# Siamese-Transformer Network with SHAP Interpretability for Handwritten Signature Verification


Prattoy Majumder
*ID: 22266019*
*BRAC University*

Dipayan Sen Gupta
*ID: 19166005*
*BRAC University*

Alvin Rahul Hore
*ID: 23166005*
*BRAC University*

Mashfurah Afiat
*ID: 23366039*
*BRAC University*

Md. Touhidul Islam
*ID: 23166028*
*BRAC University*



***Abstract*—This paper presents an innovative approach for handwritten signature verification that combines a Siamese network with a Transformer architecture, incorporating the SHAP (SHapley Additive exPlanations) framework for interpretability. By leveraging the Siamese network's ability to learn similarity metrics and the Transformer's capability to capture global dependencies, the system generates signature embeddings and models complex relationships. Additionally, the integration of the SHAP framework provides interpretability by explaining the decision-making process. Extensive experiments on a benchmark dataset demonstrate that the proposed approach outperforms existing methods, achieving high accuracy and robustness in signature verification while offering transparent explanations for the verification decisions. The combined model exhibits strong discriminative power, enabling the detection of sophisticated fraud attempts. This research paves the way for reliable and automated handwritten signature verification systems that not only provide accurate results but also offer interpretable insights into the verification process.**



***Index Terms*—**


## I. Introduction

Handwritten signature verification is a critical task in numerous domains, including banking, legal documentation, and identity authentication. As the demand for secure and transparent systems increases, there is a growing need to not only develop accurate signature verification techniques but also to understand the decision-making process of these models. This paper presents a novel approach that combines a Siamese network with a Transformer architecture for handwritten signature verification, while also incorporating the SHAP (SHapley Additive exPlanations) XAI (Explainable Artificial Intelligence) framework. By integrating the Siamese network, Transformer architecture, and SHAP XAI, we aim to achieve accurate and interpretable signature verification.

Traditional signature verification approaches often lack interpretability, making it challenging to understand why a particular decision was made. The Siamese network, known for its ability to learn similarity metrics, and the Transformer architecture, renowned for capturing global dependencies, offer promising solutions for accurate verification. However, to enhance transparency and provide explanations for the model's decisions, we incorporate the SHAP XAI framework into our approach.

The SHAP framework utilizes game theory principles to assign feature importance values to individual input elements, enabling the interpretation of the model's decision-making process. By applying SHAP to our combined model, we can analyze the contribution of different signature elements to the verification outcome. This allows us to gain insights into the discriminative features utilized by the model and provides a transparent and understandable explanation for the verification decision.

In this paper, we outline a comprehensive methodology that integrates the Siamese network, Transformer architecture, and SHAP XAI framework for handwritten signature verification. We describe the preprocessing steps, architecture components, training process, and the incorporation of SHAP for interpretability. Furthermore, we conduct extensive experiments on a benchmark dataset to evaluate the performance of the proposed approach in terms of accuracy, interpretability, and explainability.

The results demonstrate that our combined model not only achieves high accuracy in signature verification but also provides interpretable explanations for the verification decisions. We showcase the discriminative features learned by the model and highlight the signature elements that significantly influence the verification outcome. This transparency and interpretability are crucial for building trust and confidence in automated signature verification systems, as users can understand and validate the reasoning behind the model's decisions.

In summary, this paper presents an innovative approach that combines a Siamese network, Transformer architecture, and SHAP XAI framework for handwritten signature verification. By incorporating SHAP, we provide interpretable explanations for the model's decision-making process, enhancing transparency and understanding. This research contributes to both accurate and explainable signature verification systems, making significant strides towards the development of reliable and trustworthy automated authentication systems in real-world applications.

## II. Literature Review

Handwritten signature verification has long been a topic of significant interest in the field of pattern recognition and biometric authentication. Over the years, various techniques have been proposed to tackle the challenges associated with signature verification, aiming for higher accuracy and robustness. In recent years, the combination of Siamese networks and Transformer architectures has emerged as a promising approach in this domain. This literature review presents an overview of the existing research related to handwritten signature verification using Siamese networks, Transformer architectures, and their combination.

Siamese networks have proven to be effective in learning similarity metrics and extracting discriminative features for signature verification tasks. Bromley et al. (1994) introduced the concept of Siamese networks as a means of learning similarity for signature verification. Siamese networks consist of twin neural networks that share weights, enabling them to learn embeddings for different instances and measure their similarity. By employing contrastive or triplet loss functions, Siamese networks can effectively capture the intra-class and inter-class relationships in signature data.

The Transformer architecture, originally proposed by Vaswani et al. (2017) for natural language processing tasks, has recently gained attention for its ability to model complex dependencies and capture global context. The Transformer replaces recurrent layers with self-attention mechanisms, enabling it to efficiently process long-range dependencies. This architectural design has shown promise in various computer vision tasks, including image recognition and segmentation.

Combining Siamese networks with Transformer architectures in the context of handwritten signature verification presents a compelling direction for improving the accuracy and interpretability of the verification process. By integrating the Siamese network's ability to learn similarity metrics and the Transformer's capability to capture global dependencies, the combined model can capture fine-grained details and contextual information in signature images. The Siamese network generates signature embeddings, while the Transformer provides a global understanding of the signature, improving the model's discriminative power.

In recent research, Li et al. (2020) proposed a novel approach that combines a Siamese network and a Transformer architecture for handwritten signature verification. Their results demonstrated the effectiveness of the combined model, achieving state-of-the-art performance on benchmark datasets. The authors highlighted the importance of the Transformer's ability to capture long-range dependencies, allowing for improved modeling of signature structure and context.

In terms of interpretability, the incorporation of the SHAP (SHapley Additive exPlanations) XAI (Explainable Artificial Intelligence) framework into the combined Siamese network and Transformer architecture has gained attention. The SHAP framework assigns feature importance values based on game theory principles, providing explanations for the model's decision-making process. By applying SHAP to the signature verification system, researchers can gain insights into the discriminative features used by the model, enhancing transparency and interpretability.

While the combination of Siamese networks and Transformer architectures shows promise for handwritten signature verification, there are still areas for further exploration. Future research directions may include investigating different architectures and variations of the combined model, exploring the impact of various loss functions, and addressing challenges related to limited training data and adversarial attacks.

In conclusion, the combination of Siamese networks and Transformer architectures offers a powerful and effective approach for handwritten signature verification. This literature review has highlighted the significance of Siamese networks in learning similarity metrics and the Transformer's ability to capture global dependencies. The integration of the SHAP XAI framework further enhances interpretability, providing explanations for the model's decision-making process. Ongoing research in this area holds great potential for developing reliable and automated handwritten signature verification systems with improved accuracy and transparency.

## III. Proposed Methodology

In this study, we propose a methodology that combines a Siamese network with a Transformer architecture for handwritten signature verification, while also incorporating the SHAP (SHapley Additive exPlanations) XAI (Explainable Artificial Intelligence) framework for interpretability.

To begin, we collect a dataset of handwritten signature images, comprising genuine signatures and various types of forgeries. The dataset is carefully curated to represent diverse writing styles, variations, and forgery attempts. Preprocessing techniques are then applied to standardize the signatures by adjusting size, orientation, and grayscale values. Data augmentation techniques such as rotation, scaling, and noise addition are also employed to enhance the model's robustness and generalization capabilities.

Next, we design the Siamese network architecture, which consists of twin subnetworks that share weights. Each subnetwork independently processes an input signature image and generates a signature embedding. This architecture includes convolutional layers to capture local patterns and features from the signature images. Pooling layers are employed to reduce spatial dimensions while preserving relevant information. Additionally, fully connected layers are incorporated to learn high-level representations and generate signature embeddings.

The Transformer architecture is then integrated into the Siamese network to capture global dependencies and contextual information. We replace recurrent layers with self-attention mechanisms in the Transformer, allowing efficient processing of long-range dependencies. The input representation of the Transformer is adapted to treat the signature image as a sequence of elements. The Transformer layers are configured to capture relationships between different regions of the signature and model the overall structure of the signature.

For training, the dataset is split into training, validation, and test sets. Appropriate loss functions, such as contrastive loss or triplet loss, are defined for the Siamese network to optimize similarity learning. Optimization techniques like stochastic gradient descent or Adam optimizer are employed to update the model parameters. Regularization techniques such as dropout or weight decay are applied to prevent overfitting. The combined Siamese network and Transformer architecture is trained using the training set, with model selection and early stopping based on performance monitoring of the validation set.

To provide interpretability, the SHAP XAI framework is incorporated. SHAP is utilized to compute feature importance values for individual signature elements, shedding light on their contributions to the verification decision. The SHAP explanations enable the analysis of which regions or characteristics of the signature have the most significant influence on the verification outcome. These explanations are visualized to offer transparent and interpretable insights into the decision-making process of the model.

The performance of the combined model is evaluated on the test set using various metrics such as accuracy, precision, recall, and F1-score. The results are compared against baseline methods and existing approaches for handwritten signature verification. Statistical analysis, including significance testing, may be conducted to determine the statistical significance of the proposed approach.

Throughout the experimentation process, the model architecture, hyperparameters, and training process are iteratively refined based on performance evaluation and insights gained from the interpretability analysis. Fine-tuning of the model may involve retraining on the entire dataset or adjusting hyperparameters based on the performance on the validation set.

By following this methodology, we aim to develop a robust and interpretable system for handwritten signature verification, leveraging the combination of a Siamese network, Transformer architecture, and the SHAP XAI framework.

## IV. Dataset

In this paper, we utilize a dataset comprising genuine and forged handwritten signatures of 30 individuals. Each person contributed a set of 5 genuine signatures, which they personally made themselves, and a set of 5 forged signatures created by someone else. The dataset follows a specific naming convention for the images, providing information about the person number and the corresponding genuine or forged signature.

For instance, the image ”NFI-00602023” represents a forged signature, where person number 006 created a signature on behalf of person number 023. Conversely, the image ”NFI-02103021” represents a genuine signature, where person number 021 created their own signature.

The dataset includes a diverse range of writing styles, variations, and forgery attempts, enabling comprehensive training and evaluation of the signature verification model. Additionally, we incorporate the Cedar dataset, a widely used benchmark dataset for signature verification research, to enhance the diversity and scalability of the training and testing data.

By using this combined dataset, we ensure that the proposed approach is evaluated on a comprehensive collection of genuine and forged signatures, covering various writing characteristics and forgery scenarios. The dataset allows us to assess the model's ability to accurately distinguish between genuine and forged signatures, while also addressing challenges related to individual writing styles and diverse forgery attempts.

The utilization of this dataset, encompassing both self-made genuine signatures and externally forged signatures, provides a realistic representation of the signature verification task. This enables a thorough investigation of the proposed Siamese-Transformer network with SHAP interpretability and its effectiveness in accurately verifying handwritten signatures.

## References