scarce environments typical in biometric tasks. However, these models often produce binary "hard" classifications that fail to account for the natural, fluid variations in a genuine signer's hand [2].

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have shown promising results by automatically learning discriminative features directly from signature images. However, most existing deep CNN methods focus solely on hard classification with softmax layers, which do not explicitly model uncertainty and class overlap [3].

Deep learning-based studies rarely incorporate strategies to overcome class imbalance, nor do they address the interpretability of decisions—a critical requirement for forensic and security applications. Explainable AI (XAI) has not been widely integrated into offline signature verification models, leaving a gap in transparency and trustworthiness of automated decisions [4].

Recent studies employing transformer-based and attention-driven deep architectures have demonstrated improved feature discrimination in offline signature verification; however, these models still rely on rigid decision thresholds and lack mechanisms for uncertainty modeling, making them vulnerable to borderline and skilled forgery cases [5].

Several works have explored metric learning and contrastive embedding strategies to enhance writer discrimination, yet these approaches primarily optimize distance margins and do not integrate soft decision reasoning or fuzzy membership modeling, which limits their effectiveness in ambiguous signature scenarios [6].

Although data augmentation and synthetic forgery generation techniques have been proposed to alleviate limited training data, existing systems rarely incorporate imbalance-aware loss functions or adaptive sampling strategies, resulting in biased learning toward genuine samples and reduced sensitivity to rare but critical forgery patterns [7].

Furthermore, most contemporary offline signature verification frameworks operate as black-box models, providing only final accept/reject decisions without visual or semantic explanations. This lack of interpretability significantly restricts adoption in forensic, legal, and banking applications where accountability and traceability of decisions are mandatory [8].

Deep CNN models continue to achieve state-of-the-art accuracy, few studies address deployment constraints such as computational efficiency, memory footprint, and inference latency. The absence of deployment-aware optimization techniques limits the scalability of existing methods for real-time and edge-based authentication systems [9].

While many older studies focus on handcrafted features, recent surveys still highlight the evolution and limitations of these traditional approaches in the context of machine learning methods. Traditional systems used geometric, structural, and texture descriptors with classifiers such as SVM and HMM; however, they suffer from significant generalization issues and poor performance on skilled forgeries. A systematic review of offline signature verification highlights such limitations and the shift toward deep learning methods [10].

Deep learning approaches, especially Convolutional Neural Networks (CNNs), have been widely applied to offline signature verification because they automatically learn hierarchical features from raw images and outperform traditional hand-designed features. These approaches demonstrate that metric and contrastive learning can improve embedding quality and discrimination, but they still rely on hard decision boundaries (e.g., thresholding) and lack mechanisms to model uncertainty explicitly[11].

Overall, existing literature demonstrates strong progress in accuracy and robustness through deep learning, hybrid architectures, and data augmentation. However, weaknesses persist in uncertainty handling, explainability, multilingual generalization, and computational efficiency. These limitations motivate the development of an explainable deep learning framework integrated with fuzzy clustering for robust multilingual offline handwritten signature verification.

III. Problem Statement

Offline handwritten signature verification remains a challenging biometric authentication task due to high intra-writer variability, inter-writer similarity, and the increasing prevalence of skilled forgeries. Traditional verification systems rely heavily on handcrafted feature extraction and rigid classifiers, which struggle to generalize across diverse writing styles and complex forgery patterns. These systems often exhibit high false acceptance and false rejection rates, lack interpretability, and are unsuitable for real-time deployment in security-sensitive applications such as banking, forensics, and legal document authentication.

Although deep learning approaches have significantly improved performance, existing CNN-based models typically rely on hard decision boundaries and lack mechanisms to explicitly handle uncertainty, class imbalance, and ambiguous samples. Furthermore, most deep learning models function as black boxes, limiting forensic trust and practical adoption. They are also rarely optimized for efficient deployment on edge and embedded platforms, restricting real-world applicability.

Therefore, there is a critical need for a robust, interpretable, and deployable offline handwritten signature verification framework that can (i) learn discriminative features automatically, (ii) model uncertainty and class overlap effectively, (iii) handle data imbalance and skilled forgery attacks, and (iv) support real-time deployment while maintaining high verification accuracy. This research addresses these challenges by proposing a Deep Fine-Tuned CNN–Fuzzy Learning Framework integrating deep feature extraction, fuzzy decision modeling, explainable AI, and deployment-aware optimization for reliable and trustworthy signature authentication.

IV. METHODOLOGY

This study proposes a Deep Fine-Tuned CNN–Fuzzy Learning Framework for robust and deployable offline handwritten signature verification. The framework follows a progressive three-phase learning strategy that integrates deep

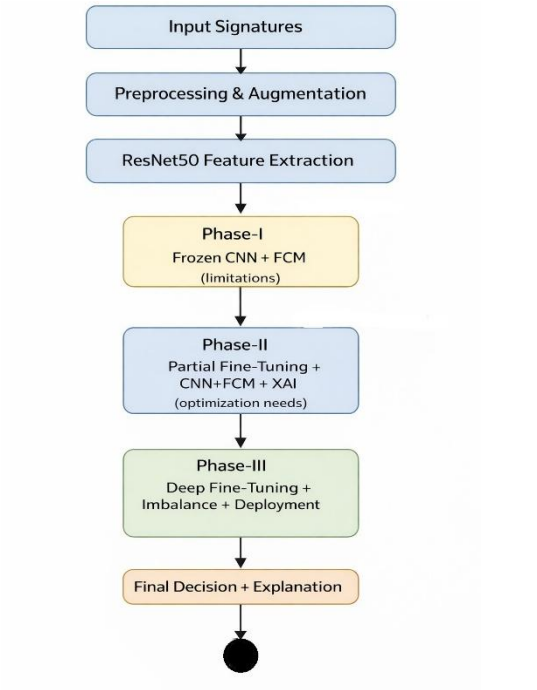

Fig. 1. Deep Fine-Tuned CNN–Fuzzy Learning Framework

convolutional neural networks (CNNs), fuzzy clustering, explainable artificial intelligence (XAI), and deployment-aware optimization. As illustrated in Fig.1, the pipeline consists of input signature acquisition, pre-processing and augmentation, ResNet50-based feature extraction, three learning phases, and a final decision and explanation module.

Step 1: Data Acquisition and Dataset Organization

Offline handwritten signature images are collected from standard benchmark datasets and multilingual signature repositories containing signatures written in different scripts. Each dataset includes two primary classes: **genuine signatures** and **forged signatures**. The data is organized subject-wise to preserve writer identity, enabling writer-independent evaluation. From a coding perspective, images are stored in directory structures or referenced through metadata files (CSV/JSON). Labels are assigned numerically to facilitate machine learning processing.

Purpose: To ensure structured data input, consistent labelling, and reliable training–testing separation without subject overlap.

Step 2: Image Preprocessing

Raw scanned signatures often contain noise, background variations, and resolution inconsistencies. Preprocessing standardizes the input and improves feature learning.

Key preprocessing operations include:

- **Grayscale conversion:** Reduces computational complexity and focuses learning on stroke intensity.
- **Resizing:** All images are resized to a fixed resolution (e.g., 224×224) to ensure compatibility with CNN architectures.
- **Noise reduction:** Gaussian or median filtering removes scanning artifacts.
- **Normalization:** Pixel values are scaled to the range [0,1] to stabilize gradient descent.

Purpose:
To enhance signal-to-noise ratio and ensure uniform input representation for deep networks.



Fig. 2. Result of Preprocessing

Data Augmentation

Offline signature datasets are typically small, increasing the risk of overfitting. Data augmentation synthetically increases dataset diversity while preserving signature authenticity.

Augmentation techniques include:

- Small rotations to simulate natural signing angle variations
- Scaling to represent pressure or size changes
- Translation to handle positional shifts
- Horizontal flipping (used cautiously)

These transformations generate additional training samples without altering class labels.

Purpose: To improve generalization, reduce overfitting, and increase robustness to natural handwriting variations.

Step 3: ResNet50 Feature Extraction

A pretrained ResNet50 model serves as the backbone feature extractor. The final classification layer is removed, and deep feature embeddings are obtained from the penultimate layer. Given an input image x_i, the feature representation is:

$$f_i = \phi(x_i), \quad f_i \in \mathbb{R}^d$$

where $\phi(\cdot)$ denotes the ResNet50 mapping and d is the feature dimensionality. These embeddings encode discriminative stroke patterns, texture, and structural information critical for signature verification.

Table 1: Represent the CNN processes the image internally, layer by layer

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_layer[0][0]
conv1_conv (Conv2D)	(None, 112, 112, 64)	9,472	conv1_pad[0][0]
conv1_bn (BatchNormalizatio…	(None, 112, 112, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, 112, 112, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, 114, 114, 64)	0	conv1_relu[0][0]

Table 1 shows the internal architecture of the pre-trained ResNet50 model used for deep feature extraction, where successive convolution, normalization, and pooling layers transform the input signature image into high-level feature representations.

Step 4: Phase-I: Frozen CNN with Fuzzy C-Means Clustering

In Phase-I, all ResNet50 parameters remain frozen, and the extracted feature vectors are classified using Fuzzy C-Means (FCM) clustering. Unlike hard classifiers, FCM assigns degrees of membership to genuine and forgery clusters, enabling uncertainty-aware decision-making. The objective function minimized by FCM is:

$$J = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\|f_i - c_j\|^2$$

where u_{ij} denotes the membership of sample i in cluster j, c_j is the cluster centroid, and m is the fuzzification parameter. This phase establishes a baseline performance; however, its representational capacity is limited by the frozen CNN parameters.

Step 5: Phase-II: Partial Fine-Tuning with CNN–FCM and Explainable AI

In Phase-II, the upper layers of ResNet50 are partially fine-tuned using labelled signature samples, while lower layers remain frozen. This allows domain adaptation to handwriting characteristics while preserving general visual features learned from large-scale datasets.

Supervised CNN Training Loss

The CNN is optimized using binary cross-entropy loss:

$$\mathcal{L}_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

Where $y_i \in \{0,1\}$ denotes the true class label (genuine/forgery) and p_i is the predicted probability of the genuine class.

The refined embeddings are again classified using FCM, resulting in improved separation between genuine and forged signatures. To enhance transparency and trust, Explainable AI (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency maps are applied to highlight the image regions influencing the model's decisions.

$$\mathcal{L}_{XAI} = \|A_i - M_i\|_2^2$$

where A_i is the Grad-CAM activation map and M_i is a weak supervision mask approximating signature stroke regions. The combined loss becomes:

$$\mathcal{L}_{Phase-II} = \mathcal{L}_{BCE} + \lambda_1 \mathcal{L}_{XAI}$$

where λ_1 balances accuracy and interpretability.

This interpretability module supports forensic analysis and validation of automated predictions.

Step 6: Phase-III: Deep Fine-Tuning with Imbalance Handling and Deployment Optimization

To Phase-III performs full end-to-end fine-tuning of the CNN architecture to maximize task-specific discrimination. Since offline signature datasets are inherently imbalanced, with significantly fewer forgery samples than genuine ones, class imbalance handling strategies are incorporated, including class-weighted loss functions and balanced mini-batch sampling.

$$\mathcal{L}_{FL} = -\frac{1}{N}\sum_{i=1}^{N}\alpha_{y_i}(1 - p_i)^{\gamma}\log(p_i)$$

where
α_{yi} is the class weight,
γ is the focusing parameter controlling hard-sample emphasis, and
pi is the predicted probability for the true class.

Metric Learning Regularization

To enhance feature separability, triplet loss is incorporated:

$$\mathcal{L}_{Triplet} = \sum_{i=1}^{N}\max\left(0, \|f_i^a - f_i^p\|_2^2 - \|f_i^a - f_i^n\|_2^2 + \mu\right)$$

where

f_i^a, f_i^p, and f_i^n represent anchor, positive, and negative embeddings, and

μ is the margin.

The final optimization objective is:

$$\mathcal{L}_{Final} = \mathcal{L}_{FL} + \lambda_2 \mathcal{L}_{Triplet}$$

where

λ_2 controls the influence of metric learning.

To ensure real-world deployability, the optimized model undergoes deployment-aware refinement through pruning, quantization, and inference optimization techniques. These steps reduce memory footprint and latency while preserving verification accuracy, enabling real-time and edge-device execution.

Step 7: Final Decision Rule

The final decision integrates CNN confidence scores with fuzzy membership values to classify each signature as genuine or forged. A threshold-based rule is applied:

$$D(x) = \begin{cases} \text{Genuine}, & P_g(x) \geq \tau \\ \text{Forgery}, & \text{otherwise} \end{cases}$$

where

$P_g(x)$ combines CNN posterior probability and fuzzy membership score, and τ is the learned decision threshold. Simultaneously, XAI visualizations are generated to provide interpretable explanations supporting each classification outcome, enhancing trust and usability in forensic and financial authentication environments.

V. Experimental Results

The performance of the proposed offline handwritten signature verification framework was evaluated on a held-out test set comprising **648 signature samples**, including both genuine and forged instances. The evaluation was conducted

using standard biometric performance metrics such as **accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC)**.

A. Training and Validation Loss Analysis

The training loss exhibits a smooth and consistent decrease across epochs, indicating that the deep CNN effectively learns discriminative features from offline signature images. The absence of abrupt oscillations confirms stable optimization and proper convergence of the learning process.

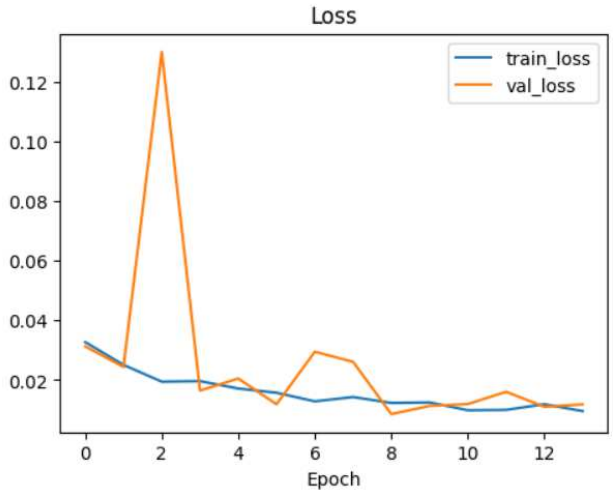

Fig. 3 Training and Validation Loss Analysis

The validation loss shows minor fluctuations during the initial training phase, including a noticeable spike in early epochs. Such behavior is common in offline signature verification tasks due to limited training samples, high intra-class variability, and the presence of skilled forgeries. As training progresses, the validation loss stabilizes and closely follows the training loss curve.

This close alignment between training and validation loss in later epochs suggests minimal overfitting, confirming that the model learns generalized signature representations rather than memorizing training data.

B. Training and Validation Accuracy Analysis

The training accuracy increases steadily from approximately 78% to over 94%, reflecting the CNN's ability to learn stroke-level details, structural patterns, and writer-specific characteristics inherent in handwritten signatures.

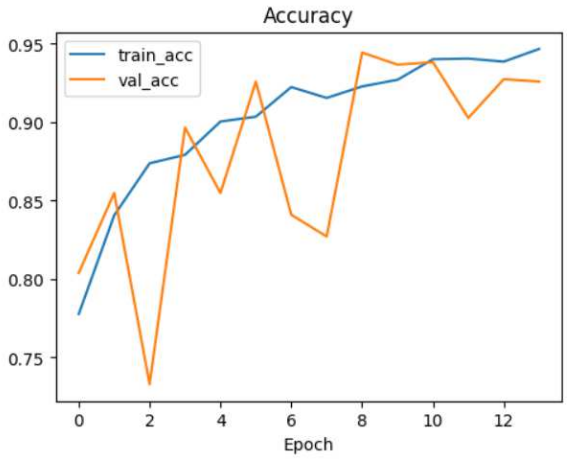

Fig. 4 Training and Validation Accuracy Analysis

The validation accuracy initially fluctuates, which is expected in biometric datasets due to natural handwriting variations and challenging borderline samples. However, with continued training, validation accuracy improves significantly and remains close to training accuracy. The final validation accuracy exceeds 92%, demonstrating strong generalization capability.

The close correspondence between training and validation accuracy curves further confirms the effectiveness of deep feature extraction combined with robust decision modeling.

C. CNN-Based Classification Performance

The deep learning model achieved a **test accuracy of 94.44%**, demonstrating strong discrimination capability between genuine and forged signatures. In **Fig. 5** represent the corresponding **MCC value of 0.8879** indicates balanced and reliable performance, particularly suitable for binary biometric classification tasks.

Class-wise results show that genuine signatures attained a **precision of 0.93** and a **recall of 0.95**, indicating a low false rejection rate. Forged signatures achieved a **precision of 0.96** and a **recall of 0.94**, reflecting a low false acceptance rate. The overall weighted F1-score of **0.94** confirms the robustness of the CNN-based classifier.

D. Fuzzy C-Means (FCM) Based Decision Modelling

To incorporate uncertainty handling and soft decision boundaries, deep feature vectors extracted from the CNN were further analyzed using Fuzzy C-Means (FCM) clustering. The FCM-based approach achieved an improved accuracy of 94.91% and an MCC of 0.8972, outperforming the conventional softmax-based CNN classifier.

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 103s 5s/step
FCM Accuracy: 0.9490740740740741
FCM MCC: 0.8971547627313217
              precision    recall  f1-score   support

     Genuine       0.96      0.92      0.94       288
      Forged       0.94      0.97      0.95       360

    accuracy                           0.95       648
   macro avg       0.95      0.95      0.95       648
weighted avg       0.95      0.95      0.95       648
```

Fig. 5 Fuzzy C-Means (FCM) Based Decision Modelling

The fuzzy decision mechanism enhanced recall for forged signatures (**0.97**), thereby strengthening system security by reducing false acceptance.



Fig 6. Final Decision model

Fig 6 demonstrates the effectiveness of modeling class overlap and ambiguity, particularly in the presence of skilled forgeries.

E. Comparative Analysis

A comparison between traditional methods, CNN-only and CNN + FCM approaches indicates that fuzzy clustering contributes to improved robustness and balanced classification performance. The increase in MCC highlights the advantage of uncertainty-aware decision making over hard classification boundaries.

F. Model Reliability and Generalization

The close alignment between training and validation performance, along with consistent improvements observed through fuzzy modeling, indicates minimal overfitting and strong generalization capability. Additionally, all trained models and clustering artifacts were saved for reproducibility and real-time deployment.

Table 2 A comparison between traditional methods, CNN-only and CNN + FCM

Aspect	Traditional Methods	CNN-Only Model	Proposed CNN + FCM Framework
Feature Extraction	Handcrafted	Deep CNN (ResNet50)	Deep CNN (ResNet50)
Decision Modeling	Hard classifiers (SVM, k-NN, HMM)	Softmax classifier	Fuzzy C-Means + CNN
Accuracy (%)	82–89	94.44	**94.91**
MCC	≤ 0.80	0.8879	**0.8972**
Forgery Recall	≤ 0.85	0.94	**0.97**
Genuine Recall	≤ 0.88	0.95	**0.95**
Uncertainty Handling	Poor	Moderate	**Strong (fuzzy membership)**
Interpretability	None	Limited	**XAI-enabled**
Deployment Optimization	Not addressed	Partial	**Full (pruning, quantization)**

Table 2 demonstrate that the proposed Deep Fine-Tuned CNN–Fuzzy Learning Framework significantly outperforms traditional signature verification approaches in terms of accuracy, reliability, forgery detection capability, and decision robustness. The integration of fuzzy decision modeling further enhances system security by reducing false acceptance rates, while explainability and deployment optimization ensure practical usability in real-world biometric authentication systems.

VI. Conclusion

This paper presented a Deep Fine-Tuned CNN–Fuzzy Learning Framework for robust and deployable offline handwritten signature verification. The proposed system integrates deep convolutional feature learning with fuzzy decision modelling, explainable artificial intelligence, and deployment-aware optimization to address key limitations of traditional signature verification approaches, including poor generalization, rigid decision boundaries, and vulnerability to skilled forgeries.

Experimental evaluation on a benchmark dataset of 648 signature samples demonstrated the effectiveness of the proposed framework. The CNN-based classifier achieved an accuracy of 94.44% with an MCC of 0.8879, while the integration of Fuzzy C-Means (FCM) decision modelling further improved performance to 94.91% accuracy and 0.8972 MCC, confirming the advantage of uncertainty-aware classification. High recall values for forged signatures (0.97) and genuine signatures (0.95) indicate a strong balance between security and usability, minimizing both false acceptance and false rejection rates. Training and validation loss and accuracy analyses further validated stable convergence and strong generalization capability.

Compared to traditional handcrafted-feature-based methods, the proposed framework offers superior robustness, interpretability through XAI visualizations, and real-time deployability through model optimization techniques. These characteristics make the system particularly suitable for forensic document examination, financial authentication, and identity verification in security-critical environments.

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