Writer Independent Signature Verification (WISV) system using SNN

This study explores the use of deep neural networks for offline handwritten signature verification, a critical task in identity authentication.

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Introduction

Significance of Handwritten Signatures

Handwritten signatures are essential for legal documents, attendance verification, and transaction authorization due to their uniqueness.

Challenges of Manual Verification

The manual verification of handwritten signatures is labor-intensive and prone to human error. This can lead to reliability issues.

Proposed Solution

This project focuses on developing a signature verification system using the UTSig dataset, which includes pairs of genuine and forged signatures. A Siamese Neural Network (SNN) was employed to train the model for effective classification of these signature pairs.

Objective

Develop an accurate and efficient system to minimize human intervention and improve verification reliability.

History

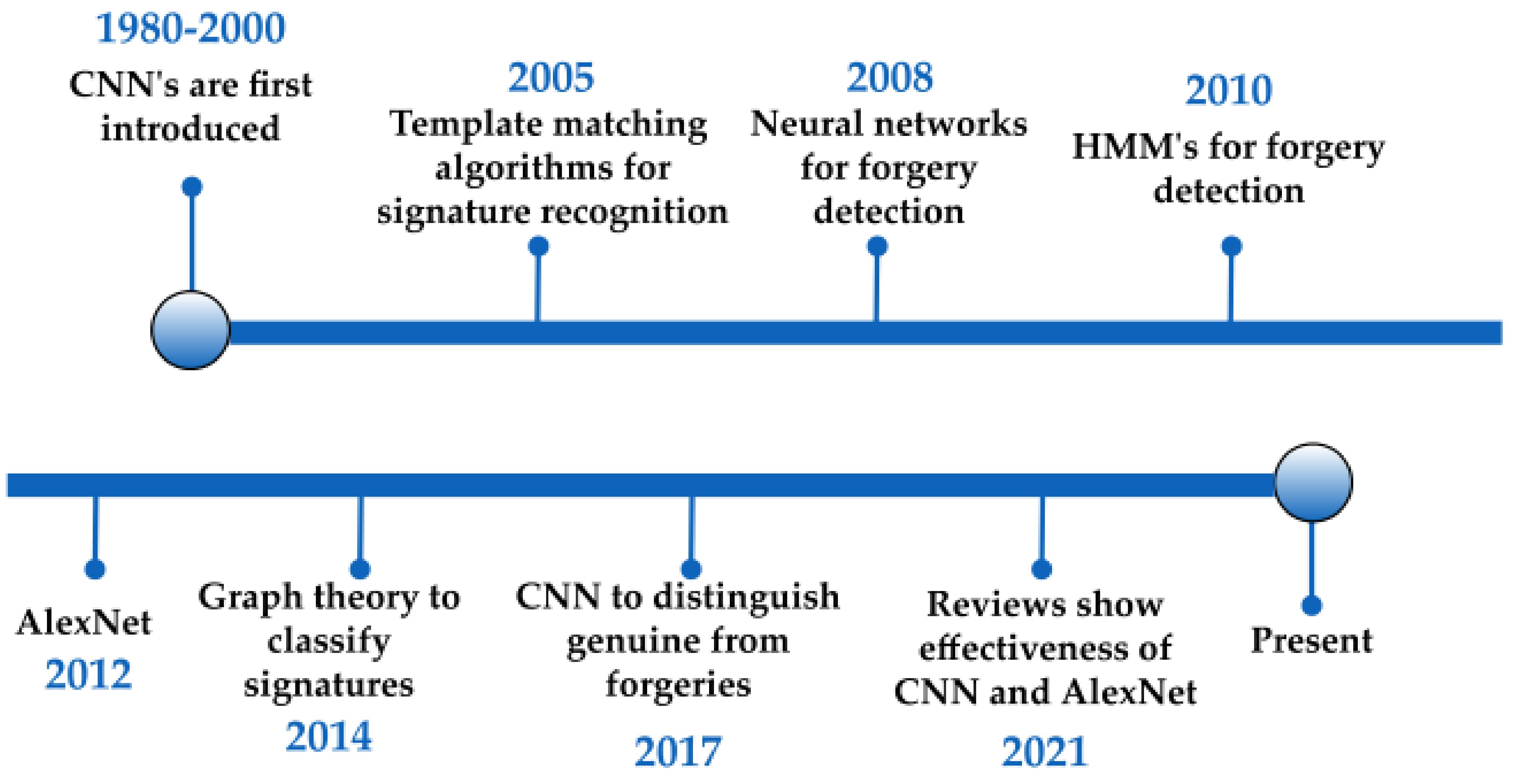
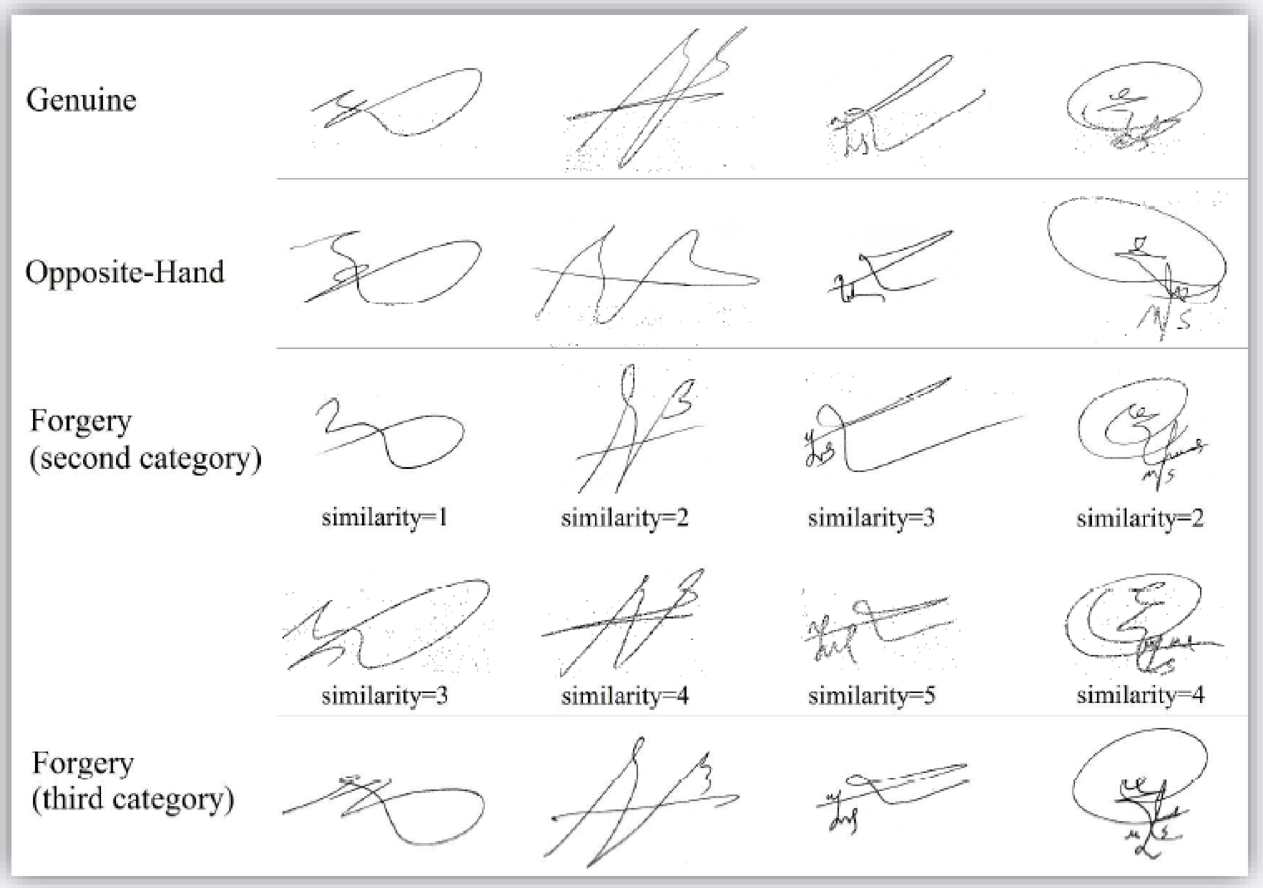


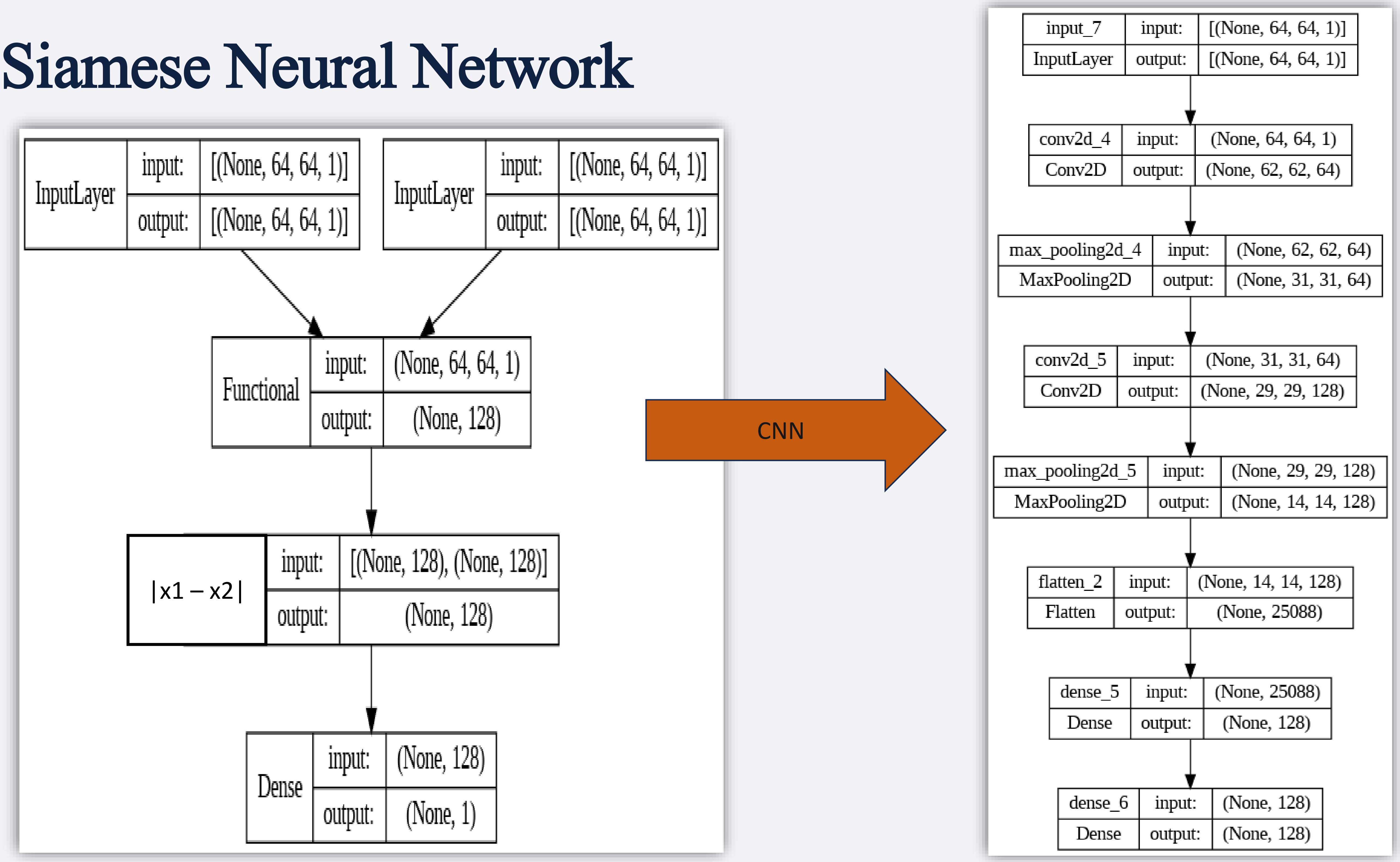
Figure 1. Historical timeline of research on the problem of signature recognition.

Dataset and Preprocessing

UTSig consists of 8280 images from 115 classes. Each class has 27 genuine signatures and 45 forgery images. For model training and evaluation, we partitioned the dataset using a 0.8 ratio, resulting in 92 classes for train and 23 classes for test. Then 30 percent of the training set is split for validation purpose. The images were converted to gray-level, resized to 64x64 pixels.

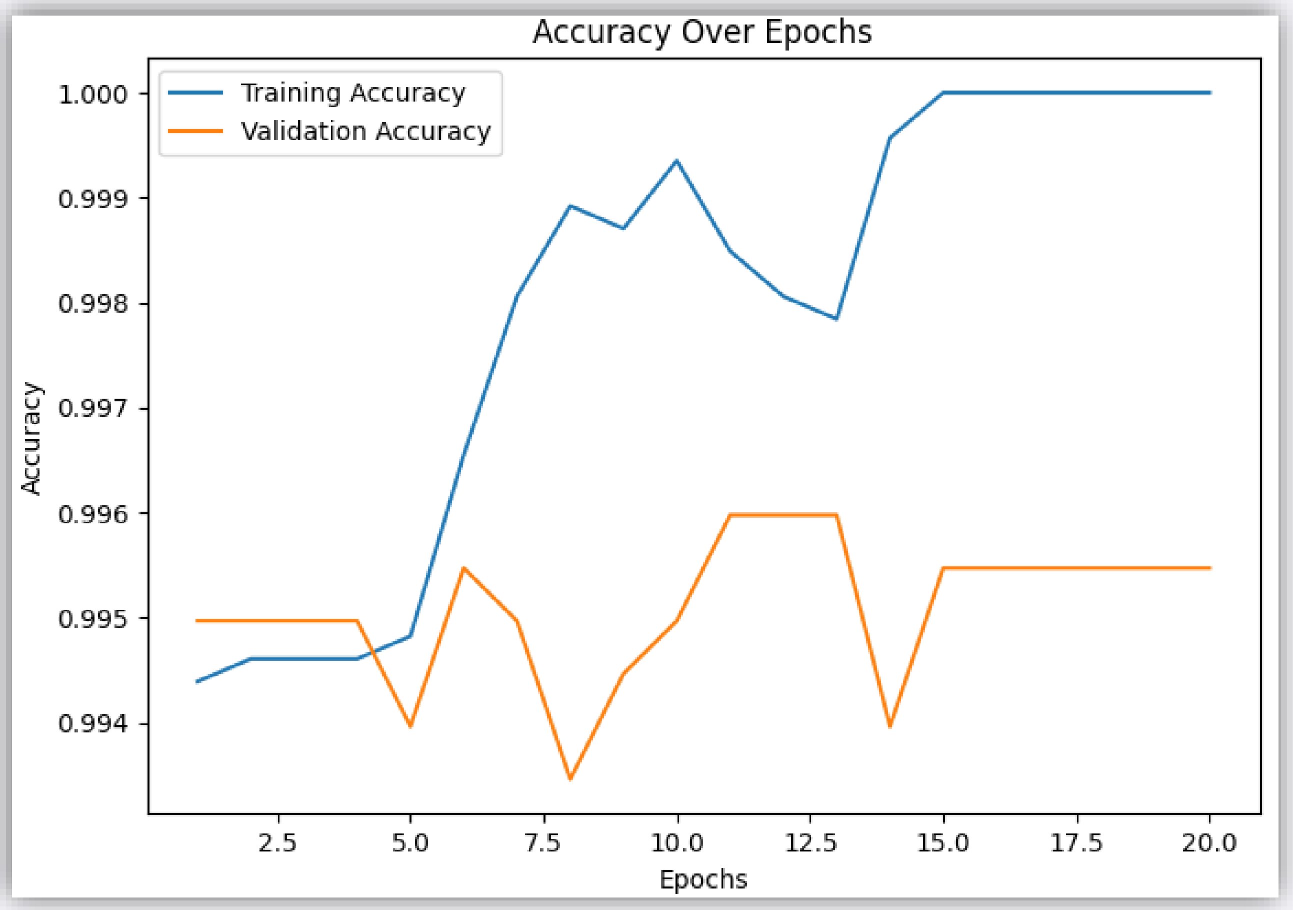


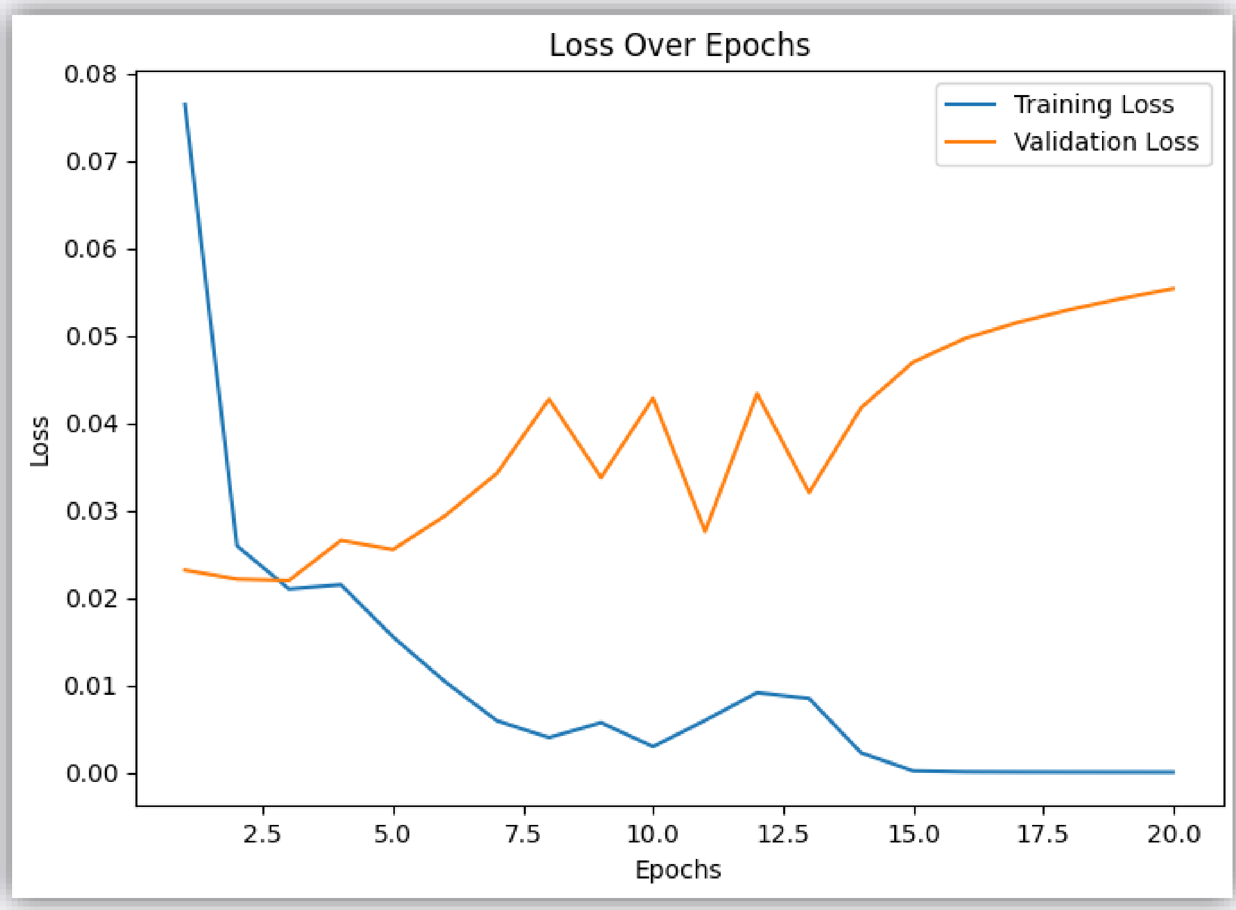
Siamese Neural Network



Results Overview

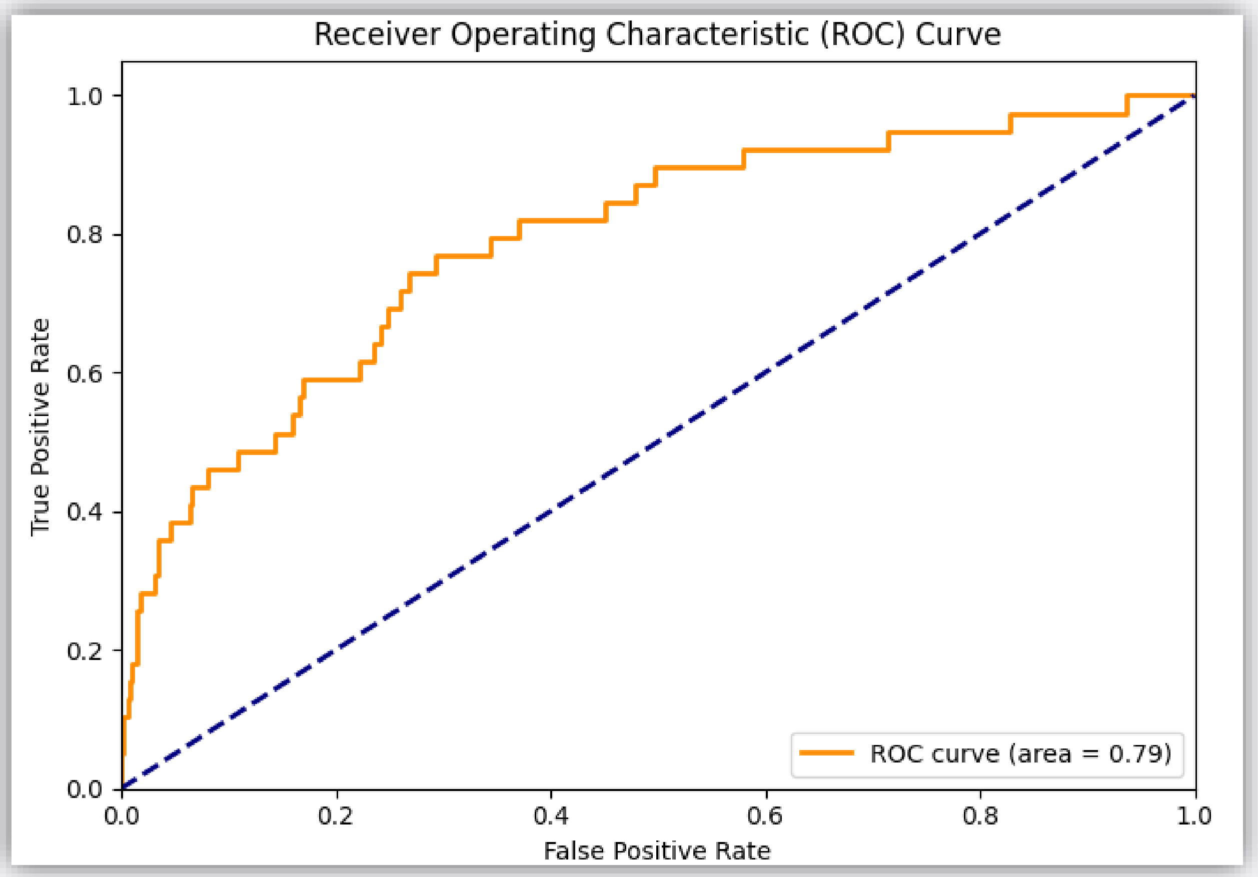
Accuracy and Loss

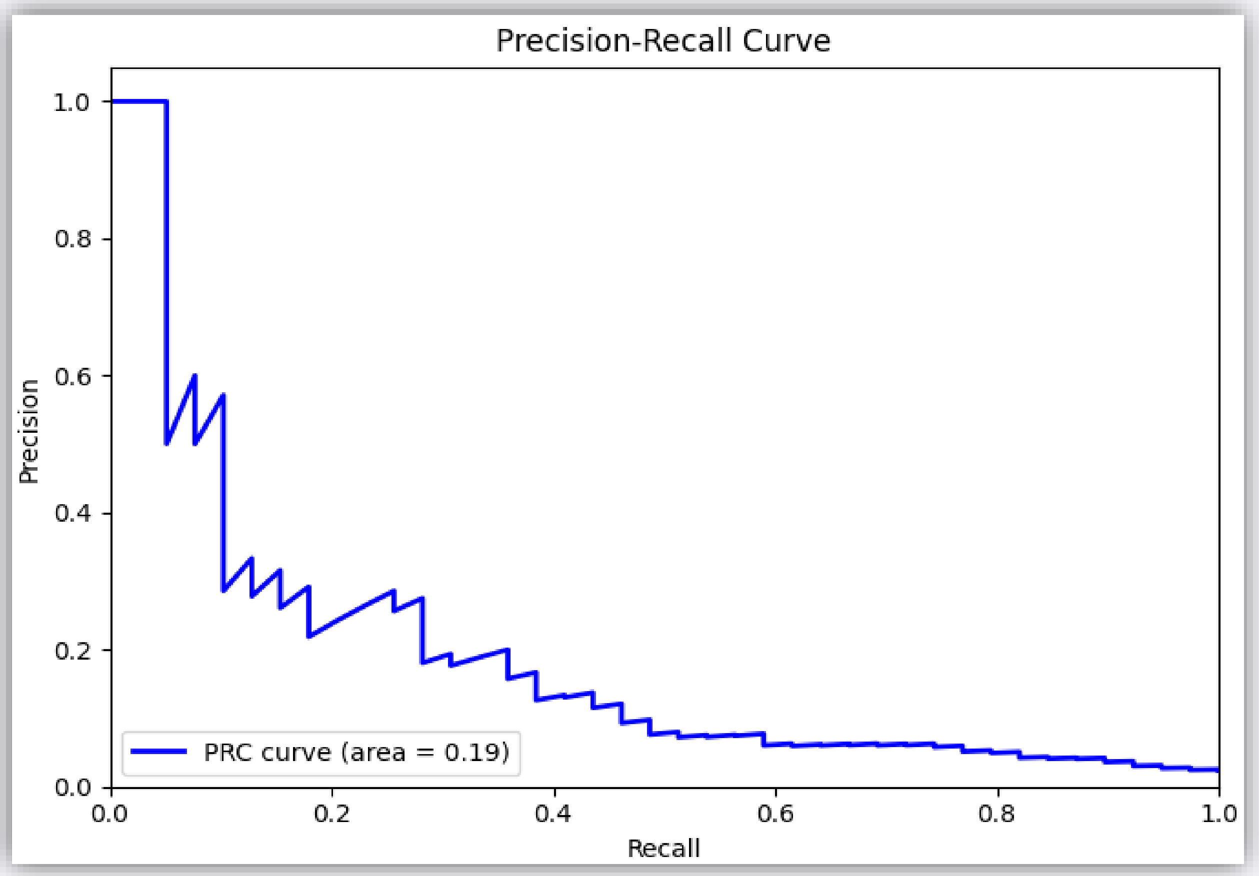




Results Overview

ROC and PCR





Results Overview

Confusion Matrix

The confusion matrix for the model's predictions is as follows:

	Predicted Genuine	Predicted Forged
Actual Genuine	**1144**	**473**
Actual Forged	**9**	**30**

Table 1: Confusion matrix

- True Positives (TP): 30 (genuine signatures correctly classified as genuine)
- True Negatives (TN): 1144 (forged signatures correctly classified as forged)
- False Positives (FP): 473 (forged signatures incorrectly classified as genuine)
- False Negatives (FN): 9 (genuine signatures incorrectly classified as forged)

The confusion matrix provides insight into the model's performance, illustrating how many genuine and forged signatures were correctly and incorrectly classified.

The results indicate that while the model demonstrates a high accuracy in identifying genuine and forged signatures, there are still areas for improvement. The FAR and FRR values suggest that there are instances where the model struggles to balance the rates of false acceptances and rejections. The confusion matrix further highlights the number of misclassifications, providing a clearer picture of where the model's performance could be enhanced.

The ROC and AUC analysis confirms that the model has a strong discriminative capability, but optimizing the threshold and addressing the balance between FAR and FRR are crucial for improving overall performance.

Overall, these results provide valuable insights into the model's effectiveness and areas where further refinements can be made to enhance signature verification accuracy and reliability.

Thank you for your attention