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Classification of Offline Signature Authenticity Based on Digital Imagery Using Convolutional Neural Network

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Abstract
Verification of digital image-based signature authenticity is an automated approach to distinguishing between genuine and forged signatures. This study aims to develop a classification model for signature authenticity using a Convolutional Neural Network (CNN). The study used the CEDAR dataset, which consists of 2,640 images comprising 1,320 genuine signatures and 1,320 forged signatures from 55 writers. The research stages included image preprocessing through resizing to 128 × 128 pixels and pixel value normalization, stratified dataset splitting, data augmentation on the training subset, and training of a CNN consisting of four convolutional blocks with regularization. Model evaluation was conducted on 396 test images using accuracy, precision, recall, F1-score, a confusion matrix, and the Receiver Operating Characteristic (ROC) curve. The test results showed that the model achieved an accuracy of 98.48%, with 390 correctly classified images and six misclassified images. These findings indicate that the developed CNN model can classify genuine and forged signatures with high accuracy under the dataset and testing scheme applied. However, these results do not establish the superiority of the proposed architecture over other methods because this study did not include a comparative model.

Keywords: Digital Signature; Image Classification; Convolutional Neural Network; CEDAR.

Abstrak
Verifikasi keaslian tanda tangan berbasis citra digital merupakan salah satu pendekatan untuk membedakan tanda tangan asli dan palsu secara otomatis. Penelitian ini bertujuan mengembangkan model klasifikasi keaslian tanda tangan menggunakan Convolutional Neural Network (CNN). Dataset yang digunakan adalah CEDAR, yang terdiri atas 2.640 citra, meliputi 1.320 tanda tangan asli dan 1.320 tanda tangan palsu dari 55 penulis. Tahapan penelitian mencakup prapemrosesan citra melalui pengubahan ukuran menjadi 128 × 128 piksel dan normalisasi nilai piksel, pembagian dataset secara terstratifikasi, augmentasi data pada subset pelatihan, serta pelatihan CNN yang terdiri atas empat blok konvolusi dengan regularisasi. Evaluasi dilakukan menggunakan 396 citra pengujian berdasarkan akurasi, precision, recall, F1-score, confusion matrix, dan kurva Receiver Operating Characteristic (ROC). Hasil pengujian menunjukkan bahwa model memperoleh akurasi sebesar 98,48%, dengan 390 citra diklasifikasikan secara benar dan enam citra mengalami kesalahan klasifikasi. Hasil ini menunjukkan bahwa model CNN yang dikembangkan mampu mengklasifikasikan tanda tangan asli dan palsu dengan tingkat ketepatan yang tinggi pada dataset dan skema pengujian yang digunakan. Namun, hasil tersebut belum menunjukkan keunggulan arsitektur yang diusulkan dibandingkan metode lain karena penelitian ini belum melibatkan model pembanding.

Kata Kunci: Tanda Tangan Digital; Klasifikasi Citra; Convolutional Neural Network; CEDAR.

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1. Introduction

Signatures are a form of behavioral biometric identity widely used in administrative document ratification, financial transactions, and legal procedures. Because signatures play a central role in these activities, verifying their authenticity is an important requirement (Lopes *et al*., 2022). Verification becomes difficult when forged signatures closely resemble genuine ones during visual inspection. At the same time, genuine signatures produced by the same individual can vary in shape, size, slant, and stroke patterns, making authenticity assessment challenging. Hameed *et al*. (2021) noted that manual signature examination requires precision and experience and becomes less efficient when the volume of documents to be verified is large. Therefore, an image processing-based approach is needed to distinguish between genuine and forged signatures more systematically. Digital signature analysis can be performed through online and offline approaches. The online approach uses dynamic information captured during the writing process, such as pen pressure, writing speed, and stroke sequence. In contrast, the offline approach uses static signature images acquired after the writing process is completed. Because dynamic writing information is unavailable in the offline approach, the analysis relies on visual image characteristics, such as shape, contour, line thickness, and stroke arrangement (Liu *et al*., 2021). Furthermore, the visual difference between a genuine signature and a forgery can be minimal, particularly in skilled forgeries produced through careful imitation, while the absence of dynamic information in offline signature images poses an additional challenge during feature extraction (Parcham *et al*., 2021). Under these conditions, a method capable of learning visual signature characteristics is required to support authenticity classification.

One method commonly used to process signature images is the Convolutional Neural Network (CNN), a deep learning architecture designed to learn image features through multi-stage convolutional operations. In the early layers, the network learns simple patterns, such as lines and contours, and subsequently combines them into more complex representations. This capability allows CNNs to extract image characteristics automatically without relying entirely on manual feature engineering. In signature verification research, Parcham *et al*. (2021) integrated a CNN into CBCapsNet, combining it with a Capsule Neural Network to improve the representation of spatial signature characteristics. Similarly, Liu *et al*. (2021) leveraged CNN-based Siamese networks and deep metric learning to measure signature similarity based on local features. Both studies indicate that CNN-based feature learning is effective for signature analysis, even though their model designs and evaluation objectives differ. Research on CNN-based signature analysis has also been conducted using various architectural configurations. Alkattan and Tahir Aldabagh (2022) developed an offline signature verification method that combined a CNN with signature length normalization and Histogram of Oriented Gradients (HOG) features on the SIGMA dataset, achieving an accuracy of up to 97.1%. Fatihia *et al*. (2023) implemented batch normalization adjustments in a CNN for offline handwritten signature verification and obtained a test accuracy of 84.84%, although the training analysis indicated overfitting. Subsequently, Fatihia *et al*. (2024) developed a CNN for mobile signature verification applications and reported an accuracy of 86.36%. While these studies demonstrate the potential of CNNs in signature analysis, model performance is influenced by dataset characteristics, preprocessing stages, model configurations, and evaluation protocols. Consequently, these findings must be interpreted within the context of their respective experimental conditions and cannot be compared solely on the basis of accuracy values.

Further developments in signature verification incorporate hybrid architectures, similarity learning, and model interpretability. Tsourounis *et al*. (2022) utilized knowledge transfer from handwritten writer identification tasks to support feature learning in offline signature verification. Sharma *et al*. (2022) used a Siamese CNN to learn similarities between paired signatures, whereas Xiao and Ding (2022) proposed a two-stage Siamese network to address signature representation challenges. Longjam *et al*. (2023) combined a CNN and Bidirectional Long Short-Term Memory (BiLSTM) in a writer-independent signature verification approach. More recently, Zheng *et al*. (2025) developed HTCSigNet by combining a CNN and a Vision Transformer to capture both local and global signature features, while Li *et al*. (2025) proposed a multi-scale architecture integrating a CNN and CrossViT for offline signature recognition and verification. Beyond architectural modifications, recent studies have also examined the explainability of model predictions. Yoldar *et al*. (2025) investigated CNNs, Vision Transformers, attention mechanisms, and Explainable Artificial Intelligence (XAI) for signature forgery detection on the CEDAR dataset, reporting accuracies of 93.19% for Xception and 91.04% for ResNet50 alongside interpretability evaluations of image regions contributing to model decisions. These studies confirm that the CEDAR dataset remains relevant in deep learning-based forgery detection, although their architectural designs and evaluation schemes differ from the direct classification configuration examined in the present work. Although CNNs have been widely applied to

signature analysis on the CEDAR dataset, there remains a need to empirically evaluate a streamlined CNN configuration designed for the direct binary classification of signature images into genuine and forged classes. Rather than proposing a complex hybrid architecture or claiming superiority over all existing methods, this study focuses on developing and evaluating a four-block convolutional CNN with cascading filter sizes of 32, 64, 128, and 256 on the CEDAR dataset, which comprises 2,640 images (1,320 genuine and 1,320 forged signatures). Each convolutional block is followed by max pooling for dimensionality reduction, after which the extracted features are passed through a flatten layer, a dense layer with L2 regularization and dropout, and a sigmoid output layer to generate class probabilities. The research workflow encompasses image preprocessing, stratified dataset splitting into training, validation, and testing subsets, brightness and contrast augmentation on the training data, and regularized model training, with performance evaluated using a confusion matrix, ROC curve, accuracy, precision, recall, F1-score, and ROC-AUC. This study provides an empirical baseline regarding the capability of a four-block CNN in distinguishing genuine and forged signature images and serves as a foundation for future research exploring more complex deep learning verification frameworks.

2. Methodology

This study employed an experimental approach by applying a Convolutional Neural Network (CNN) to classify signature images into two classes: genuine signatures and forged signatures. The research was conducted through six main stages, comprising dataset collection, image preprocessing, dataset splitting, data augmentation, CNN model design and training, and model evaluation, as illustrated in Figure 1. A CNN was selected because it can learn visual image characteristics automatically through convolutional layers without requiring manual feature engineering (Kao & Wen, 2020). Each stage was designed to generate uniform input data, train the model on the training subset, and evaluate classification performance objectively based on the model's direct predictions on the unseen test subset.

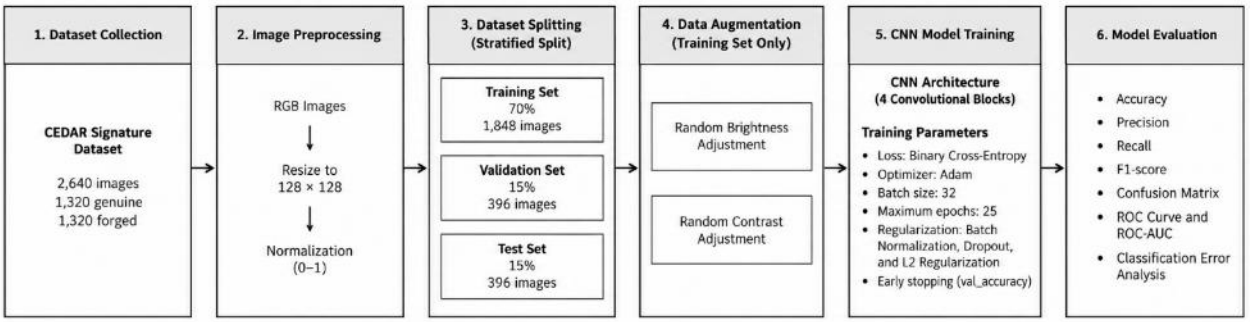


Figure 1. Stages of the Research Method

The data preparation pipeline encompassed the first four stages of the workflow: 1) Dataset collection used the CEDAR Signature Dataset obtained from Kaggle, which consists of 2,640 signature images from 55 writers, evenly divided into 1,320 genuine signatures and 1,320 forged signatures (Kalera *et al.*, 2004). The images were organized by class label, where label 0 was assigned to genuine signatures and label 1 was assigned to forged signatures. Initial verification was performed by counting the images in each class and checking file integrity prior to preprocessing, ensuring a balanced class distribution across the dataset so that evaluation would not be dominated by either class (Kao & Wen, 2020). 2) Image preprocessing was then performed to standardize input characteristics before the images were fed into the CNN model. Each image was read in three-channel RGB format and resized to 128 × 128 pixels, after which pixel intensity values were normalized from the range of 0–255 to 0–1 by dividing each pixel value by 255. This preprocessing procedure was applied consistently across the training, validation, and testing subsets (Sanchez-Gordon, 2022; Tariq *et al.*, 2023). 3) Dataset splitting was subsequently carried out using a two-stage stratified split via the train_test_split() function in the Scikit-learn library based on class labels, with random_state = 42 set to ensure reproducibility. In the first stage, 70% of the data (1,848 images) was allocated to the training set, while the remaining 30% was reserved for validation and testing. In the second stage, the remaining data was divided equally into validation and testing sets of 396 images each (15% per subset). This stratified partitioning preserved an equal class balance across all subsets, resulting in 924 genuine and 924 forged images in the training set, and 198 genuine and 198 forged images in both the

validation and testing sets. The training set was used to update model weights, the validation set to monitor performance during training, and the test set to perform the final evaluation (Ebrahimpour, 2019). 4) Data augmentation was applied exclusively to the training data to introduce visual variations during learning, using random brightness adjustment (max_delta = 0.2) and random contrast adjustment (within the range of 0.8–1.2), followed by clipping pixel values back to the 0–1 range. The validation and test sets were not augmented so that model monitoring and evaluation relied solely on images subjected to standard preprocessing (Poornima & Roopa Banakar, 2023; Xiao & Ding, 2022). In the fifth stage, the CNN model was designed and trained to learn the visual characteristics of signatures progressively through multiple convolutional layers. As shown in Figure 2, the architecture consists of four convolutional blocks with cascading filter counts of 32, 64, 128, and 256, respectively. Each block applies convolutional and max-pooling operations to extract features and reduce spatial dimensions, while Batch Normalization and Dropout are incorporated as regularization mechanisms to control the learning process (Parcham *et al.*, 2021).

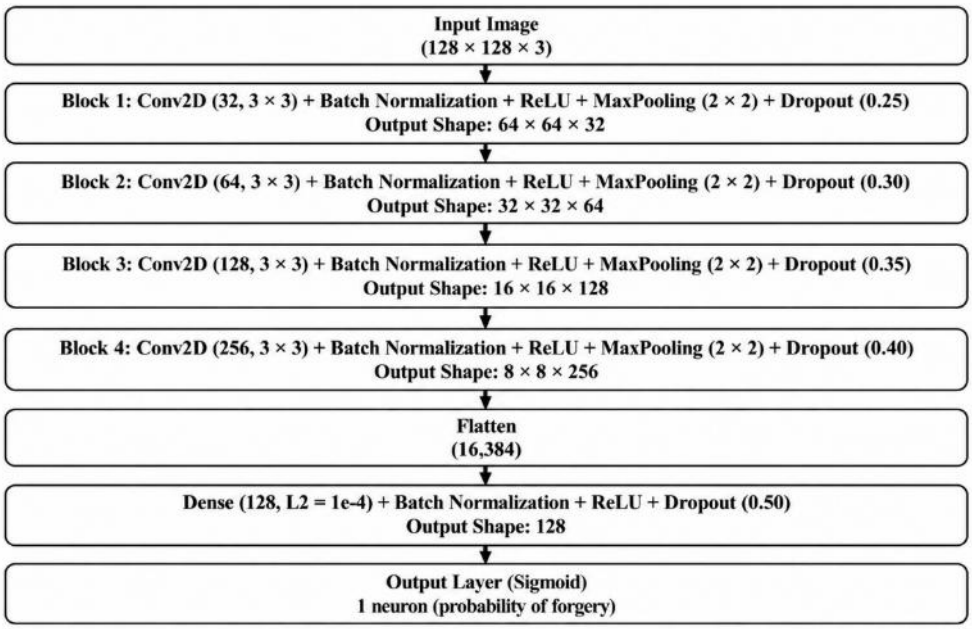


Figure 2. CNN Architecture Diagram

Based on Figure 2, an input image of size 128 × 128 × 3 is processed through the four convolutional blocks to produce a final feature map of size 8 × 8 × 256. This feature representation is then converted by the Flatten layer into a one-dimensional vector of 16,384 elements and passed to a Dense layer containing 128 neurons with L2 regularization. The output layer consists of a single neuron with a sigmoid activation function that outputs the probability of the positive class (forged signature), which is converted into a binary class label using a threshold of 0.5. Model training was executed using the binary cross-entropy loss function and the Adam optimizer with a learning rate of 10^{-4}, a batch size of 32, and a maximum of 25 epochs. An Early Stopping mechanism was implemented by monitoring validation accuracy to terminate training automatically once validation performance ceased to improve. In the final stage, model evaluation was conducted on the 396 test images that were excluded from weight updates and training termination monitoring. Using the 0.5 probability threshold, where forged signatures were defined as the positive class (label 1) and genuine signatures as the negative class (label 0), classification performance was quantified using accuracy, precision, recall, F1-score, and specificity, where precision and recall measure forged signature detection performance and specificity measures the accurate identification of genuine signatures. Additionally, a confusion matrix was constructed to detail the number of correct and incorrect predictions per class, while the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (ROC-AUC) were analyzed to assess class separability across various probability thresholds. All evaluation metrics were computed directly from the raw prediction probabilities and labels generated by the model on the test set without post-prediction adjustments. Furthermore, false positives (genuine signatures misclassified as forged) and false negatives (forged signatures misclassified as genuine) were examined from the confusion matrix to characterize the specific error patterns made by the model rather than relying solely on overall accuracy (Kao & Wen, 2020; Ruiz *et al.*, 2020).

3. Results and Discussion

3.1 Dataset Distribution and Preprocessing Results

This study utilized the CEDAR Signature Dataset comprising 2,640 signature images, evenly distributed between 1,320 genuine signatures (50%) and 1,320 forged signatures (50%). This balanced composition established equal initial conditions for model learning and classification evaluation so that neither class dominated the training process. Through the stratified split procedure (70% training, 15% validation, and 15% testing), the dataset was partitioned into 1,848 training images, 396 validation images, and 396 test images, with each subset preserving an identical 1:1 class ratio, as detailed in Table 1.

Table 1. Dataset Distribution

Subset	Genuine	Forged	Total
Training	924	924	1,848
Validation	198	198	396
Testing	198	198	396
Total	1,320	1,320	2,640

Prior to model training, image preprocessing standardized all inputs into three-channel RGB images resized to 128 × 128 pixels with pixel intensities normalized from 0–255 to 0–1. While dimensional uniformity enables consistent batch processing and normalization stabilizes neural network optimization, downsampling alters the spatial resolution of the original images, as illustrated in Figure 3. In this example, reducing an initial image of approximately 534 × 385 pixels to 128 × 128 pixels compresses the spatial representation, which can affect fine stroke details that serve as discriminative visual cues in signature verification.

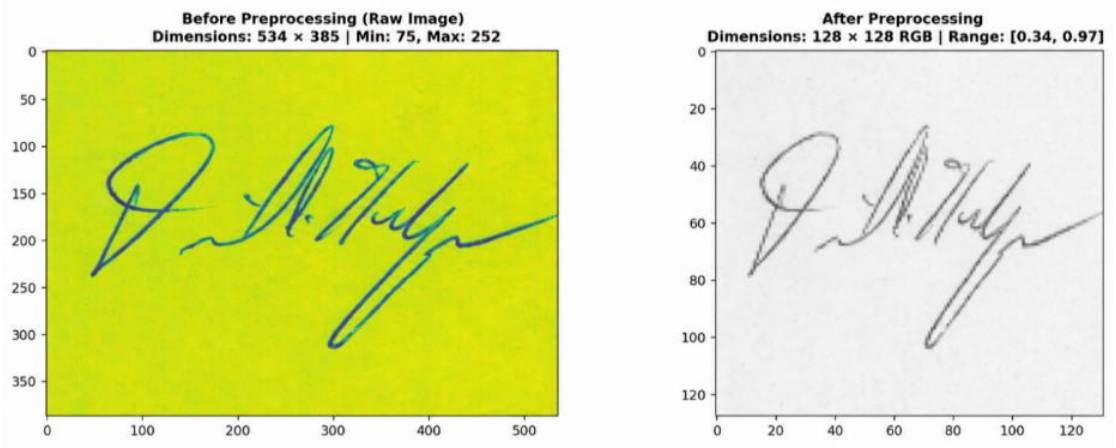


Figure 3. Comparison of Signature Image Before and After Preprocessing

To enrich visual diversity during learning without altering class labels, brightness and contrast augmentations were applied exclusively to the training subset, whereas the validation and testing subsets retained their standard preprocessed appearance for unbiased evaluation. Representative results of this transformation are displayed in Figure 4, where the first panel shows the preprocessed signature image prior to augmentation and the subsequent three panels illustrate variations generated through random brightness and contrast adjustments. Introducing these intensity variations during training encourages the CNN model to learn signature stroke characteristics that remain robust against illumination and contrast differences.

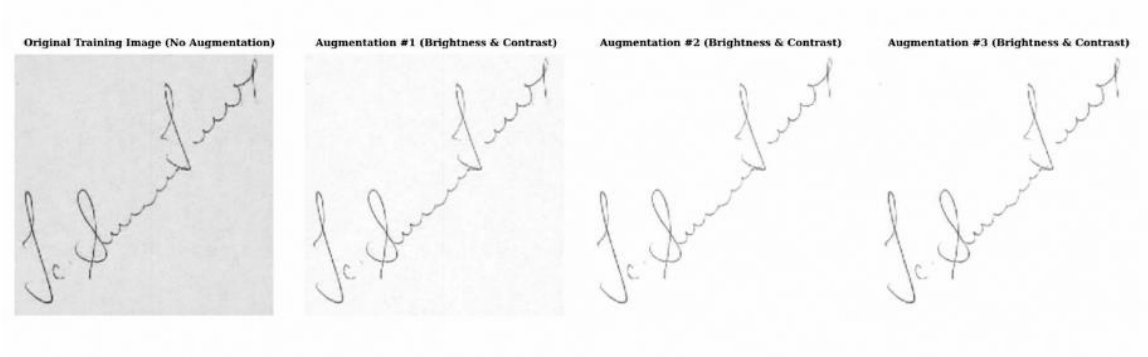


Figure 4. Example of Signature Image Augmentation on Training Data

3.2 Model Training and Classification Performance

The training process was monitored across epochs by tracking accuracy and loss trajectories on both the training and validation subsets to assess learning progression and stability. Under the Early Stopping mechanism, training concluded at epoch 23, with the resulting learning curves presented in Figure 5.

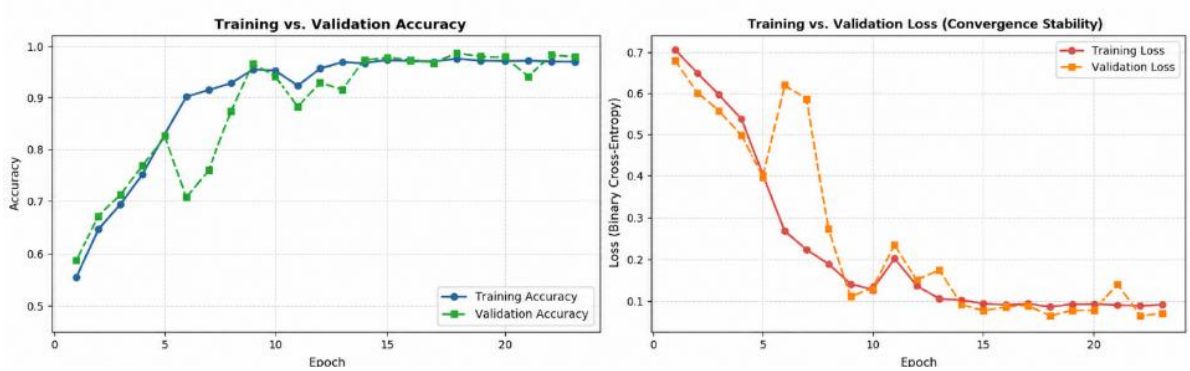


Figure 5. Comparison of Accuracy and Loss on Training and Validation Data

Based on Figure 5, training accuracy rose from approximately 55% in the first epoch to 97% by the end of training, while validation accuracy similarly increased from approximately 59% to 98% over the final epochs. A corresponding downward trend occurred in the loss curves, where training loss declined from roughly 0.71 to 0.09 and validation loss decreased from about 0.68 to 0.08. Despite minor fluctuations across intermediate epochs, the close alignment and convergence of the training and validation trajectories demonstrate that the CNN model effectively learned discriminative signature patterns without exhibiting severe overfitting.
Following the training phase, classification performance was evaluated on the 396 unseen test images (198 genuine and 198 forged signatures) using the confusion matrix shown in Figure 6 alongside accuracy, precision, recall, F1-score, specificity, and ROC-AUC metrics.

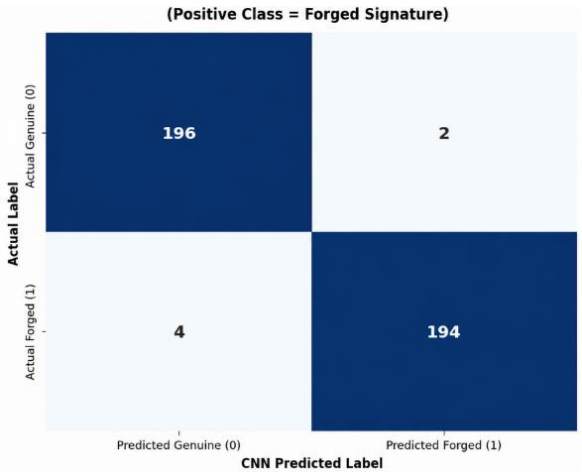


Figure 6. Confusion Matrix

Based on Figure 6, the CNN model correctly classified 196 genuine signature images and 194 forged signature images, resulting in 390 correct predictions out of 396 test samples and an overall accuracy of 0.9848 (98.48%). Conversely, two genuine signatures were misclassified as forged (false positives), and four forged signatures were misclassified as genuine (false negatives). Because false negatives represent undetected counterfeits that can compromise verification security, performance was further examined across class-specific metrics, as summarized in Table 2.

Table 2. CNN Model Performance Evaluation Results

Class	Precision	Recall	F1-Score
Genuine	0.9800	0.9899	0.9849
Forged	0.9898	0.9798	0.9848
Overall Accuracy			0.9848

As shown in Table 2, the model achieved an overall accuracy of 0.9848 with balanced performance across both classes. For the forged signature class (positive class), a precision of 0.9898 indicates that nearly all samples predicted as forged were actual forgeries, while a recall of 0.9798 reflects the successful detection of 194 out of 198 forged signatures, yielding an F1-score of 0.9848. Meanwhile, a specificity (genuine class recall) of 0.9899 confirms that the model accurately identified 196 out of 198 genuine signatures, accompanied by a genuine class precision of 0.9800 and an F1-score of 0.9849.

3.3 Visual Prediction, ROC Curve, and Error Analysis

To complement the quantitative metrics, sample test predictions were visualized alongside their actual labels, predicted classes, and raw sigmoid output probabilities, as shown in Figure 7.

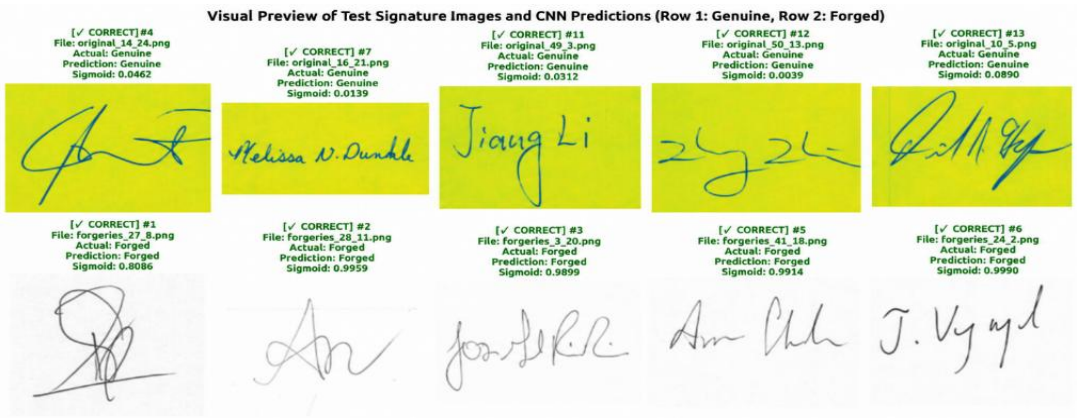


Figure 7. Visualization of CNN Prediction Results

Based on Figure 7, the CNN model correctly classified all ten displayed test samples according to their ground-truth labels, where the top row represents genuine signatures and the bottom row represents forged signatures. Under the 0.50 classification threshold, the genuine signature samples yielded low sigmoid probabilities ranging from 0.0039 to 0.0890, indicating a minimal estimated likelihood of forgery, whereas the forged signature samples produced high sigmoid probabilities between 0.8086 and 0.9990, demonstrating strong prediction confidence for both classes. Beyond evaluation at a fixed 0.50 threshold, the model's discriminative capacity across varying decision thresholds was examined using the Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), and the Youden index, as depicted in Figure 8.

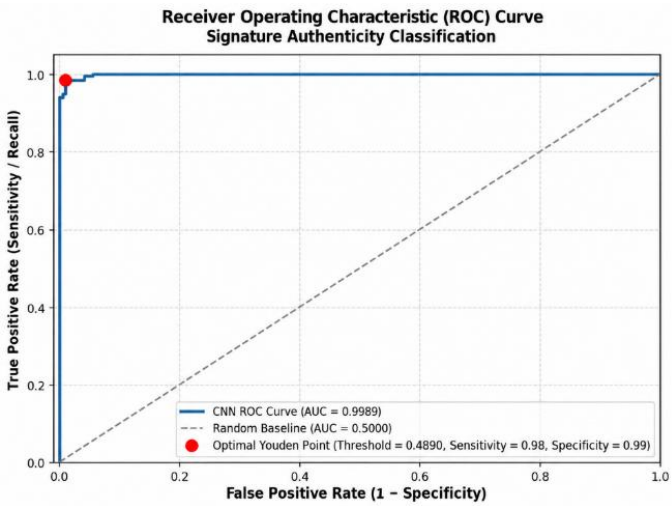


Figure 8. ROC Curve Analysis

Based on Figure 8, the ROC curve approaches the upper-left corner and achieves an AUC of 0.9989, indicating high class separability on the evaluated test set. The optimal threshold identified via the Youden index was 0.4890, corresponding to a sensitivity of approximately 0.98 and a specificity of approximately 0.99. This demonstrates that near the 0.50 operating point, the model maintains high sensitivity to forged signatures while keeping the false rejection rate of genuine signatures low. Nevertheless, because the AUC reflects aggregate separability across thresholds rather than error-free classification, these results must be interpreted within the applied experimental protocol based on the model's raw test probabilities. To further investigate the limitations of the model, the six misclassified test images were visually inspected alongside their predicted probabilities, as presented in Figure 9.

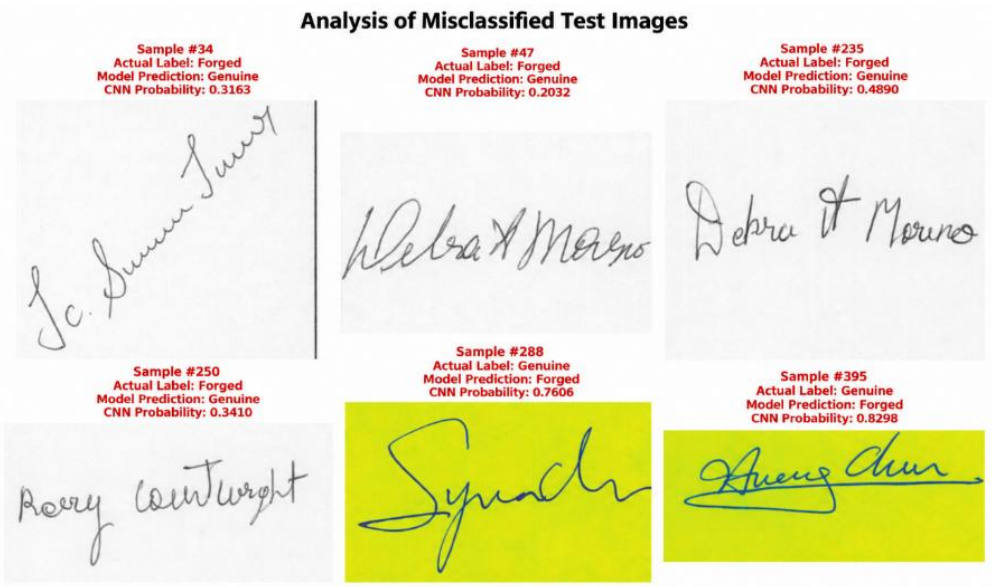


Figure 9. Misclassified Test Samples

Based on Figure 9, classification errors occurred in both directions: four forged signatures (samples 34, 47, 235, and 250) were falsely predicted as genuine, whereas two genuine signatures (samples 288 and 395) were falsely predicted as forged. The displayed sigmoid values reveal the model's output confidence on these ambiguous cases under the 0.50 threshold. Specifically, sample 395 (a genuine signature) received a forgery probability of 0.8298 and was consequently misclassified as forged, whereas sample 34 (a forged signature) received a forgery probability of 0.3163 and was misclassified as genuine. These misclassified instances indicate that subtle visual similarities between skilled forgeries and genuine stroke variations remain challenging for the four-block CNN architecture when images are compressed to 128 × 128 pixels.

4. Conclusion

This study developed a Convolutional Neural Network (CNN) model for classifying the authenticity of offline handwritten signatures on the CEDAR dataset, which consists of 2,640 images evenly divided into 1,320 genuine and 1,320 forged signatures from 55 writers. The classification workflow involved image preprocessing, stratified dataset splitting, data augmentation on the training subset, and model training using a four-block convolutional architecture with regularization. Based on the evaluation of 396 unseen test images, the model achieved an accuracy of 98.48%, correctly classifying 390 images (196 genuine and 194 forged signatures) while misclassifying six images. These findings demonstrate that the developed CNN model can distinguish between genuine and forged signatures with high classification accuracy under the dataset and experimental protocol employed in this study. However, because no baseline or ablation model was included in the experiments, the individual contributions of the four-block architecture and data augmentation cannot be established independently. Future research should therefore incorporate comparative experiments involving a baseline CNN without augmentation, transfer-learning architectures, and Siamese-based networks, as well as further investigate misclassified samples and evaluate model generalizability across additional signature datasets.

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