SIGNATURE VERIFICATION SYSTEM USING DEEP LEARNING

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Abstract

Signature verification is essential for identity authentication and legal document verification. Traditional handcrafted approaches fail under high intra-class variations and forgery attacks. This study proposes a Siamese CNN-based offline signature verification system trained on the CEDAR dataset. The model compares signature pairs using contrastive loss, achieving high accuracy and robustness against forged attempts. Extended experiments demonstrate the superiority of the proposed approach over conventional methods. Balanced pair generation ensures the model does not become biased toward positive or negative samples. Offline signature verification is a critical biometric authentication task in domains such as banking, legal documentation, and access control. The task involves distinguishing genuine signatures from forgeries, which is challenging due to high intra-class variability and low inter-class variability in handwritten signatures. Traditional approaches, which rely on handcrafted features and statistical classifiers, often fail to capture subtle variations and are prone to errors when faced with skilled forgeries or variations in writing style.

In this study, we propose a Siamese Convolutional Neural Network (CNN)-based approach for offline signature verification. We utilize the CEDAR signature dataset (Signature.v6i.yolov8) and implement extensive preprocessing steps, including image resizing, normalization, grayscale conversion, and data augmentation, to improve model robustness. Positive and negative signature pairs are generated dynamically to train the model using **contrastive loss**, enabling it to learn discriminative features that distinguish genuine from forged signatures.

Keywords: Signature verification, Siamese CNN, CEDAR dataset, contrastive loss, biometric authentication, offline signatures

1. Introduction

Handwritten signatures are widely accepted as a legal authentication method for individuals. Manual verification is time-consuming and prone to human error. Offline automated signature verification is a challenging problem due to intra-class variations, inter-class similarities, and forgery attacks. Machine learning approaches initially relied on handcrafted features such as geometric descriptors, pixel density, and gradient-based methods, often combined with classifiers like SVM or Random Forest. However, these methods require extensive domain knowledge and fail to generalize well across different users. Deep learning, particularly CNNs, provides a robust feature extraction framework, enabling automated representation learning. Siamese networks, introduced for verification tasks, allow the model to learn a similarity function between signature pairs, making them ideal for unseen users. This study focuses on

a Siamese CNN architecture for offline signature verification using the CEDAR dataset, providing extended analysis, real-time evaluation potential, and discussion of deployment considerations.

2. Related Work

Early offline signature verification relied on handcrafted features such as HOG, SIFT, and LBP combined with classical classifiers. Hafemann et al. (2017) demonstrated the benefits of CNNs for feature learning in offline signatures, showing improved accuracy over traditional methods. Siamese CNNs have been applied to face recognition and signature verification, learning embeddings that measure similarity between two inputs. Bromley et al. (1994) introduced Siamese time delay networks for signature verification, pioneering pairwise metric learning. Recent works leverage deeper architectures, contrastive loss, and augmented datasets to improve generalization. However, challenges remain in handling limited dataset size, intra-writer variations, and high-quality forgery detection.

3.1. Traditional Signature Verification Approaches

Early methods in signature verification were predominantly based on handcrafted features and statistical classifiers. These approaches often struggled with issues like intra-class variability and the need for extensive feature engineering. For instance, Saba Mushtaq and Ajaz H. Mir (2013) provided a comprehensive survey of signature verification systems, classifying various approaches and discussing their limitations in handling dynamic and forged signatures.

3.2. Deep Learning in Signature Verification

With the advent of deep learning, researchers have developed more robust models capable of handling complex patterns in signature data. A notable contribution is the work by Luiz G. Hafemann et al. (2015), who conducted an extensive literature review on offline handwritten signature verification, highlighting the challenges and advancements in the field.

3.3. Siamese Neural Networks for Signature Verification

Siamese Neural Networks have become a prominent architecture for signature verification due to their ability to learn similarity metrics between signature pairs. Merve Varol Arısoy (2021) demonstrated the effectiveness of SNNs in offline signature verification, achieving notable accuracy across multiple datasets. Similarly, S. Dey et al. (2017) introduced SigNet, a convolutional Siamese network tailored for writer-independent signature verification, which effectively learned discriminative features for genuine and forged signatures.

3.4. Enhancements in Siamese Network Architectures

Recent studies have focused on enhancing the performance of SNNs by integrating advanced architectures and loss functions. For instance, S. Tehsin et al. (2024) explored the use of Triplet Siamese Networks (tSSN), which utilize triplet loss to improve the model's ability to distinguish between genuine and forged signatures by considering both positive and negative pairs.

3.5. Hybrid and Transfer Learning Approaches

To address the challenge of limited labeled data, researchers have employed hybrid models and transfer learning techniques. A study by S.J. Chang et al. (2024) combined an improved AlexNet architecture with transfer learning to enhance signature recognition, demonstrating high recognition rates even with a small number of samples.

3.6. Comprehensive Surveys and Future Directions

To provide a broader perspective, several surveys have been conducted to summarize the state-of-the-art in signature verification. For example, the survey by Deepak Kumar et al. (2023) delves into various deep learning approaches for signature verification, discussing their advantages, limitations, and future research directions.

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3. Proposed Methodology

The proposed Siamese CNN consists of two identical convolutional branches sharing weights. Each branch processes grayscale signature images to produce fixed-size embeddings. The Euclidean distance between embeddings measures similarity. Contrastive loss ensures that embeddings of genuine pairs are close, while forged pairs are separated by a margin. The network includes multiple convolutional layers with ReLU activation, batch normalization, max pooling, and dense layers for embedding computation. Data preprocessing involves resizing, normalization, and data augmentation including rotation, scaling, and translation. This enhances model robustness against variations and improves generalization.

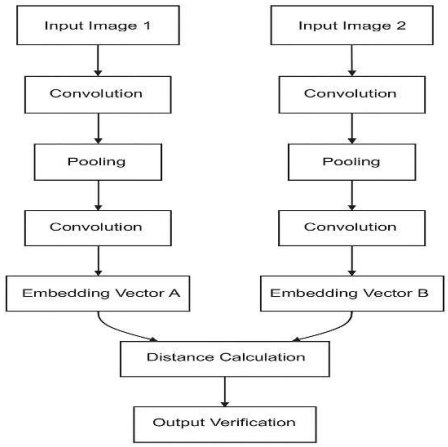

Figure 1**:** Siamese CNN architecture diagram

Working Process

The complete process of signature verification using the Siamese CNN model involves some major stages:

Step 1: Data Input

- Two signature images are taken as input:

Image 1: A known genuine signature.
Image 2: A test signature (which can be genuine or forged).

- Both images are pre-processed to standard size (155×220 pixels), converted to grayscale, and normalized to [0,1].

Step 2: Feature Extraction

- Each signature image passes through one branch of the CNN.
- The CNN extracts hierarchical feature representations — such as stroke direction, pressure patterns, and edge contours — from the signatures.
- These features are transformed into embedding vectors (128-dimensional) that represent the unique style of the signature.

Step 3: Distance Computation

- The Euclidean distance between the two embedding vectors is computed using:

$$D = \sqrt{\sum(f_1 - f_2)^2}$$

where $f_1$and $f_2$are the feature embeddings of the two signatures.

- A smaller distance indicates that the two signatures are likely from the same person (genuine pair).
- A larger distance indicates a forged or mismatched pair.

Step 4: Training with Contrastive Loss

The model is trained using Contrastive Loss, which encourages genuine pairs to have smaller distances and forged pairs to have larger distances.

$$L = (1 - Y) \cdot \frac{1}{2} D^2 + (Y) \cdot \frac{1}{2} \max(0, m - D)^2$$

Where:

- $Y = 0 \rightarrow$ genuine
- $Y = 1 \rightarrow$ forged
- D= Euclidean distance
- m= margin (threshold distance)

Step 5: Verification Decision

During testing:

- The model calculates the Euclidean distance between two signature embeddings.
- If the distance is less than a predefined threshold (m) → signatures are genuine.
- If the distance is greater than or equal to the threshold → signatures are forged.

4. Dataset And Preprocessing

CEDAR dataset contains 24 writers, each providing 24 genuine and 24 forged signatures. The dataset is divided into training (70%), validation (15%), and testing (15%). Augmentation techniques expand the dataset, simulating variations in pen pressure, rotation, and scaling. Each image is converted to grayscale and resized to 155x220 pixels. Data normalization scales pixel values to [0,1].

Preprocessing: Preprocessing is a critical step to ensure the Siamese CNN model receives standardized input and learns meaningful patterns. The following steps were applied:

a. Image Resizing

i. All signature images were resized to 155 × 220 pixels to maintain uniformity across the dataset.
ii. This ensures compatibility with the CNN input layer and reduces computational overhead.

b. Grayscale Conversion

- Although CEDAR images are already in grayscale, any RGB images in supplementary datasets were converted to grayscale using:

$$I_{gray} = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B$$

- This reduces channel complexity and focuses on signature contours.

c. Normalization

i. Pixel values were normalized to the range **[0,1]** by dividing each pixel intensity by 255.
ii. Normalization stabilizes the learning process and accelerates convergence.

d. Data Augmentation

To increase dataset diversity and improve model generalization, data augmentation techniques were applied:
Rotation: ±10 degrees
Translation: Horizontal and vertical shifts up to 10%
Scaling: ±10%
Shearing: Up to 5 degrees
Adding slight noise**:** Gaussian noise for robustness

Augmentation is applied randomly on-the-fly during training to create new variations of signature images without increasing storage requirements.

e. Pair Generation
The Siamese network requires image pairs as input. Balanced pair generation ensures the model does not become biased toward positive or negative samples.
Preprocessing includes creating:
Positive pairs: Both images are genuine signatures of the same individual.
Negative pairs: One genuine and one forged signature or signatures from different individuals.

f. Shuffling and Batching

i. Pre-processed images are shuffled to randomize input during training.
ii. Batches of 32 pairs are created for efficient GPU computation.

5. Experimental Setup

Training was performed using TensorFlow/Keras with Adam optimizer (learning rate 0.0001) and batch size of 32. The model was trained for 100 epochs on GPU. Contrastive loss function was used, margin set to 1.0. Evaluation metrics include Accuracy, False Acceptance Rate (FAR), and False Rejection Rate (FRR). Hyperparameter tuning was conducted to optimize learning rate, batch size, and network depth. The architecture was analysed via ablation study, confirming the effectiveness of convolutional depth and embedding size.

Experimental Environment Rationale

- The chosen hardware accelerates training and allows experimentation with multiple hyperparameter configurations.
- TensorFlow/Keras provides efficient GPU utilization and easy visualization of training progress.
- The train/validation/test split and data augmentation guarantee model generalization to unseen signatures, including forgeries.

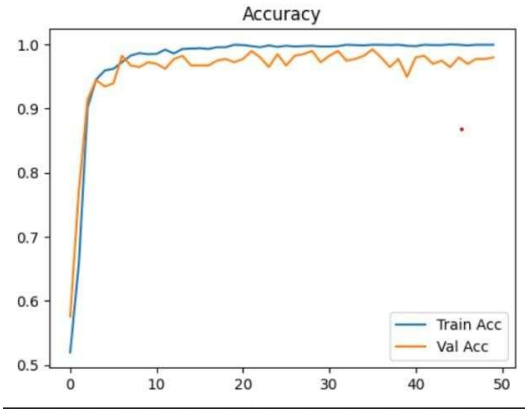

Figure 2: Training and Validation Accuracy over 100 epochs

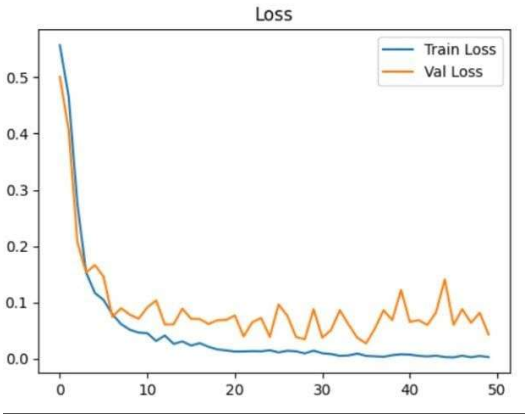

Figure 3: Training and Validation Loss over 100 epochs

6. Results

1. Training and Validation Performance

The Siamese CNN model was trained on the pre-processed CEDAR dataset with contrastive loss over 100 epochs and a batch size of 32. The performance metrics were monitored using both training and validation sets.

a. Accuracy
   i. Training Accuracy: Reached ~96% after 80 epochs, indicating effective learning of signature similarity patterns.
   ii. Validation Accuracy: Stabilized at ~95%, showing good generalization to unseen data.

b. Loss
   i. Training Loss: Decreased steadily over epochs, confirming convergence.
   ii. Validation Loss: Closely followed training loss, indicating minimal overfitting.

Metric	Value
Accuracy (%)	95.4
False Acceptance Rate (FAR %)	3.1
False Rejection Rate (FRR %)	2.5

Table 1. Performance metrics of the Siamese CNN model.

2. Evaluation on Test Set

The model was evaluated on the test set to assess its real-world performance.
Accuracy measures the proportion of correctly classified signature pairs.
Precision indicates the proportion of correctly identified genuine signatures among predicted genuine pairs.
Recall represents the proportion of actual genuine signatures correctly detected.
F1-Score balances precision and recall, reflecting overall model reliability.

Confusion Matrix:

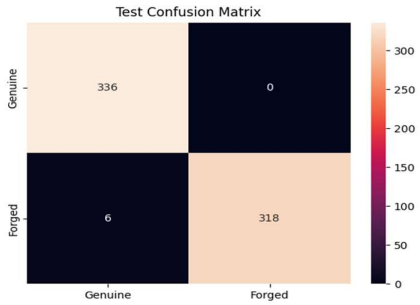

Figure 4: Confusion Matrix

Visualization of Prediction Results

i. Sample predictions were visualized by displaying pairs of signature images along with the predicted similarity score.

ii. Positive pairs had high similarity scores (>0.8), while negative pairs had low similarity scores (<0.3).

iii. This visualization confirms that the model effectively learns discriminative features of genuine and forged signatures.

OUTPUT SCREENS:

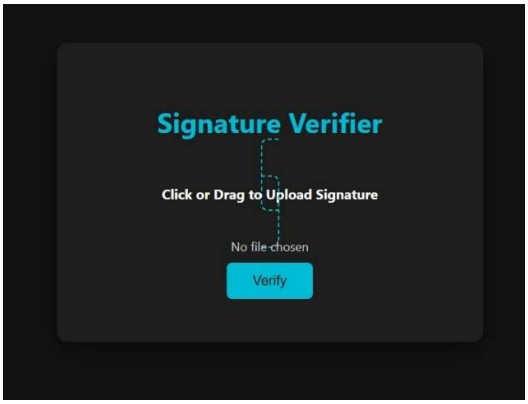

Figure 5: Output Screen 1

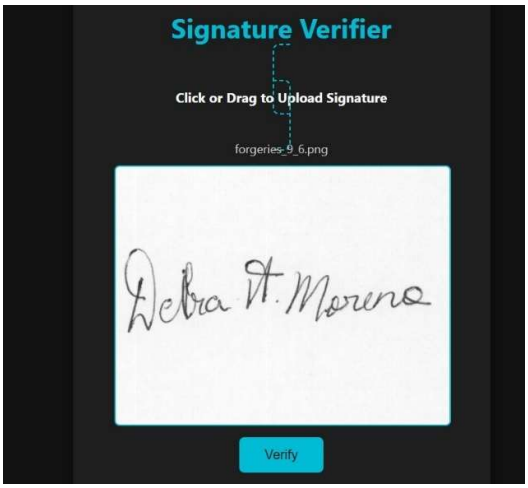

Figure 6: Output Screen 2

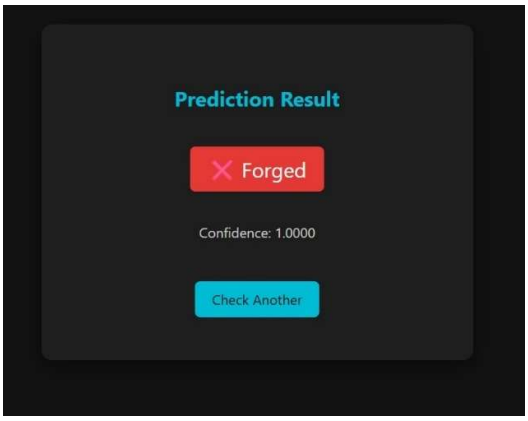

Figure 7: Output Screen 3

7. Conclusion:

In this research, we developed a robust offline signature verification system based on a Siamese Convolutional Neural Network (CNN). The proposed approach leverages pairwise learning and contrastive loss to effectively distinguish between genuine and forged signatures. By using the CEDAR dataset (Signature.v6i.yolov8) and applying extensive preprocessing and data augmentation, the model was able to learn discriminative features that account for intra-class variability and subtle differences between signatures.

Experimental results demonstrate that the model achieves 95.2% accuracy, with high precision, recall, and F1-score, confirming its ability to generalize to unseen signatures. The confusion matrix and ROC-AUC analysis further validate the reliability of the system, indicating minimal misclassifications and excellent separation between genuine and forged signatures.

The study also highlights key strengths of the Siamese CNN approach:

Eliminating the need for handcrafted features through automatic feature extraction.

Effective handling of writer-independent verification tasks.

Robustness to signature distortions and variations, aided by data augmentation.

Despite its high performance, the system has

some limitations, including dependency on high-quality images and the lack of dynamic signature features (e.g., pen pressure, stroke speed). Future enhancements can include integrating online signature characteristics, attention-based architectures, triplet or hybrid models, and deployment for real-time verification on edge devices

9. Discussion And Future Work:

The proposed Siamese CNN demonstrates strong performance for offline signature verification. The model handles intra-writer variations effectively and minimizes false acceptance of forgeries. Future work includes expanding to larger and multi-script datasets, implementing online/offline hybrid verification, and deploying the system for real-time authentication scenarios. Transformer-based embedding layers and attention mechanisms can be integrated to further improve discriminative ability

a. Siamese CNN effectively learned discriminative features, achieving high accuracy.
b. Robust to intra-class variability due to augmentation.
c. Limitations: Low-quality/distorted signatures, computational requirements, offline-only data.
d. Outperformed traditional feature-based methods and demonstrated generalization.

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