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Handwritten Signature Recognition through ANN Approach

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ABSTRACT

The fact that signatures are widely used as a means of personal verification emphasizes the need for an automated verification system. Every person has his/her unique signature that is used mainly for personal identification and verification of important documents or legal transactions. The signature verification can be done in two ways i.e. online or offline depending on the application. That is either statically or dynamically. In both ways, we can use different approaches to verify the signature. Online recognition uses the information that it acquires by capturing the signature when it is made. Whereas the offline recognition system uses a digitalized image of the signature that is already made. The proposed system can use different algorithms to verify the signature. The proposed recognition system is based on some features that we use in our algorithm. Those features may include a tilt angle, aspect ratio, normalized area, centre of gravity, number of side points, number of diagonal points and line slope, etc. But, to extract these features, we need to pre-process the digitalized image to isolate the signature part and remove any other noise. After that, we can verify the signature with the signatures that are already present in the database through the ANN system. Here the proposed system has discussed how this signature verification can be done through different algorithms and able to solve real-world problems.

Keywords**:** Signature Recognition, Verification, Identification, Artificial Neural Network(ANN), Pre-processing, Data Learning.

1. Introduction

A signature is a person's name that is written in a distinct way as a form of identification in authorizing a cheque or a document or concluding a letter. But if we need to authorize a huge number of cheques or documents then we need to check all the signatures, which is practically impossible and takes a lot of time and effort. But a signature is a unique way to identify different persons through ages. A Signature can be a legal mark that represents a particular person. Since a signature is so widely used, there are many malicious actors trying to forge the signature for some personal gain; hence very good signature forgery detection methods are necessary. Since a signature act as a confirmation in any binding legal or financial process, its authenticity has to be established and it needs to be verified. The study of handwritten signature verification is getting more in-depth as machine learning and artificial intelligence grow. However, we require a database with many signatures in it in order to verify a signature. In terms of signature data collection methods, there are mainly two kinds: offline signature images and online signature data. Offline signature image refers to the handwritten name of the author on the paper which is captured and converted to an image. Whereas online signature data refers to the data of some features collected such as pen pressure, coordinates, etc. After the data related to the signatures are taken, we need to verify the signature for authentication. For that, there are two main difficulties in signature verification. One is that both within- and between-class variability is quite high. It is vital to extract and choose more thorough and representative signature elements because the author's actual signature will also change with time, age, and other circumstances. In addition, the forger will copy the signature after extensive training.

2. Literature Survey

In paper [1] Sulong, G., Ebrahim, A. Y., & Jehanzeb, M. (2014). Offline handwritten signature identification using adaptive window positioning techniques. arXiv preprint arXiv:1407.2700.

In this paper, data was collected from the GPDS dataset because it is one of the well-known and widely used databases in signature identification and verification applications and research. In this study, the photos from the chosen dataset were converted into binary images of the signature using Otsu's algorithm's global threshold. Here the division is carried out by positioning small windows over the signature in a way that will exploit most of the redundancy in the signature and produce signature fragments that make it possible to compare these fragments in a meaningful way. And here they assume that all images are almost of the same image size and scanned in the same resolution. Therefore this can't be used everywhere. Here, the pre-processing mechanisms describe converting the image from a grey-level image into a binary image with minimal consideration of the noise model. In order to evaluate the performance of the proposed method, they used three standard evaluation criteria: False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (ERR).

In paper [2] Zhou, Y., Zheng, J., Hu, H., & Wang, Y. (2021). Handwritten signature verification method based on improved combined features. Applied Sciences, 11(13), 5867.

The current research paper on signature verification concentrates on feature extraction algorithms that mainly extract signature texture features, geometric features, and dynamic features. Here for offline images and online data, SVM and DTW were used for verification, and two scores Score1 and Score2 were obtained. And then they both were fused to get the result. This paper used a smart pen with a camera and a pressure sensor in order to sign on a piece of paper with tiny dots. So that the image and trajectory data of the signature can be obtained in real-time. Here In the pre-processing stage grey processing, binarization and normalization are carried out for the offline signature image. This article hoped to realize the combination of offline images and online data, but it is still difficult to obtain publicly available data sets that can simultaneously exist as offline images and corresponding online data. Therefore they used collected data of 1200 signatures for experiments. They used FAR, FRR, AER, and Accuracy as evaluation indicators.

In paper [3] Qiu, S., Fei, F., & Cui, Y. (2021). Offline signature authentication algorithm based on the fuzzy set. Mathematical Problems in Engineering, 2021.

According to this paper, a handwritten signature is a behavioural feature acquired for a period of time, and it belongs to the individual behavioural biological feature. In this paper, it is discussed that signatures can be affected by emotions, posture, fatigue, and other factors from psychological analysis, which can lead to fluctuations in my signature to a certain extent. Here, a segmentation model is constructed based on the theory of fuzzy set to extract the signature completely. Then, stability analysis and quantification models are proposed to identify the stability of data and features.

In paper [4] Subramaniam, M. M., Teja, E., & Mathew, N. A. SIGNATURE FORGERY DETECTION USING MACHINE LEARNING

A CNN is used as a feature extractor and a classifier in the proposed method. CNN can extract effective features for distinguishing behavioural characteristics of forgery, such as drawing the complicated sections of a signature. They have done pre-processing on the data to fit with their training model and make the signature verification easier to detect signature forgeries using a CNN. The next step is to perform feature extraction, which is a dimensionality reduction process. It will basically take the signature images and generates data like angles, curvature, arc length, etc. of the signature images. This data is used to train our CNN model. The trained model is used to predict the signature threshold which represents the authenticity of the signature.

In paper [5] Sannappa, S. K. D., Kiran, S. K. V. R., & Jagadeesh, Y. Offline Signature Verification based on Edge Histogram using Support Vector Machine.

Offline signature verification based on edge histograms using a support vector machine system has been proposed. They have used techniques such as RGB2Gray conversion, filtering, adjustment, thresholding, and clever edge detection, the signature for pre-processing. The proposed method is more efficient and thoroughly tested to detect segmented signatures of the original image with different image processing methods.

In paper [6] S Jerome Gideon, Anurag Kandulna, Aron Abhishek Kujur, A Diana, Kumudha Raimond, Handwritten Signature Forgery Detection using Convolutional Neural Networks.

A handwritten signature is now a widely recognised personal characteristic for confirming identity in all fields. The handwritten signature is a behavioural biometric that is based on the behaviour that varies over time rather than any physiological aspects of the individual signature.

In paper [7] JOUR Gupta, Punit, Hashim, Zainab Ahmed, Hanaa M.Alkhayyat, Ahmed Hussein, A Comparative Study among Handwritten Signature Verification Methods Using Machine Learning Techniques.

A sort of biometric method used for the identification of people is the identification and verification of signatures. By examining the handwriting style, which is prone to intra- and inter-personal variance, a person can be identified by his signature. Dataset pre-processing, feature extraction, and classification are the three steps that make up the problem of signature recognition and verification.

In paper [8] JOUR Almehmadi, Abdulaziz,A biometric-based verification system for handwritten image-based signatures using audio to image matching, IET Biometrics.

Visual investigations were used to first identify signature forgeries. An investigator carefully compared a signature with an authentic signature that had been preserved. This method is flawed and frequently returns misleading negative results. Here, two distinct methods are used to verify the handwriting. Offline, where elements like the starting point, contour, and angle, among other static image-based attributes, are extracted from a static signature using image processing algorithms. And online, where information about a signature's speed, pressure, velocity, and duration is gathered as it is being created.

In paper [9] Dr M. Narayana Professor, L. Bhavani Annapurna. (2017), OFFLINE SIGNATURE VERIFICATION

Here, they want to solve four issues for better outcomes. They are: to discover the user's signature's angle of inclination; to extract the Region of Interest (ROI); to eliminate the noise in the signature; and to eliminate the effects of the scaling factor.

In paper [10] José A. P. Lopes, Bernardo Baptista, Nuno Lavado, (2022) Offline Handwritten Signature Verification Using Deep Neural Networks.

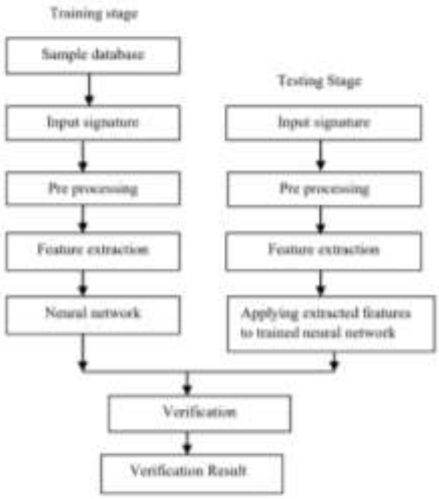
The current work proposes a method to automate the verification in order to increase the process quality and speed, Verification and verification of signatures

3. Data Collection

The below data is collected from the references.

4. Methodology

The suggested signature verification system examines a person's provided signature to determine its legitimacy. A system's design is separated into two stages: 1) Training period Stage 2: testing stage. There are four main steps in the training stage. (1) Getting a signature image from a database (2) Preparing the image (3) Feature extraction 4) Practice with neural networks. There are five main steps in the testing stage. 1) Obtaining a test signature from a database; 2) image preparation 3) Extracting features 4) Applying extracted characteristics to a neural network that has been trained 5) Examining neural network output that has been produced.



Both the training and testing phases use the pre-processing step. Signatures are grayscale scanned. To facilitate feature extraction, a grayscale signature image is transformed into binary. Thinning renders the retrieved features insensitive to aspects of the image, such as paper and pen quality. Thinning is the process of reducing binary shapes or objects to single-pixel width strokes. In signature verification systems, it is vital to select a robust set of features. A feature vector is made using the features that were extracted during this stage. A feature vector is normalised before being input to the trained neural network that determines if a signature is authentic or fake.

5. Results and Discussion

Many signatures are used for system testing and training. The "Grupo de Procesado Digital de Senales" (GPDS) signature database was used to obtain the results in this study. This study used 1440 signatures in total to produce its findings. There are 24 samples of real signatures and 24 samples of forgeries among the 1440 signatures, which are split into 30 sets (i.e., from 30 different people). A portion of this information was used to train the algorithm, which includes 19 real samples from each of the 30 different people and 19 forgeries created by various people for one signature. If the output neuron produces a value near +1 after applying a feature vector of the test signature, the test signature is deemed genuine; otherwise, it is

deemed fake. In order to determine if the neural network successfully classifies a signature as real or counterfeit, the testing phase applies the genuine and forged signature samples used for training. It is termed as recall.

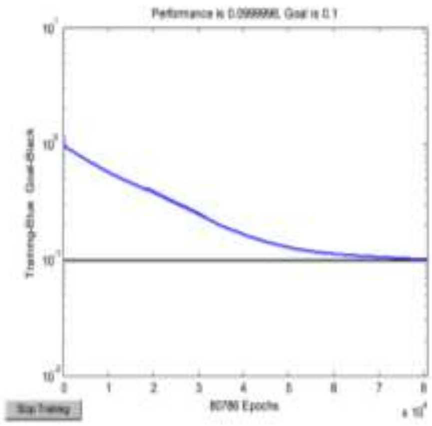


Fig. Performance graph of handwritten signature verification using neural network

When given 150 authentic signatures from 30 separate people, the neural network identified 120 of those autographs as real while classifying the remaining 30 as forgeries. Therefore, the system's FRR is 20%. When a neural network was given 150 falsified signatures as input, it identified 22 as real and 128 as forgeries. The system's FAR is 14.66% as a result. Therefore, the generalization's Correct Classification Rate is 82.66%.

Samples presented	Genuine	Forged	FAR	FRR	CCR In Generalization
150 genuine	120	30	-	20%	82.66%
150 forged	22	128	14.66 %	-	

Fig. Result of Testing Neural Network with New Signatures Samples from Database

6. Conclusion

Marks or signatures are exceptional examples of handwriting, including exceptional letters and phrases. Many signatures can be ambiguous. They are a kind of stunning handwritten object. However, text or signatures can be treated as images and can be recognized using computer vision and fake nervous system strategies. Letters or signatures are exceptional examples of handwriting, including exceptional letters and phrases. Many signatures can be ambiguous. They are a kind of stunning handwritten object. However, text or signatures can be treated as images and can be recognized using computer vision and fake nervous system strategies. These papers have also helped us learn more about Signature identification and verification through different methods.

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