Signature Classification using Siamese Network:

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***Abstract*—Handwritten signature verification plays a critical role in ensuring document authenticity and detecting forgery in various fields such as banking, legal documentation, and identity verification. This project focuses on developing a robust and efficient solution for signature verification using Siamese Neural Networks (SNNs). The Siamese Network is designed to learn a meaningful distance metric between pairs of signature images, enabling it to distinguish between genuine and forged signatures.**

The data set consists of genuine and forged signature pairs, organized into training and testing sets. Each pair is labeled to indicate whether the signatures are from the same person (genuine) or different people (forged). The network uses Contrastive Loss during training, which encourages the model to minimize the distance between embeddings of genuine pairs and maximize the distance between embeddings of forged pairs.

The methodology involves pre-processing the data set, creating signature pairs, and training the Siamese Neural Network. After training, the model is evaluated on unseen test data using metrics such as accuracy, precision, recall, and F1 score. The results demonstrate the model's ability to generalize well, achieving high performance in distinguishing between genuine and forged signatures.

This approach provides a scalable and reliable solution for signature verification tasks, with the capability to handle intra-class variability and inter-class similarity effectively. The proposed system can be extended to other biometric authentication applications, such as face or fingerprint verification.

***Index Terms*—Signature Verification, Siamese Neural Networks, Contrastive Loss, Handwritten Signatures, Forgery Detection, Deep Learning, Biometric Authentication, Metric Learning, Image Similarity, Feature Embedding**

I. Introduction

Handwritten signature verification is a crucial task in ensuring the authenticity of documents in both digital and non-digital formats. With the rise of technology and electronic records, signature forgery has become increasingly common, necessitating robust and efficient methods for signature verification. The problem involves determining whether two given signature images belong to the same individual (genuine) or different individuals (forged). Traditional methods rely on feature extraction and statistical models, which are often limited by their ability to generalize across various writing styles and forgery techniques. To overcome these challenges, deep learning methods, particularly Siamese Neural Networks (SNNs), provide a powerful solution. Siamese Networks use metric learning to map input images to a feature space where similar samples (genuine signatures) are close together, and dissimilar samples (forged signatures) are far apart. This makes them ideal for signature classification tasks. In this problem, we aim to build a Siamese Neural Network that :

- Learns the similarity between signature pairs.
- Classifies signatures as genuine or forged based on their feature distance.
- Achieves high performance metrics (Accuracy, Precision, Recall, F1-Score).

A. About Dataset

The dataset consists of images of handwritten signatures, categorized into two classes:

- **Genuine signatures:** Signatures from the original person.
- **Forged signatures:** Signatures created to imitate someone else's handwriting.

1) Dataset Structure: The dataset is divided into two folders: train and test.

- **Train folder:** Contains 158 subfolders, each corresponding to a unique individual. Each subfolder contains multiple genuine and forged signature images.
- **Test folder:** Follows a similar structure with unseen individuals and their genuine/forged signatures.

2) Key Challenges:

- **Intra-class variability:** The handwriting of the same person can vary significantly due to environmental or physical conditions.
- **Inter-class similarity:** Forged signatures may closely resemble genuine ones, making distinction difficult.
- **Imbalanced data:** Genuine signatures often outnumber forged ones, requiring careful handling.

3) Preprocessing Requirements:

- Resize images to a fixed dimension.
- Convert images to grayscale, as color information is irrelevant for signature verification.
- Apply data augmentation (rotation, scaling, etc.) to improve generalization.

II. Methodology

A. Approach

The proposed solution involves building a Siamese Neural Network trained with Contrastive Loss. The steps include:

1) Data Preparation:

- Load the dataset and preprocess the images.
- Create pairs of signature images:
- **Positive pairs:** Two genuine signatures from the same person.
- **Negative pairs:** A genuine and a forged signature.
- Assign labels to the pairs: 0 for positive pairs, 1 for negative pairs.

2) Network Architecture:

- The Siamese Network consists of two identical branches of a Convolutional Neural Network (CNN).
- Each branch extracts features from an input image, mapping it to a 128-dimensional feature space.
- The Euclidean distance between the feature embeddings of the two branches determines their similarity.

3) Loss Function: Contrastive Loss is used to train the network. It ensures that:

- Genuine pairs (label 0) have a small distance in the feature space.
- Forged pairs (label 1) have a large distance, at least exceeding a specified margin.

4) Evaluation: The trained model is tested on unseen signature pairs from the test set. Performance metrics include:

- Accuracy , Precision , Recall and F1-Score

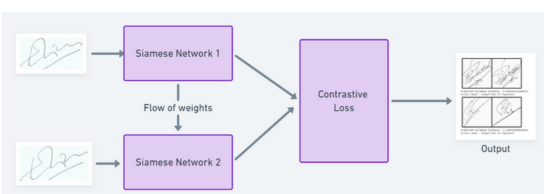
B. Siamese Neural Network

Siamese neural network is an artificial neural network that use the same weights while working in tandem on two different input vectors to compute comparable output vectors. Often one of the output vectors is precomputed, thus forming a baseline against which the other output vector is compared.

This is similar to comparing fingerprints or more technical as a distance function for Locality-sensitive hashing.

In Siamese network we keep the basic network for getting features of entities(images/text) same and pass the two entities we want to compare through the exact same network. By the exact same network it is meant that both the entities are passed through the same architecture having same weights as shown in the figure.

At the end of common network we get a vectored representation of our input which can then be used for measuring or quantifying the similarity between them.



1) Contrastive loss ::

- Contrastive loss is widely used in unsupervised and self-supervised learning. Originally developed by Hadsell et al. in 2016 from Yann LeCun's group, this loss function operates on pairs of samples instead of individual samples. It defines a binary indicator Y for each pair of samples stating whether they should be deemed similar, and a learnable distance function $D_W(x_1, x_2)$ between a pair of samples x_1, x_2, parameterized by the weights W in the neural network.

$$\text{Contrastive Loss} = Y \cdot D_W^2(x_1, x_2) + (1 - Y) \cdot \max(0, m - D_W(x$$

where $m > 0$ is a margin. The margin defines a radius around the embedding space of a sample so that dissimilar pairs of samples only contribute to the contrastive loss function if the distance D_W is within the margin.
Intuitively, this loss function encourages the neural network to learn an embedding that places samples with the same labels close to each other, while distancing the samples with different labels in the embedding space.

2) Convolutional Layers:

- Extract hierarchical features from the signature images (edges, strokes, etc.).

3) Fully Connected Layers:

- Map the features into a lower-dimensional embedding space

4) Distance Metric:

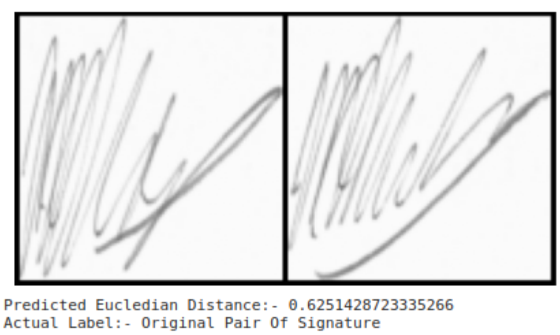
- Compute the Euclidean distance between the embeddings of two input images.

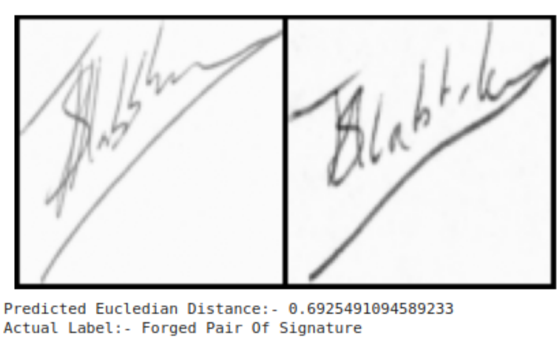
III. Experimental Results

Metric	Value
Accuracy	0.4830
Precision	0.5385
Recall	0.0094
F1-Score	0.0185

TABLE I

Performance Metrics for Signature Classification on testset





Predicted Eucledian Distance:- 1.179945468902588
Actual Label:- Forged Pair Of Signature

Predicted Eucledian Distance:- 0.7837536931037903
Actual Label:- Forged Pair Of Signature

Predicted Eucledian Distance:- 0.634527862071991
Actual Label:- Forged Pair Of Signature

IV. Conclusions

This problem tackles a real-world challenge of signature verification, where traditional approaches fall short. Using a Siamese Network trained with Contrastive Loss, we aim to create a robust and scalable solution for classifying signatures as genuine or forged. The proposed methodology ensures effective feature learning, high generalization, and adaptability to diverse datasets, making it suitable for deployment in both digital and non-digital domains.