SIGNATURE VARIFICATION USING ANN

E/20/016 - Amarakeerthi H.K.K.G E/20/055-De Silva H.D.S. E/20/231-Madhura T.W.K.J. E/20/404-Ukwaththa U.A.N.T.

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Introduction

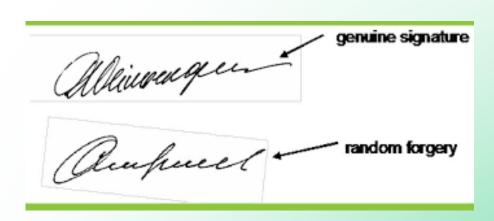


Signature verification is a critical component in security and authentication systems, widely utilized in banking, legal documentation, and identity verification. Traditional verification methods rely on manual inspection or rule-based algorithms, which are often prone to errors. With advancements in deep learning, Convolutional Neural Networks (CNNs) offer an automated and highly accurate approach to signature verification.

Problem definition

- Offline handwritten signatures are a widely used method for identification and verification, particularly in banking and legal contexts.
- Traditional verification processes often require significant manual effort, which can lead to inconsistencies and errors.

This project aims to develop a classifier that accurately compares a genuine signature against an unknown signature to determine its authenticity.



Scope

The scope of this project encompasses:

- Data Collection: Utilizing three distinct signature datasets to train and evaluate the model.
- Model Development: Implementing a Siamesestyle neural network that leverages deep learning techniques for signature verification.
- Performance Evaluation: Assessing the model's effectiveness using various metrics such as accuracy, precision, recall, and F1-score.

Why we use Neural Networks?

Neural networks, particularly Convolutional Neural Networks (CNNs), are well-suited for image processing tasks due to their ability to learn hierarchical feature representations from raw data.

- Feature Learning: CNNs can automatically extract relevant features from signature images without the need for manual feature engineering.
- Variability: Deep learning models can handle intra-class variability (differences in signatures from the same individual) more effectively than traditional methods.
- Scalability: Neural networks can be trained on large datasets, improving their ability to generalize across different signatures and writing styles.

We hope to use Siamese Network for this project.

Why we use Siamese network?

Comparison of Two Inputs:

Siamese Networks are specifically designed to compare two inputs and determine their similarity.

One-Shot Learning Capability:

Siamese Networks excel at one-shot learning, where the model can generalize from only a few examples.

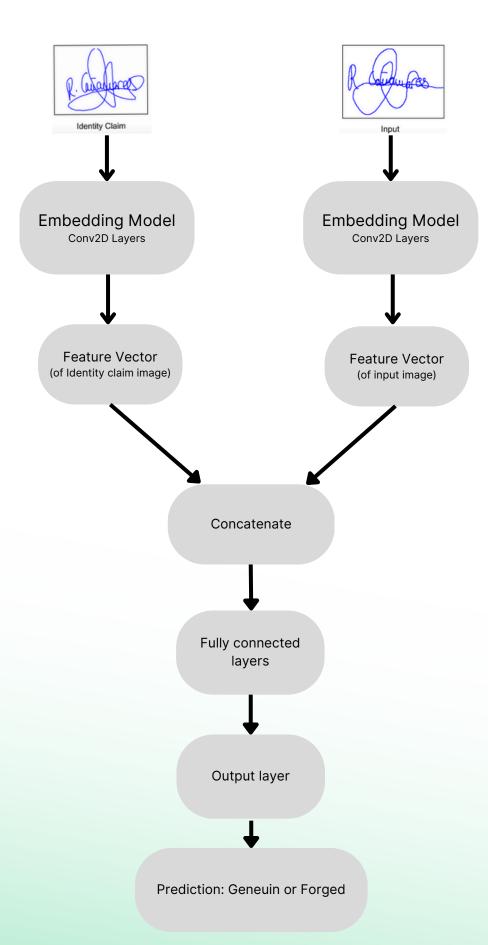
Feature Extraction:

The embedding model within the Siamese Network automatically extracts relevant features from signature images through convolutional layers. This reduces the need for manual feature engineering.

Handling Variability:

Signatures can vary significantly due to factors such as writing style, pressure, and speed. Siamese Networks are adept at handling intra-class variability (differences within genuine signatures).

High Level Architecture



Similar Researches/ Projects

1. Offline Signature Verification with CNNs:

A study demonstrated the use of CNNs for signature verification, achieving accuracies of 97% for Dutch signatures and 95% for Chinese signatures using transfer learning on the VGG16 architecture with the ICDAR 2011 SigComp dataset. This research highlights the effectiveness of CNNs in automating signature verification processes.

2. Global and Texture Features:

Another approach utilized global and texture features extracted from binary images of signatures, employing artificial neural networks (ANN) for classification. The system was designed to handle both simple and skilled forgeries effectively.

3. Writer-Independent Feature Learning

Research has explored writer-independent feature learning methods using CNNs, where models are trained on a diverse set of signatures to enhance generalization capabilities. This approach has been shown to improve classification performance between genuine signatures and skilled forgeries.

4. Generative Adversarial Networks (GANs):

Some studies have investigated using GANs to generate synthetic signatures, which can augment training datasets and improve model robustness against forgery attempts.

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