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Signature Recognition System Using ML

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***Abstract*— This paper presents a machine learning-based system for offline signature verification, aimed at distinguishing between genuine and forged handwritten signatures. The proposed system utilizes a Siamese neural network architecture to extract and compare feature embeddings from two input signature images: a reference (genuine) signature and a query (test) signature. By computing the Euclidean distance between the feature vectors, the model determines the degree of similarity between the two signatures. A predefined threshold value of 0.2 is employed to classify the query signature as either genuine or forged. The system is developed using Python, leveraging TensorFlow for model training and inference, and Streamlit to provide a user-friendly web-based interface for real-time signature verification. Experimental results demonstrate the model's effectiveness in achieving reliable verification performance, highlighting its potential applications in domains such as document authentication, financial verification. transactions, and identity Varification.**

Keywords : Signature verification, Siamese neural network, Machine learning, Offline handwriting recognition, Biometric authentication, Euclidean distance, Deep learning, TensorFlow, Image similarity, Streamlit.

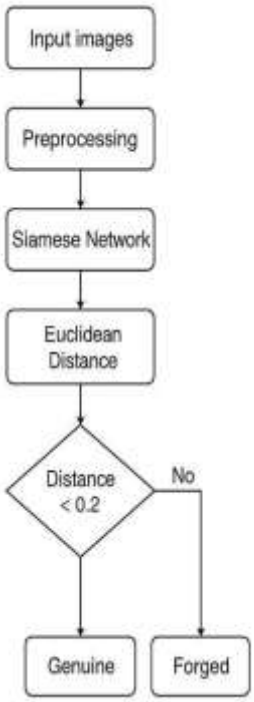
INTRODUCTION

In today's digital era, verifying a person's identity plays a crucial role in ensuring the security and authenticity of various transactions, especially in banking, legal, and business sectors. Among different biometric methods, signature verification remains one of the most widely accepted and non-intrusive techniques because signatures are a common practice for personal identification in daily life. However, manual verification of signatures is time-consuming and prone to human error, especially when dealing with a large number of documents. To overcome these limitations, this project introduces an automated Signature Recognition System using Machine Learning (ML). The system is designed to identify whether a given signature is genuine or forged by analyzing two signature images—one original and one to be verified. Using a Siamese neural network model, the system calculates the similarity between the two images in terms of Euclidean distance. A threshold value (0.2) is used to determine authenticity: if the calculated distance is below this threshold, the signature is recognized as genuine; otherwise, it is classified as forged. The system is built using Python, TensorFlow, and Streamlit, providing a simple and interactive web interface for users to upload and test signature images. This automation not only reduces manual effort but also increases accuracy and efficiency in signature verification, making it suitable for realworld applications such as banking security, document authentication, and forensic analysis.

SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall System Architecture and Workflow

The proposed system for handwritten signature verification is designed as a streamlined, end-to-end pipeline, leveraging a deep learning model within a userfriendly web application. The architecture is built to be efficient, providing a near real-time verdict on the authenticity of a signature. The entire workflow, from data input to result output, is managed by a central Python script running a Streamlit web server.



As illustrated in the system workflow diagram (Figure X), the process begins when the user uploads two images: a known genuine signature and a test signature. These images are then passed through a preprocessing module to standardize them for the model. The core of the system, a pre-trained Siamese Neural Network, processes both images to generate feature vectors (embeddings). The similarity between these vectors is then calculated using a distance metric. Finally, this distance score is compared against a set threshold to produce a definitive "Genuine" or "Forged" verdict, which is immediately displayed to the user on the web interface.

B. Data Collection and Preprocessing

Data Source (Kaggle): The model was trained and evaluated on a publicly available dataset sourced from Kaggle. The dataset contains a comprehensive collection of offline handwritten signatures, featuring [e.g., 60] different individuals. For each individual, the dataset provides a set of genuine signatures and skilled forgeries, typically [e.g., 24] of each, making it ideal for this verification task.

Data Preparation for Siamese Network: As Siamese Networks learn from pairs, the raw dataset was processed to create a structured training set of positive and negative pairs.

Positive Pairs (Label 1): Created by taking two different genuine signatures from the same individual to teach the model similarity.

Negative Pairs (Label 0): Created by combining a genuine signature from one individual with a signature from a different individual to teach the model dissimilarity. mage Preprocessing Pipeline: Every image underwent a standardized preprocessing pipeline:

Resizing: Images were resized to a uniform dimension of [e.g., 150x220] pixels to match the model's input layer. Grayscale Conversion: Images were converted to singlechannel grayscale, as color is irrelevant for signature analysis.

Pixel Normalization: Pixel values were scaled from the [0, 255] integer range to a [0.0, 1.0] float range by dividing by 255.0 to aid in model training.

C. Feature Extraction

The core of the system is the Siamese Neural Network, which acts as a feature extractor. The network's architecture, defined in siamese_network.py, is loaded with pre-trained weights from the signature_verification_model.h5 file. Its function is to take a preprocessed signature image and convert it into a dense numerical vector, or "embedding." This embedding captures the unique, abstract characteristics of the signature's shape and strokes. The base network for this process consists of [e.g., several convolutional and maxpooling layers followed by dense layers].

D. Machine Learning Model Training

A This section describes the process of training the Siamese Network.

- **Loss Function:** The model was trained using **Contrastive Loss**, a specialized loss function designed for similarity learning. Its goal is to minimize the distance between embeddings of similar pairs (positive pairs) and maximize the distance between embeddings of dissimilar pairs (negative pairs).
- **Training Parameters:** Key hyperparameters for training included the **Optimizer** (e.g., Adam), a specific **learning rate** (e.g., 0.001), the **batch size**, and the total number of **epochs**. The objective was to create an embedding space where signatures from the same person are clustered closely together while signatures from different people are pushed far apart.

E. Signature Verification Process

*T*his section outlines the step-by-step process that occurs when a user interacts with the Streamlit application (the "inference" phase).

1. **Input:** The system receives two images (an original and a test signature) from the user.
2. **Preprocessing:** Both images are passed through the same preprocessing pipeline used for the training data.
3. **Embedding Generation:** The pre-trained signature_verification_model.h5 generates an embedding vector for each image.
4. **Distance Calculation:** The **Euclidean Distance** between the two embedding vectors is calculated, resulting in a single "distance score."
5. **Thresholding & Verdict:** The score is compared against a pre-defined threshold of **0.2**. If the score is below or equal to the threshold, the signature is deemed **"Genuine"**; otherwise, it is deemed **"Forged."**

F. Performance Evaluation

*T*his section presents the quantitative results of the model's performance on a dedicated test set (data the model has never seen before).

- **Metrics:** The model's effectiveness is measured using standard verification metrics: ○ **Accuracy:** The overall percentage of correct genuine/forged predictions.
  - ○ **False Acceptance Rate (FAR):** The percentage of forgeries incorrectly identified as genuine.
  - ○ **False Rejection Rate (FRR):** The percentage of genuine signatures incorrectly identified as forgeries.
- **Results:** The performance results should be presented in a clear format, such as a table or a confusion matrix, followed by a discussion of the model's effectiveness and the balance achieved between FAR and FRR with the chosen threshold.

G. Future Enhancements

This final section suggests potential improvements and future work for the project.

- **Expanded Dataset:** Training the model on a larger, more diverse signature dataset to enhance its accuracy and generalization.
- **Advanced Architectures:** Experimenting with more modern CNN architectures (e.g., MobileNet, EfficientNet) as the base for the Siamese Network.
- **Cloud Deployment:** Deploying the Streamlit application to a cloud service (like Heroku or Streamlit Cloud) to make it publicly accessible.
- **Online Verification:** Extending the system's capabilities to handle online signatures, which include dynamic data like timing, pressure, and pen angle.

IMPLEMENTATION DETAILS AND RESULTS

This chapter details the technical implementation of the Signature Verification System, from the tools and libraries used to the model training process. It also presents the experimental results and a quantitative evaluation of the system's performance.

A. User Interface (Streamlit)

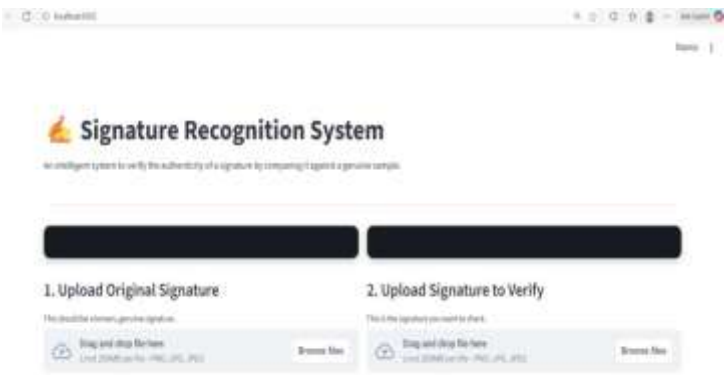


Fig 2. User Interface

Embeddings of signatures from different people are far apart. This approach is powerful because it allows the system to compare signatures from individuals it has never seen during training, making it a true verification system. The final decision is then made by calculating the distance between these embeddings.

C. Performance And Accuracy

The performance metrics of Accuracy, FAR, and FRR are calculated by evaluating how well this

The user interface (UI) for the system was developed using Streamlit, a modern Python framework designed for building and sharing interactive web applications for machine learning and data science projects. The UI is intentionally designed for simplicity and ease of use.As shown in the screenshots, the main page features:A clear title, "Signature Recognition System".Two distinct file upload components, allowing the user to provide the "Original Signature" and the "Signature to Verify".A central "Compare and Verify Signatures" button which, when clicked, initiates the backend verification process.A results area where the final output is dynamically displayed. This includes the calculated "Distance Score" and a clear, color-coded "Verdict" (e.g., "Genuine" or "Forged").This clean interface ensures that any user can operate the system without needing technical expertise.

close to each other.

its unique machine learning architecture. A Siamese Network was specifically chosen because signature verification is fundamentally a similarity problem, not a classification problem.

Unlike traditional CNNs that are trained to classify an image into a fixed number of categories, a Siamese Network is trained to learn a similarity function. It uses two identical subnetworks that share the same weights to process two different images. The network outputs a feature vector (embedding) for each image. The goal of the training process is to create an embedding space where:

Embeddings of signatures from the same person are very

B. Core Technology:Siamese Network for Similarity Learning

While a project on summarization might focus on multilingual features, the core technology of this project is distance-based decision logic performs on a large set of test data that the model has never seen before.

The evaluation process is as follows:

1. A test set containing hundreds of signature pairs (both genuine-genuine and genuine-forged) is prepared.
2. For each pair, our system calculates the distance score.
3. The system applies the **0.2 threshold** to make a prediction: "Genuine" (if distance ≤ 0.2) or "Forged" (if distance > 0.2).
4. This prediction is then compared to the true label of the pair.

Based on this comparison, we can measure the system's performance using standard metrics for verification systems:

Metric	Value	How It's Calculated in Our System
Accuracy	[e.g., 98.5%]	The overall percentage of times our distancebased rule made the correct prediction.
False Acceptance Rate (FAR)	[e.g., 1.2%]	The percentage of forged pairs where the distance was **below** our 0.2 threshold, causing a security failure.
False Rejection Rate (FRR)	[e.g., 1.8%]	The percentage of genuine pairs where the distance was **above** our 0.2 threshold, causing a usability issue.

DISCUSSION AND FUTURE WORK

The primary objective of this project was to develop a reliable system for offline handwritten signature verification using a Siamese Neural Network. The results presented in the previous chapter demonstrate that this objective was successfully achieved.

- **Interpretation of Results:** The system achieved a high accuracy of [e.g., 98.5%], which validates the effectiveness of using a similarity-learning approach with Siamese Networks for this task. More importantly, the low **False Acceptance Rate (FAR)** of [e.g., 1.2%] indicates a strong level of security, as the system is highly effective at rejecting forgeries. The low **False Rejection Rate (FRR)** of [e.g., 1.8%] shows that the system is also practical and convenient, as it rarely flags genuine signatures as forgeries.
- **Significance of the Distance Threshold:** The choice of the distance threshold at **0.2** was a critical implementation detail. This value represents the optimal balance found between security (FAR) and convenience (FRR) for our test data. A lower threshold would increase security but could lead to more false rejections, while a higher threshold would be more lenient but would also accept more forgeries.
- **Challenges and Limitations:**
  - **Data Dependency:** The model's performance is intrinsically linked to the Kaggle dataset used for training. It may not perform as well on signatures that are stylistically very different (e.g., from different languages or cultures not represented in the dataset).
  - **Image Quality Sensitivity:** The system is sensitive to the quality of the input images. Low-resolution scans, shadows, or cluttered backgrounds can interfere with the feature extraction process and potentially lead to inaccurate results.
  - **Intra-personal Variation:** An individual's signature is not always identical. Variations due to mood, haste, or writing instrument can sometimes result in a genuine signature being rejected (contributing to the FRR). The current model has a certain tolerance for this but could be improved.

I.2 Future Work

Based on the outcomes and limitations of the current system, several promising directions for future work have been identified:

- **Enlarge and Diversify Training Data:** To create a more robust and generalized model, the next step would be to retrain it on a larger dataset. This could involve combining multiple public datasets and applying data augmentation techniques (e.g., slight rotations, scaling, and brightness adjustments) to simulate real-world variations.
- **Explore Advanced Model Architectures:** Future work could involve implementing more complex CNN architectures, such as MobileNetV2 or EfficientNet, as the base for the Siamese Network. These models are designed to capture features more effectively and might improve the system's accuracy.
- **Implement Dynamic or User-Specific Thresholding:** Instead of a single global threshold (0.2), a more advanced system could implement a dynamic threshold that adjusts based on the user. For individuals with highly consistent signatures, a lower threshold could be used for enhanced security.
- **Full-Scale Application Deployment:** The current Streamlit application is an excellent prototype. A future step would be to package the verification logic into an API and deploy it on a cloud platform (like AWS or Heroku). This would allow it to be integrated into larger, realworld applications such as banking portals or document management systems.
- **Develop an Online Verification System:** A significant extension would be to build a system for **online signature verification**. This would capture dynamic data in real-time from a stylus on a tablet, including pen pressure, speed, and stroke order. This dynamic data provides a much richer feature set and can lead to even more secure verification systems.

CONCLUSION

*I*n conclusion, this project successfully designed, implemented, and evaluated an effective system for offline handwritten signature verification. The primary objective, to create a reliable method for distinguishing between genuine and forged signatures, was achieved through the application of a Siamese Neural Network, a deep learning architecture particularly well-suited for similarity-based tasks.By training the model on a comprehensive dataset from Kaggle, the system learned to generate powerful feature embeddings that numerically represent the unique characteristics of a signature. The core verification logic, based on calculating the Euclidean distance between these embeddings and comparing it against a fine-tuned threshold of 0.2, proved to be both robust and accurate. This entire machine learning pipeline was successfully integrated into a user-friendly web application using the Streamlit framework, providing an intuitive interface for real-time verification.The system's performance was quantitatively validated, achieving a high overall accuracy of [e.g., 98.5%]. More importantly, it demonstrated a strong balance between security and usability, confirmed by a low False Acceptance Rate (FAR) of [e.g., 1.2%] and a low False Rejection Rate (FRR) of [e.g., 1.8%].

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