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# Offline Signature Verification and Forgery Detection using CNN

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**Abstract**
In this work, signature forgery is detected/classified using Convolutional Neural Network (CNN). Signature forgery detection is a challenging field with a lot of critical issues. Signature forgery drives cooperates and business organizations to huge financial loss and also effects their security reputation. Highly accurate automatic systems are needed in order to prevent this kind of crimes. Handwriting forgery detection is one of the hotspots in forensic science, and economic cases of handwritten forged signatures are increasing. At the same time, forgery identification of documents is important evidence in criminal proceedings. This paper introduces an automatic offline system for signature forgery detection. Different features were extracted and their effect on system recognition ability was reported. The computed features including run length distributions, slant distribution, entropy, Histogram of Gradient features, and Geometric features. Finally, different machine learning techniques were applied on computed features. Here in this project, we will classify signature forgery using Convolutional Neural Networks (CNN). Experimental results show that this model is better than Support Vector Machine (SVM) feature classifier a machine learning technique.

**Index Terms—CNN, LBP, HoG, Signature verification, Forgery detection**

## Introduction

This paper discusses the importance of a signature verification and recognition system. It explains how it can be implemented and developed by using certain features. Signature verification has an advantage over various forms of biometric security verification techniques; including recognition. It is used to identify a person carrying out daily routine procedures, i.e. bank operations, document analysis, electronic funds transfer, and access control, by using his handwritten signature.

Biometrics is defined as an automated use of the physiological or behavioral characteristics of an individual for identification/authentication purposes. Many different biometric identification systems have been proposed as a means of determining or verifying personal identity using different behavioral characteristics. Signatures, as one of the behavioral human characteristics, are extensively used as proof of identity for legal purposes on many documents such as bank cheques, credit cards, and wills in our daily lives. Considering the large number of signatures handled daily through visual inspection by authorized persons, the construction of an efficient automatic system to handle such a huge volume of signatures has many potential benefits for signature authentication to reduce fraud and other crimes.

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Signature verification aims to verify the identity of a person through his/her chosen signature. Signature is considered to be a behavioral biometric that encodes the ballistic movements of the signer; as such it is difficult to imitate. Compared to physical traits such as fingerprint, iris or face, a signature typically shows higher intra-class and time variability. Furthermore, as with passwords, a user may choose a simple signature that is easy to forge. On the other hand, the signature's widespread acceptance by the public and niche applications (validating paper documents and use in banking applications) make it an interesting biometric.

### 1.1 Problem Identification

Signature forgery in legal document,bank cheque can lead to huge consequences. Although signature forgery are often manually detected by experts but still high accuracy is not always achieved. Automatic recognition system can play an effective role in verifying signatures with high accuracy and in differentiating between genuine and forged signatures.

## 2. Literatur Survey

This paper aims at developing a support vector machine for identity verification of offline signature based on the feature values in the database. A set of signature samples are collected from individuals and these signature samples are scanned in a gray scale scanner. These scanned signature images are then subjected to a number of image enhancement operations like binarization, complementation, filtering, thinning and edge detection. From these pre-processed signatures, features such as centroid, centre of gravity, calculation of number of loops, horizontal and vertical profile and normalized area are extracted and stored in a database separately. The values from the database are fed to the support vector machine which draws a hyper plane and classifies the signature into original or forged based on a particular feature value. The developed SVM is successfully tested against 336 signature samples and the classification error rate is less than 7.16% and this is found to be convincing [1].

The paper presents a novel set of features based on surroundedness property of a signature (image in binary form) for off-line signature verification. The proposed feature set describes the shape of a signature in terms of spatial distribution of black pixels around a candidate pixel (on the signature). It also provides a measure of texture through the correlation among signature pixels in the neighborhood of that candidate pixel. So the proposed feature set is unique in the sense that it contains both shape and texture property unlike most of the earlier proposed features for off-line signature verification. Since the features are proposed based on intuitive idea of the problem, evaluation of features by various feature selection techniques has also been sought to get a compact set of features. To examine the efficacy of the proposed features, two popular classifiers namely, multilayer perceptron and support vector machine are implemented and tested on two publicly available database namely, GPDS300 corpus and CEDAR signature database [2].

Signature identification and verification are of great importance in authentication systems. The purpose of this paper is to introduce an experimental contribution in the direction of multi-script off-line signature identification and verification using a novel technique involving off-line English, Hindi (Devnagari) and Bangla (Bengali) signatures. In the first evaluation stage of the proposed signature verification technique, the performance of a multi-script off-line signature verification system, considering a joint dataset of English, Hindi and Bangla signatures, was investigated. In the second stage of experimentation, multi-script signatures were identified based on the script type, and subsequently the verification task was explored separately for English, Hindi and Bangla signatures based on the identified script result. The gradient and chain code features were employed, and Support Vector Machines (SVMs) along with the Modified Quadratic Discriminate Function (MQDF) were considered in this scheme. From the experimental results achieved, it is noted that the verification accuracy obtained in the

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second stage of experiments (where a signature script identification method was introduced) is better than the verification accuracy produced following the first stage of experiments. Experimental results indicated that an average error rate of 20.80% and 16.40% were obtained for two different types of verification experiments [3].

**3. Existing Method**

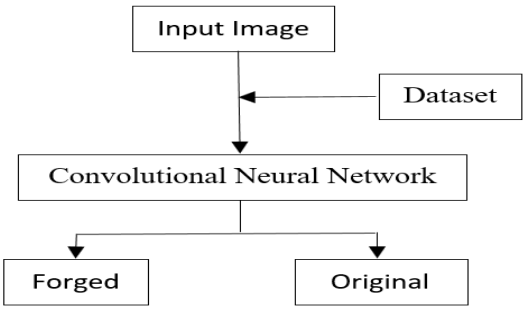
In the existing method, forgery detection is classified with two feature extraction methods commonly used in image processing are selected: Local Binary Pattern (LBP) and Global Feature Descriptor (GIST) and uses SVM as a classifier to classify the image features.

**4. Proposed Method**

Biometric authentication is the process of verifying the identity of individuals based on their unique biological characteristics. It has become a ubiquitous standard for access to high security systems. Current methods in machine learning and statistics have allowed for the reliable automation of many of these tasks (face verification, fingerprinting, iris recognition). Among the numerous tasks used for biometric authentication is signature verification, which aims to detect whether a given signature is genuine or forged. Signature verification is essential in preventing falsification of documents in numerous financial, legal, and other commercial settings. The task presents several unique difficulties: high intra-class variability (an individual's signature may vary greatly day-to-day), large temporal variation (signature may change completely over time), and high inter-class similarity (forgeries, by nature, attempt to be as indistinguishable from genuine signatures as possible).

In modern daily writing activities, the gel pen is becoming the main tool for writing. At the same time, black and blue ink are the colors often used in writing activities. Here we classified signature type whether it is done normally and forcefully. This paper applies pattern recognition method to handwriting signature forgery identification, and uses convolutional neural network for the first time to detect handwritten forgery figures. It solves the problems of relying on the experience and knowledge of the appraisers in the forensic document's identification, making judgments based on the abnormal features between handwriting and strokes, which is time-consuming and labor-intensive. However, this paper only involves the study of adding strokes to a handwriting image under a single background. In actual cases, there is a situation of complex writing background. For the purpose of network creation, we have used Deep Network Designer Toolbox in MATLAB. The block diagram of proposed model is shown below.

**Block Diagram:**




**Preprocessing & Segmentation:**

Signatures are introduced to the system as scanned images of 200 dpi resolution. Images' size are normalized. Segmentation is achieved by binarization.

**Feature Extraction:**

In the present research work, texture-based features are considered for feature extraction. Texture features, such as the Local Binary Pattern (LBP), the Local Derivative Pattern (LDP), and Grey Level Co-occurrence Matrix (GLCM), have widely been employed in different biometric systems including signature verification and some promising results have also been provided. Notable results obtained in signature verification using the texture features, especially the LBP-based features, are due to the exceptional properties of the LBP-based features, which can provide important information about the personal characteristics of a signer including such

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elements as the amount of pressure and speed changes, pen-holding, ink distribution, etc. The LBP features are also computationally efficient and these features have shown their robustness to monotonic illumination change. The LBP features are, however, sensitive to random noise and non-monotonic illumination variation.

In the basic LBP feature extraction method, an image is processed in such a way that a binary code is generated for each pixel in the image. This code determines whether the intensities of the neighbouring pixels are greater or less than the reference pixel's intensity. For instance, in a 3×3 neighbourhood with the reference pixel being the centre, a binary code of length 8 is generated according to the relative intensities of its neighbours. A histogram of 256 bins is then computed to count the number of occurrences of each binary code, describing the proportion of common textural patterns in the image. By computing the occurrence histogram, structural and statistical information is effectively combined. The LBP map detects microstructures, such as edges, lines, spots and flat areas, whereas their underlying distribution is estimated by the LBP histogram. The basic LBP-based feature extraction technique has further been extended to a generalised rotation invariant feature extraction method. The generalised LBP feature extraction (LBPP u2,R) and rotation invariant (LBPP riu2,R) methods have been derived based on a symmetric P members neighbourhood on a circle of radius R. The parameter p controls the quantisation of the angular space and R determines the spatial resolution of the operator. Similar to the authors, the LBPP riu2, R with only two variations (R = 1, P = 8 and R = 2, P = 16) is initially employed on the pre-processed original image to extract signature features.

Furthermore, an effective feature extraction technique based on under-sampled bitmaps and LBP-based features is proposed in this paper. To do so, first, an under-sampled bitmap image is created and then LBP-based features are extracted from the under-sampled bitmap image. The main reason for the use of the under-sampled image in the proposed feature extraction method is to compute the LBP-based features from the grey level low-resolution version of the input signature image. The significance of LBP-based texture features obtained from the grey images compared to the binary images has been pointed. As most of the LBP patterns in an image are generally uniform patterns, and also the uniform LBP (LBPP u2 ,R) operator can keep the distribution of the LBPs in the image, the LBPP u2 ,R with R = 1 and P = 8 is applied on the resultant under-sampled grey image to obtain a set of 59 LBP-based texture features called UB − LBPP u2 ,R. The LBP-based features extracted based on the UB-LBP8 u2 ,1, LBP8 riu2 ,1 and LBP16 riu2 ,2 from the undersampled and original signature images are concatenated to create a set of 87 (59+10+18) features. It is worth mentioning that both grey-level information as well as binary information are captured in the proposed feature set, ensuring a better interpretation of the signature images.

**5. Result**

This project presents a method for offline signature verification and recognition by using convolution neural network.As mentioned earlier, security is one of the most critical issues when it comes to signature recognition, especially when by banks and offices. One forgery signature, can mess up transactions, causes the bank and customers financial loses, and affect the security reputation of the bank, which is a damage that cannot be easily fixed. In this project offline signature verification and forgery detection is implemented using CNN which gives better results.

**6. Conclusion**

In this paper, the performance of the proposed writer-dependent interval-based symbolic representation model for off-line signature verification is demonstrated, whereby a wide range of experiments was conducted on different datasets. We experimented with several variations on signature verification tasks. We showed that convolutional neural networks do an excellent job of verifying signatures when allowed access during

training to examples of genuine and forged signatures of the same people whose signatures are seen at test time. We then conducted an experiment where we tested our network on the signatures of new people whose signatures had not been seen at all during training, which resulted in better performance compared to other algorithms.

## 7. Future Scope

Finally, we proposed a novel architecture for the comparison of signatures which has promise for future work in signature verification, specifically in situations where a possibly-forged signature can be compared to known genuine signatures of a specific signer. In future work there can be access to more resources which allows us to achieve better performance on our main task. Specifically, being able to train on a larger dataset with more signature examples.

## 8. Acknowledgement

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