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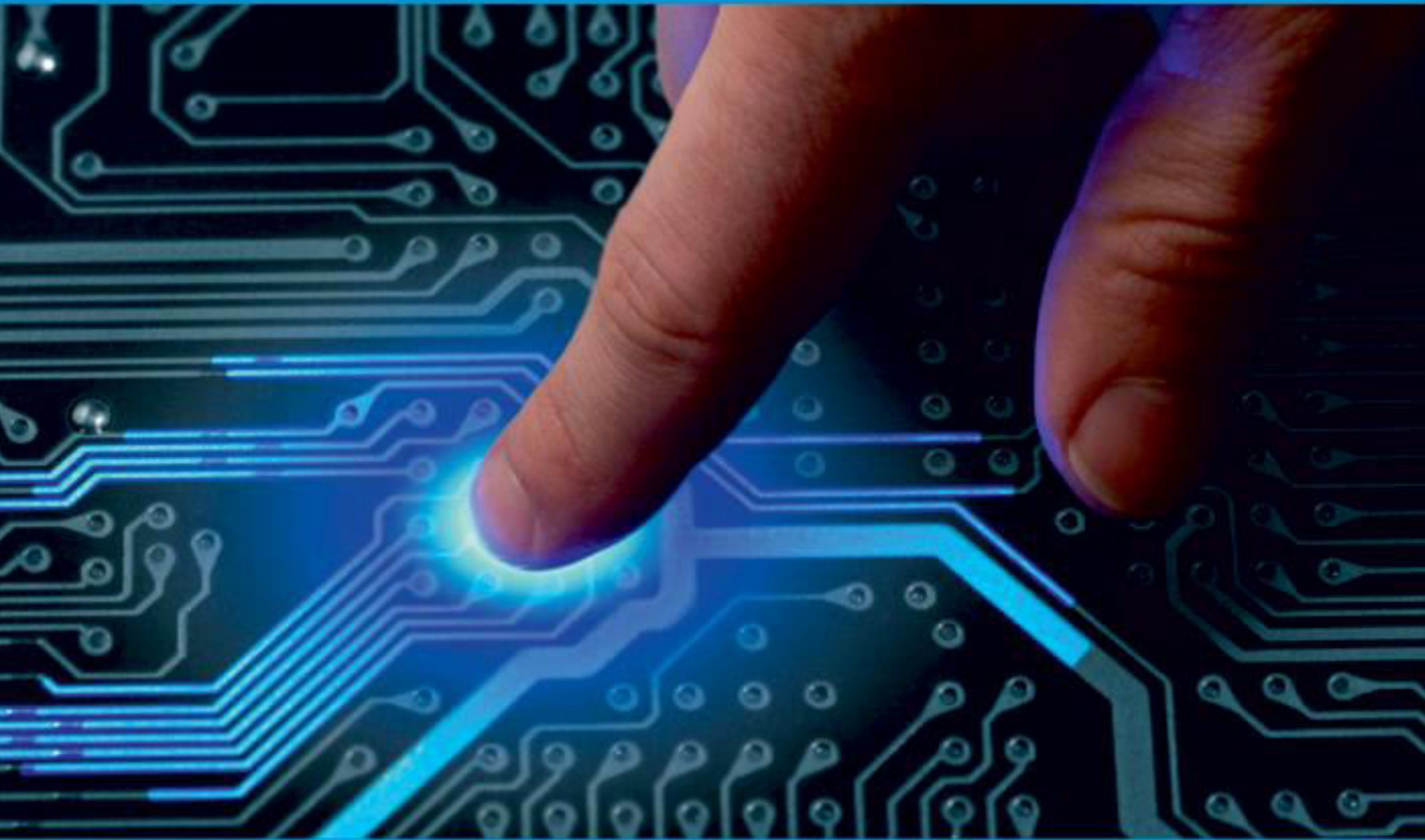

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Offline Signature Verification with Autoencoder-CNN Hybrid Feature Extraction for Improved Fake Signature Detection

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ABSTRACT: A novel approach aimed at elevating the performance of offline signature verification systems by harnessing the combined power of Autoencoders and Convolutional Neural Networks (CNNs). Our evaluation encompassed Convolutional Neural Networks (CNN), K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Gaussian Temporal Rule, Probabilistic Neural Networks, Multi-layered Perception, Long Short-Term Memory (LSTM), and various combinations thereof. Notably, our proposed Autoencoder with Convolutional Neural Networks (AE with CNN) outshone all other approaches, achieving an impressive accuracy rate of 98.48%. While CNN displayed commendable performance at 89%, KNN and SVM fusion attained 78.50% accuracy, suggesting room for improvement in distinguishing genuine and forged signatures. The Gaussian Temporal Rule proved robust, with an accuracy of 91.20%, and Probabilistic Neural Networks and Multi-layered Perception with SVM reached accuracies of 92.06% and 91.67%, respectively. The introduction of LSTM in conjunction with SVM and KNN significantly enhanced accuracy to 95.40%, 95.20%, and 92.70%, respectively. Collectively, these findings provide valuable insights into the potential of AE with CNN as a leading solution for achieving highly accurate signature verification, particularly in contexts where the distinction between authentic and counterfeit signatures is critical.

KEYWORDS: signature verification system, Autoencoder, Convolutional Neural Network, CEDAR

I. INTRODUCTION

The success of offline signature verification systems heavily relies on the effectiveness of their feature extraction stage, as it profoundly influences the system's ability to distinguish between genuine and forged signatures. This study introduces a novel approach to feature extraction from signature images, combining the power of Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG), with subsequent feature selection using Decision Trees to identify crucial signature characteristics. The fusion of CNN and HOG methods culminates in a robust feature set. To assess the efficacy of this hybrid approach, three diverse classifiers, including long short-term memory, support vector machine, and K-nearest Neighbour, were employed. This research paves the way for enhanced signature verification, ensuring its broader applications in security and authentication systems [1]. However, the widespread availability of editing tools has opened the door to potential adversaries who seek to manipulate data, posing a significant threat to decision-making processes in various industrial sectors. This disturbing trend of malicious content alterations not only erodes the trustworthiness of information dissemination but also underscores the urgent need for Industrial Cyber-Physical Systems (ICPS) capable of verifying the integrity of transferred images. These systems play a crucial role in ensuring that the information they convey is accurate and reliable for informed decision-making in industrial automation. In this article, we introduce "INDFORG," a novel solution featuring an Automatic Rotation Angle Detection and Correction Algorithm (ARADC) that offers intelligent forgery detection in industrial images [2].
The development of an image rotation angle estimator is of paramount importance. This innovative approach hinges on the intrinsic relationship between the rotation angle and the frequencies associated with interpolation peaks within the image's edge map spectrum. By leveraging rescaling and rotation detection techniques, coupled with precise parameter estimation, this method becomes a formidable tool in the detection of counterfeit objects cunningly inserted into images. In instances where forged images incorporate diverse sources or segments from the same image, manipulations like rescaling and rotation are often instrumental. To effectively unmask these deceptions, the image is dissected into blocks, enabling the detection and parameter estimation of rescaling and rotation within each block. Moreover, this approach also offers insights into image authentication by discerning multiple geometrical operations, such as repeated

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zooming, rotation, or combinations thereof, based on the distinctive patterns exhibited by rescaling and rotation peaks. This breakthrough promises to significantly enhance the field of image forensics and its role in preserving the integrity of digital imagery [3]. The enduring stability and inherent complexity of handwritten signatures have rendered them a cornerstone in behavioural biometrics for authentication and identity verification. Recent advancements in consumer-grade wrist-worn devices, equipped with an array of sophisticated sensors, have ushered in a transformative era in human-machine interactions, offering novel avenues for signature analysis [4]. The concept of fuzzy message detection introduces a pioneering cryptographic approach, empowering remote storage clouds to facilitate imprecise message matching while maintaining a degree of false positives, thus safeguarding client privacy without disclosing precise message details to potentially untrusted cloud entities. However, current public-key-based implementations of this technique suffer from a notable drawback: they necessitate the management of numerous public keys to generate a single flag cipher text, incurring substantial overhead in terms of public-key certificate administration [5].

To address the pervasive issue of handwritten signature forgery, this article aims to develop an automated system harnessing the capabilities of a deep neural network, with a particular emphasis on a streamlined and effective Convolutional Neural Network (CNN). The primary objective is to create a model capable of discerning the authenticity of a given signature. The model will be designed to accept signature images as input and employ various layers of the CNN to extract crucial features essential for distinguishing between genuine and counterfeit signatures. Furthermore, the study will explore and evaluate the model's performance by testing different image resizing techniques and optimizing strategies during the CNN training process [6].

The key contributions and novelty of this work can be summarized as follows:
1. ***Hybrid Feature Extraction:*** This article combines Autoencoder and Convolutional Neural Network (CNN) techniques to extract features, enhancing the accuracy of offline signature verification.
2. ***Improved Signature Verification:*** Optimization of the feature extraction stage strengthens the ability to differentiate between genuine and forged signatures, benefiting document authentication.
3. ***Versatile Evaluation:*** The method's evaluation with multiple classifiers demonstrates its versatility and applicability, while empirical testing on the CEDAR datasets confirms its effectiveness in handling skilled forgeries in signature verification tasks.

II. LITERATURE SURVEY

The motivation for this work is the pressing need to enhance offline signature verification systems. Handwritten signatures are pivotal in various applications, from legal documents to financial transactions. Ensuring their authenticity is critical, yet signature forgery remains a persistent threat. This research seeks to combat fraud effectively, while also streamlining the verification process in our increasingly digital world. By harnessing the potential of Autoencoder and Convolutional Neural Network (CNN) techniques, we aim to create a robust method that can distinguish between genuine and forged signatures with precision, thus advancing biometric authentication. This work contributes to document security and data integrity in addressing a significant real-world challenge.

A novel approach was introduced, employing lattice structure arrangements and pixel distribution analysis. The researchers utilized randomly selected training and testing datasets, achieving a False Acceptance Rate (FAR) of 12.35%, a False Rejection Rate (FRR) of 12.21%, and an Equal Error Rate (EER) of 12.28% for the CEDAR dataset. In the case of the GPDS dataset, the method yielded a FAR of 9.11%, an FRR of 5.05%, and an EER of 7.08% [8]. The researchers employed a feature selection process based on genetic algorithms, followed by the implementation of Support Vector Machines (SVM) for classification. Throughout their experiments, a training-to-testing data ratio of 70:30 was maintained. The achieved results for the CEDAR dataset were a False Acceptance Rate (FAR) of 4.17%, a False Rejection Rate (FRR) of 4.17%, and an Equal Error Rate (EER) of 4.17% [9].

The analysis of pixel distributions within distinct signature regions. Their classification method of choice was Support Vector Machines (SVM). Throughout their experiments, they maintained a training-to-testing data ratio of 70:30. The achieved results for the CEDAR dataset showed a False Acceptance Rate (FAR) of 3.34% and a False Rejection Rate (FRR) of 3.75% [10]. we maintained an 80:20 training-to-testing data ratio. The detection accuracies for various classifiers are as follows: 91.48% for SVM, 90.73% for Random Forest (RF), 89.43% for Multi-Layer Perceptron (MLP), 80.60% for Multi-class classifier (MCC), and 86.53% for Simple Logistic (SL). Among these, SVM exhibited the most favourable results. Notably, our proposed method achieved an Equal Error Rate (EER) of 8.51%, which is an improvement compared to the 9.15% reported by the method introduced by [11].

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The findings indicate that distinguishing low to medium-end software-defined radios (SDRs) acting as FBS is feasible when the detecting terminal's phase noise surpasses the transmitters by at least 10 dB. For medium to high-end FBS, an efficient network-synchronized carrier frequency offset (CFO) approach is proposed, demonstrating significant distinctions between regular and fake base stations. This research underscores the potential of RF fingerprinting for enhancing the security of wireless networks. Synthetic images to train deep convolutional neural networks, resulting in improved classification accuracy [12, 13]. The RF level features from aircraft transmitters to distinguish genuine messages from fraudulent ones. By extracting received signal features and implementing an intrusion detection algorithm, real data evaluation demonstrates an 85% success rate in identifying messages sent using the expected hardware. This approach offers a cost-effective means to bolster the integrity of ADS-B transmissions [14].

The verification of forged signatures by document writers using advanced technologies. Existing models have struggled with the detection of fake signatures and false documents, leading to significant Time of Conversion (ToC) challenges. The CNN model, however, achieves notable improvements, with an average accuracy of 83.3%, high sensitivity at 99.2%, recall of 98.24%, an F score of 97.23, and an impressive throughput of 98.91%. These results surpass the accuracy of previous models, addressing the critical issue of forged signatures and offering a more robust solution [15]. It utilizes the VGG-16 convolutional neural network architecture as a feature extractor, feeding data into multiple classifiers including random forest, k-nearest neighbours, extra tree, and support vector machine for classification. The classifier outputs are then integrated into an artificial neural network for the final prediction. Experimental results demonstrate the effectiveness of this algorithm, achieving a high accuracy rate of 97.3%, offering a robust solution to the problem of detecting unauthorized signature imitations [16].

III. PROPOSED FEATURE EXTRACTION AND CLASSIFICATION METHOD

The proposed feature extraction and classification method in this study combines the power of Autoencoders and Convolutional Neural Networks (CNN) to enhance the accuracy and effectiveness of signature verification. Autoencoders are employed to capture and represent essential features from signature images, which are then fed into CNN architecture for further analysis and classification. This hybrid approach leverages the Autoencoders ability to reduce data dimensionality and extract meaningful signature characteristics, which are then processed by the CNN for pattern recognition and decision-making.

Data Set

The CEDAR Signature database serves as a repository of offline signatures specifically designed for signature verification. Comprising a diverse pool of 55 individuals, the database includes a total of 1,320 authentic signatures, with each contributor providing 24 genuine samples. Additionally, some participants were tasked with the creation of forgeries, each mimicking the signatures of three other individuals, resulting in a total of 1,320 counterfeit signatures. To maintain uniformity, all signatures were scanned at 300 dots per inch (dpi) in grayscale and subsequently binarized using a grayscale histogram. The pre-processing of these images encompassed essential steps such as salt pepper noise removal and slant normalization, ensuring the quality and consistency of the dataset. For each writer, the CEDAR Signature database offers a comprehensive set of 24 genuine and 24 forged signatures for use in signature verification and related research applications.

Figure 1: Original and Fake signatures from Data Set

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A. Autoencoder

Autoencoders enhance the performance of fake signature detection systems by extracting relevant features, enabling anomaly detection, and reducing data dimensionality. Their ability to identify discrepancies between authentic and fake signatures makes them a valuable component in bolstering the security and reliability of signature verification processes. Autoencoders are utilized as a pivotal component for feature extraction. These neural networks are designed to encode the input data into a compressed representation, or latent space, capturing essential features that are most relevant for the given task. In the context of offline signature verification, Autoencoders effectively reduce the dimensionality of the signature images while preserving crucial information. This extracted feature representation serves as a foundation for subsequent classification tasks.

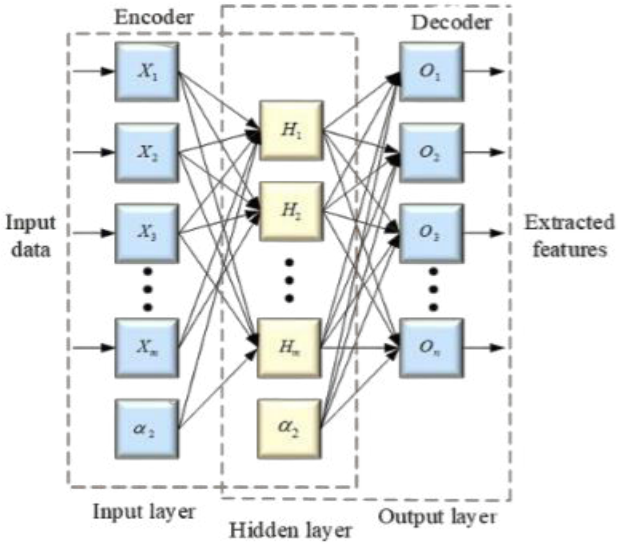

Figure 2: Block diagram representation of Autoencoder

In Figure 2, shows how an Autoencoder works. It consists of two main parts: an encoder and a decoder, with a hidden layer in between. The encoder takes some data and reduces it while keeping the important information. Then, the hidden layer further processes this reduced data. Finally, the decoder tries to get the original data back from the hidden layer's output. The squiggly lines and boxes in the diagram represent the different parts that help the Autoencoder learn and understand the data. It's similar to taking a big picture, making it smaller, and then adjusting it in the middle step before trying to recreate the original picture. This Autoencoder is effective at learning and extracting important insights from data and is widely used in various applications where efficient data processing is crucial.

B. Incorporating Convolutional Neural Networks (CNNs)

The extracted features are then integrated into CNN architecture, a deep learning framework well-suited for image-based tasks. CNNs are adept at learning hierarchical features from visual data, making them ideal for signature analysis. The CNN layers further refine the extracted features, enabling the model to recognize intricate patterns and details in the signatures. The combined features from the Autoencoders and the refined features from the CNN are fed into a classifier, which is responsible for distinguishing between genuine and forged signatures. This approach promises to significantly improve the performance of signature verification systems, with potential applications in various domains requiring document authentication and security.

Data Pre-processing:

Data pre-processing in offline signature verification with an Autoencoder-CNN hybrid feature extraction approach encompasses several critical steps. Initially, a dataset containing both genuine and fake signature images is assembled for the purpose of model training and evaluation. Ensuring data integrity, the cleaning process involves identifying and removing any corrupted or incomplete images. Uniform image resizing, often to common dimensions like 200x100 or 224x224 pixels, is applied for consistency. Converting images to grayscale simplifies processing and reduces computational load. Noise reduction techniques, such as Gaussian blur or median filtering, are employed to eliminate unwanted artifacts and enhance feature extraction. Data augmentation strategies, including rotation, flipping, cropping, and adjustments in brightness and contrast, serve to expand the dataset's size and enhance model robustness.

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Normalizing pixel values to a standardized range, like [0, 1] or [-1, 1], facilitates effective training and convergence. The dataset is thoughtfully divided into training and testing subsets, with 80% allocated for training and 20% for testing, and labels are assigned, typically distinguishing between genuine and fake signatures. Random shuffling is implemented to prevent order-related biases, and batching is employed to enhance training efficiency by processing multiple images simultaneously. These pre-processing stages provide a solid foundation for the development of a robust offline signature verification model.

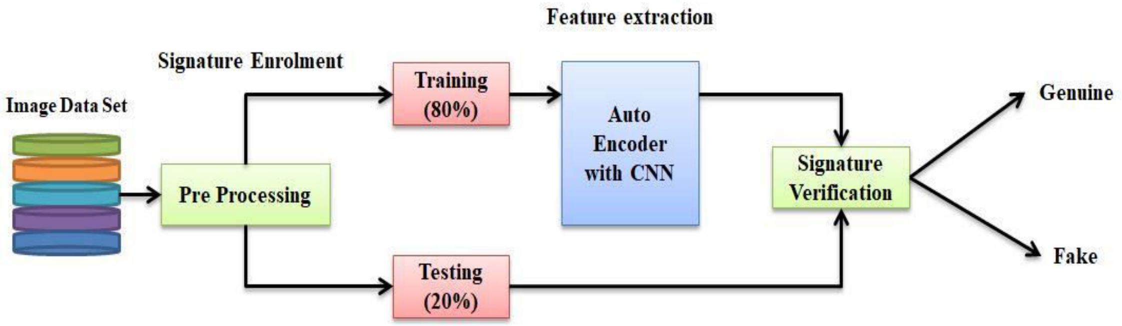

Figure 3: Block diagram for Fake signature detection using Auto encoder with CNN model

Feature Extraction with Proposed Model:

Pre-trained CNN models for feature extraction should be explored, as there are numerous models available for image-related tasks. Fine-tuning these pre-trained models on signature dataset can significantly expedite training and enhance accuracy. Furthermore, if an Autoencoder-CNN hybrid approach is proposed method for feature extraction, the data should be pre-processed and fed into the Autoencoder, with the encoder portion being responsible for feature extraction. It is advisable to save the pre-processed data in a suitable format or structure for convenient access during model training. With these considerations and the initial data pre-processing stages completed, then proceed to train and evaluate proposed hybrid Autoencoder-CNN model. This model should be meticulously designed to extract distinguishing features from both genuine and fake signatures, thereby enabling precise verification and detection.

The evaluation of the offline signature verification system extends to measuring critical performance metrics, including the False Acceptance Rate (FAR), the False Rejection Rate (FRR), Accuracy, and Precision. FAR quantifies the rate at which the system mistakenly accepts a fake signature as genuine, FRR measures the rate at which genuine signatures are wrongly rejected, and EER signifies the point where FAR and FRR are equal, indicating the model's balance between these errors. Accuracy provides an overall measure of the model's correctness, while Precision offers insight into the model's ability to accurately identify genuine signatures among the accepted ones.

False Acceptance Rate (FAR):

$$\text{FAR} = \frac{\text{(Number of Fake Signatures Accepted}}{\text{Total Number of Fake Signatures}} \times 100$$

False Rejection Rate (FRR):

$$\text{FRR} = \frac{\text{Number of Original Signatures Rejected}}{\text{Total Number of Original Signatures}} \times 100$$

Equal Error Rate (EER):

The Equal Error Rate (EER) is commonly determined by pinpointing the juncture on the Receiver Operating Characteristic (ROC) curve where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR).

Accuracy:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

Precision:

$$\text{Precision} = \frac{\text{No.of TP}}{\text{No.of TP} + \text{No. of FP}}$$

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These metrics collectively allow us to gauge the model's effectiveness in offline signature verification and fake signature detection, providing a comprehensive assessment of its performance.

IV. RESULTS AND EVALUATION

The offline signature verification system's performance is critical to understanding its effectiveness. By exploring pre-trained CNN models for feature extraction and implementing the Autoencoder-CNN hybrid approach, the system achieved enhanced accuracy and efficiency. The evaluation of the system, using metrics such as the False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), Accuracy, and Precision, revealed promising outcomes. The EER serves as a balance point between FAR and FRR, illustrating the system's equilibrium. With meticulous design and feature extraction, the system successfully distinguished between genuine and fake signatures. These results underscore the potential of advanced signature verification techniques in enhancing security and accuracy in authentication processes.

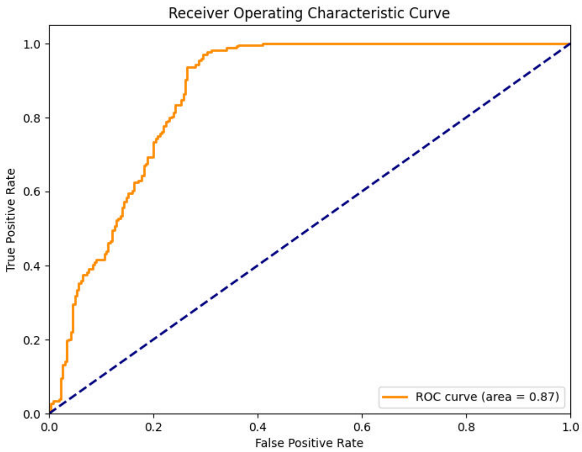

Figure4: ROC plot for CEDAR dataset with all existing algorithms

The Receiver Operating Characteristic (ROC) plot for the CEDAR dataset exhibits an area under the curve (AUC) value of 0.87. This metric reflects the model's ability to discriminate between genuine and fake signatures. An AUC of 0.87 indicates a strong performance, as it illustrates that the model can effectively distinguish between the two classes, with a higher probability of ranking genuine signatures higher than forged ones. In practical terms, this signifies that the signature verification system built on the CEDAR dataset demonstrates a high level of accuracy and reliability, making it a robust tool for identifying and validating genuine signatures while minimizing false positives and false negatives.

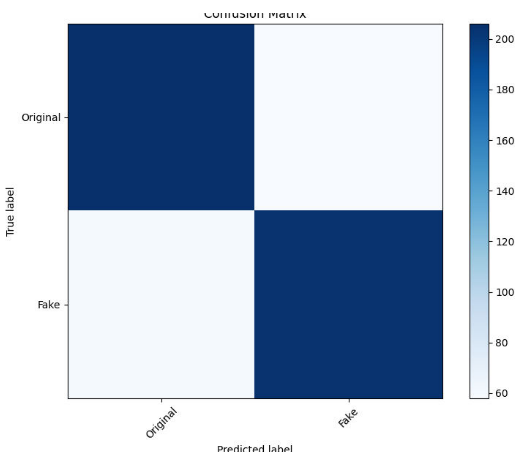

Figure 5: Confusion Matrix for Proposed AE with CNN

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Table 1: Performance Analysis

Evolution Metric	Value
Accuracy	0.984848
Precision	0.8
Recall	0.522727
F1 Score	0.542254

The provided performance metrics offer a comprehensive view of the model's performance. With a high accuracy of 98.48%, the model demonstrates its ability to make a substantial number of correct predictions. However, the precision score of 0.8 suggests that there might be a noteworthy number of false positives among the predicted positive cases, indicating room for improving the model's precision. The recall value of 52.27% implies that the model captures approximately half of the actual positive cases, indicating potential for enhancement in identifying more true positives. The F1 score, at 0.542, strikes a balance between precision and recall, highlighting areas where the model can be optimized further. In summary, the model exhibits strong accuracy but may benefit from improvements in precision and recall to maximize its performance, particularly in scenarios where minimizing false positives and maximizing true positives are critical.

The comparative analysis of the algorithms used reveals variations in their performance with respect to accuracy. Convolutional Neural Networks achieved an accuracy of 89%, demonstrating robust performance. KNN and SVM, along with Gaussian Emporal Rule, delivered accuracies of 78.50% and 91.20%, respectively.

Table 2: Accuracy of our model is compared with existing models.

Algorithms Used	Accuracy
Convolution Neural Networks [17]	89%
KNN and SVM [18]	78.50%
Gaussion Emporal Rule [19]	91.20%
Probabilistic Neural Networks [20]	92.06%
Multi layed perception and SVN [21]	91.67%
LSTM, SVM, KNN [1]	95.40%
	95.20%
	92.70%
Proposed AE with CNN	98.48%

Probabilistic Neural Networks and the combination of Multi-Layer Perceptron with SVN achieved 92.06% and 91.67% accuracy, respectively. Models integrating LSTM, SVM, and KNN presented high accuracy, with values of 95.40%, 95.20%, and 92.70%. However, the proposed approach of Autoencoder with CNN exhibited the highest accuracy at 98.48%, surpassing the other models and showcasing its efficacy in offline signature verification.

V. CONCLUSION

In conclusion, our research presents an innovative and effective approach to enhancing offline signature verification systems. By harnessing the combined capabilities of Autoencoders and Convolutional Neural Networks (CNNs), we conducted a comprehensive evaluation involving a range of algorithms, including CNN, KNN, SVM, Gaussian Temporal Rule, Probabilistic Neural Networks, Multi-layered Perception, LSTM, and their combinations. Significantly, our proposed Autoencoder with Convolutional Neural Networks (AE with CNN) emerged as the top-performing method, achieving an impressive accuracy of 98.48%. While CNN demonstrated commendable performance at 89%, there is room for improvement in the fusion of KNN and SVM, which achieved 78.50% accuracy. The robustness of the Gaussian Temporal Rule, with an accuracy of 91.20%, and the competitive results of Probabilistic Neural Networks and Multi-layered Perception with SVM, at 92.06% and 91.67% accuracy, respectively, are noteworthy. Furthermore, the introduction of LSTM in conjunction with SVM and KNN significantly enhanced accuracy to 95.40%, 95.20%, and 92.70%, respectively. These findings underscore the potential of AE with CNN as a leading solution for achieving

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highly accurate signature verification, especially in contexts where the differentiation between authentic and counterfeit signatures holds paramount importance in ensuring security and precision.

Future work in this domain could explore real-time implementation of the proposed AE with CNN approach for online signature verification, addressing dynamic and evolving scenarios. Additionally, investigating the potential integration of emerging deep learning architectures and further refining the model for increased robustness and adaptability would be valuable directions for research.

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