SIGNATURE VERIFICATION USING IMAGE PROCESSING AND DEEP LEARNING

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ABSTRACT—

Traditional bank checks, bank credits, credit cards and various legal documents are an integral part of the modern economy. They are one of the primary mediums by which individuals and organizations transfer money and pay bills. Even today all these transactions especially financial require our signatures to be authenticated. Offline Signature recognition plays an important role in Forensic issues. In this project we present a simple approach to offline signature verification, where the signature is written on a paper and transferred into an image format or captured using tablet/mobile. For recognizing the signature, we first do some eometrical and statistical calculation aiming to extract special features from the signatures then we train the neural network on these features from different signers. Finally, the extracted features from the tested signature are compared with the previously trained features and we know the signer.

KEY WORDS

CNN, max pooling, flattening, and dense layer.

INTRODUCTION

A biometric technique that uses characteristics of a person's signature (including pressure, pen lifts, speed and direction of pen strokes) to authenticate identity.Off-line signatures are scanned from paper documents, where they were written in handwritten way. Off-line Signature analysis can be carried out with a scanned image of the signature using a standard camera or scanner, and they are useful in automatic verification of signatures found on bank checks and documents. Handwritten signatures are socially and legally accepted in our day to day life.These are used as traits for the biometrics based on each person. Biometrics refers to automatic recognition of individuals based on their physiological and behavioural characteristics. The world is crying out for the simpler access controls to personal authentication systems and it looks like biometrics may be the answer. Instead of carrying bunch of keys, all those access cards or passwords you carry around with you, your body can be used to uniquely identify you.

There are two types of biometrics:

1. Behavioral

2. Physiological.

Handwriting, speech etc. come under behavioral biometrics. Iris pattern, fingerprint etc. are part of physiological biometrics. On the basis of acquisition there are two main types of signature authentication either its Offline or Online. Off-line or static signatures are scanned from paper documents, where they were written in conventional way.

Moreover, the signature of a person varies from time to time. Small variations are inherent, and these can be tolerated by the authentication system. But when there is a significant change in the signature, the verification system should be updated with the new signature database. Signatures are categorized as: simple, cursive and graphical depending on their shapes. Simple signatures are the ones containing the names of persons. Cursive signatures are the ones written in cursive form. Graphical signatures are the ones depicting some geometric patterns

Fig.Signature samples

LITERATURE SURVEY

2.1 Handwritten Signature Recognition: A Convolutional Neural Network Approach

Handwritten Signature Recognition is an important behavioral biometric which is used for numerous identification and authentication applications. There are two fundamental methods of signature recognition, on-line or off-line. On-line recognition is a dynamic form, which uses parameters like writing pace, change in stylus direction and number of pen ups and pen downs during the writing of the signature. Off-line signature recognition is a static form where a signature is handled as an image and the author of the signature is predicted based on the features of the signature. The current method of Off-line Signature Recognition predominantly employs template matching, where a test image is compared with multiple specimen images to speculate the author of the signature.

2.2 Dynamic Signature Verification System Based on One Real Signature

The dynamic signature is a biometric trait widely used and accepted for verifying a person's identity. Current automatic signature-based biometric systems typically require five, ten, or even more specimens of a person's signature to learn intrapersonal variability sufficient to provide an accurate verification of the individual's identity. To mitigate this drawback, this paper proposes a procedure for training with only a single reference signature. Our strategy consists of duplicating the given signature a number of times and training an automatic signature verifier with each of the resulting signatures.

2.3 Y. Akbari, M. J. Jalili, J. Sadri, K. Nouri, I. Siddiqi, and C. Djeddi. 2018. A novel

Database for automatic processing of Persian handwritten bank checks. Pattern

Recognition 74 (2018), 253–265.

This paper introduces a database of Persian handwritten bank checks. The database includes legal amounts, courtesy amounts, dates, receiver names, signatures and account numbers. In addition to checks, the database also comprises handwritten forms with words used in legal amounts, digits employed in the courtesy amounts and signatures of contributors. The database can be employed for evaluation of segmentation and recognition of different fields in checks as well as for verification of signatures. Data is collected and organized in two series. The first series, comprising 500 hand filled Persian checks and 500 forms contributed by 500 different individuals, supports evaluation of segmentation and recognition tasks.

2.4 W. Bouamra, C. Djeddi, B. Nini, M. Diaz, and I. Siddiqi. 2018. Towards the design of an

Offline signature verifier based on a small number of genuine samples for training. Expert

Systems with Applications 107 (2018), 182–195.

Signature verification has remained one of the most widely accepted modalities to authenticate an individual primarily due to the ease with which signatures can be acquired. Being a behavioral biometric modality, the intra-personal variability in signatures is rather high and extremely unpredictable. This leads to relatively higher error rates as compared to those realized by other biometric traits like iris or fingerprints. To address these issues, this study investigates run-length distribution features for designing an effective offline signature verification system.

2.5 Off-line signature verification based on geometric feature extraction and neural network

Classification

In this paper a method for off-line signature verification based on geometric feature extraction and neural network classification is proposed. The role of signature shape description and shape similarity measure is discussed in the context of signature recognition and verification. Geometric features of input signature image are simultaneously examined under several scales by a neural network classifier. An overall match rating is generated by combining the outputs at each scale. Artificially generated genuine and forgery samples from enrollment reference signatures are used to train the network, which allows definite training control and at the same time significantly reduces the number of enrollment samples required to achieve a good performance. Experiments show that 90% correct classification rate can be achieved on a database of over 3000 signature images.

2.6 A Perspective Analysis of Handwritten Signature Technology

During the last 40 years, a number of comprehensive surveys and state-of-the-art reviews in automatic signature verification (ASV) [170] have been published. Among a large number of papers, a couple of relevant academic articles have had a strong impact. One of the first state-of-the-art papers in this field was published in 1989 by Plamondon and Lorette [214].

Approximately 10 years later, Plamondon and Srihari published another survey [218]. In a similar span of time, Impedovo and Pirlo [123] published a comprehensive survey in 2008. From this perspective, it can be deduced that 10 years is an acceptable period of time to make a substantial upgrade to the automatic signature verification state of the art. With this in mind, we review the technology in this article, taking into account the novel advances and emerging issues of ASV in the last 10 years, from 2008 up to now. Moreover, shorter state-of-the-art papers have been published, mostly in conference proceedings or book chapters (e.g., [57, 80, 111, 126, 196]), further explaining specific advances in signature verification and also pointing out several research directions and milestones.

PROPOSED METHODOLOGY

EXISTING WORK

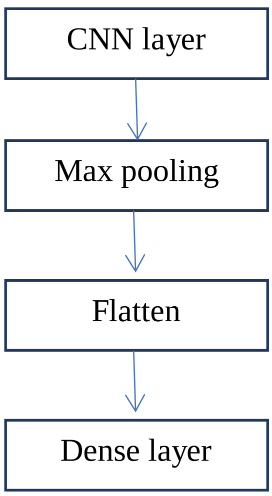
Existing algorithms uses Different feature extraction and classification techniques. Previously we used machine learning algorithms in which there is separate feature extraction and its classification so time complexity is very high for existing techniques. Existing techniques have low accuracy with high false acceptance rate. Existing Classifiers such as SVM, KNN, distance classifiers**.**

PROPOSED WORK

The first contribution of this research is pre-process on rough offline handwritten signature to make suitable for further process. The second contribution is designing a novel joint feature learning framework which can be utilized to combine intermediate features computed in a deep network. Deep learning architectures generally compute a series of intermediate features from input data and utilize the final layer of features only for representation and classification. Here we used joint-framework by auto-encoders for feature learning and soft max layer for classification.

BLOCK DIAGRAM OF PROPOSED WORK

The proposed work includes four layers: CNN, max pooling, flattening, and dense layer.



A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice. TheConvolutional Neural Network (CNN or ConvNet) is a subtype of Neural Networks that is mainly used for applications in image and speech recognition. Its built-in convolutional layer reduces the high dimensionality of images without losing its information. That is why CNNs are especially suited for this use case. CNN is an efficient recognition algorithm which is widely used in pattern recognition and image processing. It has many features such as simple structure, less training parameters and adaptability.

CNN layer: It is a class of neural networks and processes data having a grid-like topology. The convolution layer is the building block of CNN carrying the main responsibility for computation

Max pooling: Max Pooling is a pooling operation that calculates the maximum value for patches of a feature map, and uses it to create a downsampled (pooled) feature map. It is usually used after a convolutional layer.

Flatten: Flattening is used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The flattened matrix is fed as input to the fully connected layer to classify the image

Dense layer: In any neural network, a dense layer is a layer that is deeply connected with its preceding layer which means the neurons of the layer are connected to every neuron of its preceding layer. This layer is the most commonly used layer in artificial neural network networks

To implement this project we have designed following modules

1) Upload Signature Dataset: using this module we will upload own signature dataset to application

2) Pre-process Dataset: using this module we will read all images and then normalize all images pixel value and then resize them to equal size

3) Train Signatures to CNN Algorithm: Now processed images will be input to CNN model to train a signature prediction model

4) Accuracy Comparison Graph: using this module we will plot CNN accuracy and loss graph whose values are generated while training CNN

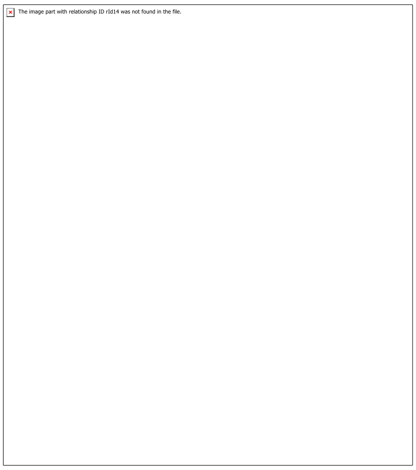
5) Predict Signature: using this module we will upload test image and then CNN will predict Signature.

DEEP LEARNING

Deep learning is the hottest field in AI right now. From Google Duplex assistant to Tesla self- driving cars the applications are endless. In the past 10 years, machine learning and artificial intelligence have shown tremendous progress. Recently deep learning plays major role for

1. Explosion of huge data
2. Cheap Computing cost

3. Improvement in ML algorithms



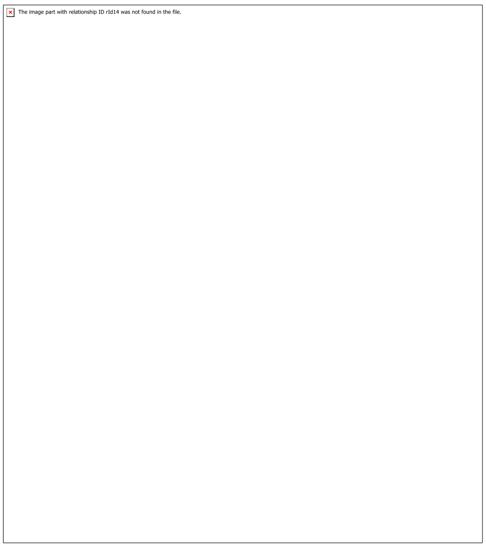


Fig : Machine learning and Deep Learning Difference

DATASET

The signature verification system would need a set of image dataset having handwritten signatures from different authors. Here we created database of 20 different images for every person we collected set of 5 images and samples are collected for 4 different students.

This section describes the projected method behind the system development. It describes the following points:

1. Signature Acquisition
2. Signature Pre-processing
3. Feature Extraction
4. Processing of signature
5. Signature Verification

1. Signature Acquisition: Signatures are scanned with 200dpi resolution, resulting in an average image size of 1000*250 pixels. This resolution has shown to be necessary to correctly interpret the line crossings

Fig: Template of Signature Database

Figure 1 shows a template of signature database of few signers taken on the same day which is ready for pre-processing. Inclusion of skilled forgeries: It is more difficult to obtain skilled forgeries than genuine signatures, but without the inclusion of skilled forgeries, quoting false rejection rates is far less meaningful.

2. SignaturePre-processing: Signature pre-processing is a necessary step to improve the accuracy of the latter algorithm, and to reduce their computational needs. Following pre-processing steps are taken into consideration:

1. Transformation from colour to gray scale, and finally to black and white.
2. Resizing the image, so that all images have a same and secure size.
3. Thinning the black and white image results always in a huge information loss.

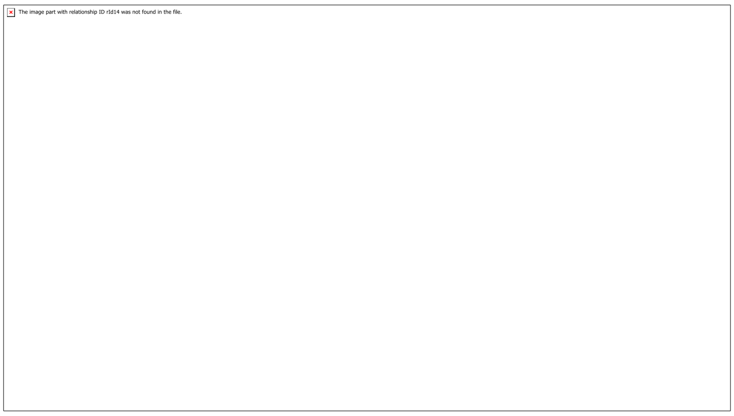


Fig.Variouspreprocessing steps

3. Feature Extraction: The features extracted from handwritten signature play a vital role in authentication process. A large number of features are extracted from signatures but not all features can be used in the feature set A good feature set would result in an successful system. It is really important to have a meaningful feature set for assurance of proper learning by NN. Feature set consist of different types of features.

4.processing of signature

Processing of signature consists of two main parts:

1. Training phase
2. Testing phase

In experiment of proposed method, eight genuine signatures of 12 individual are used to train the network, and also some skilled forgeries are introduced in the training dataset.

There are different neural networks through which we are gone through such as back propagation, self-organizing map etc. but found Cascaded feed-forward back-propagation networks giving best results. As back-propagation is having the highest classification accuracy as compared with other implemented algorithms.

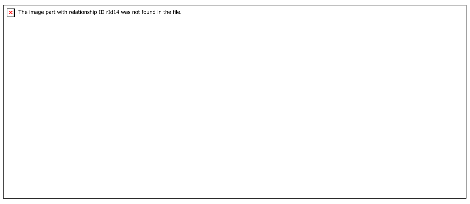


Fig. Cascaded feed-forward back propagation

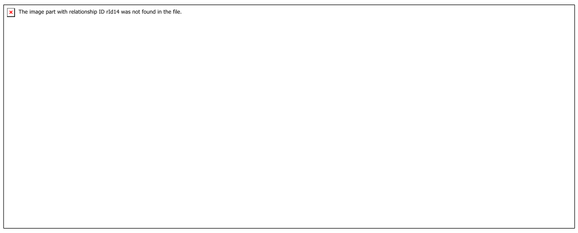
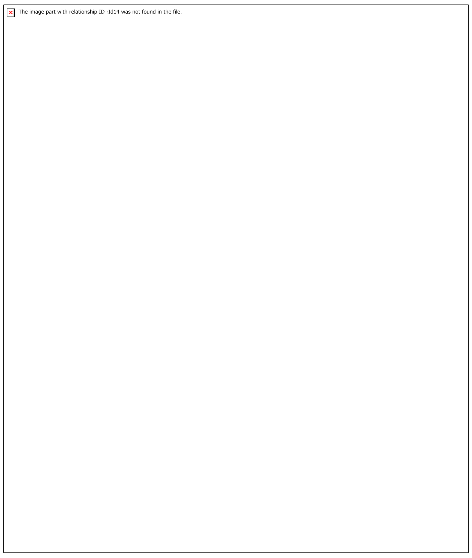


Fig . Pattern recognition network

The following performance metrics are used throughout this section: FAR (false acceptance rate): It is the rate of forgeries accepted as genuine. False acceptance rate expressed as a percentage. FRR (false rejection rate): False rejection rate expressed as a percentage. EER (Equal Error Rate): Equal error rate for evaluation comes when FRR=FAR i.e. false acceptance rate is equal to false rejection rate. OER: overall error rate (FAR + FRR).The proposed method outperforms very well in all the performance measures.



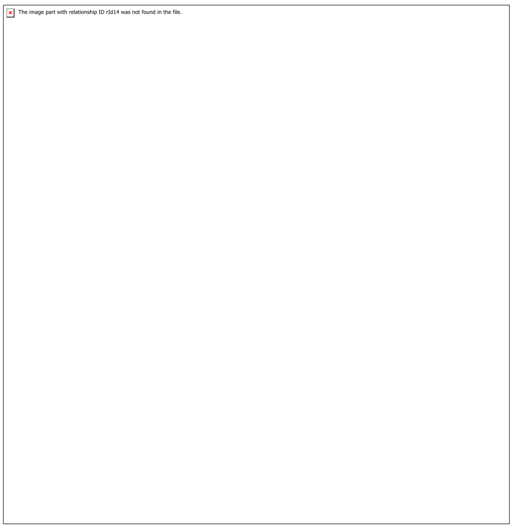
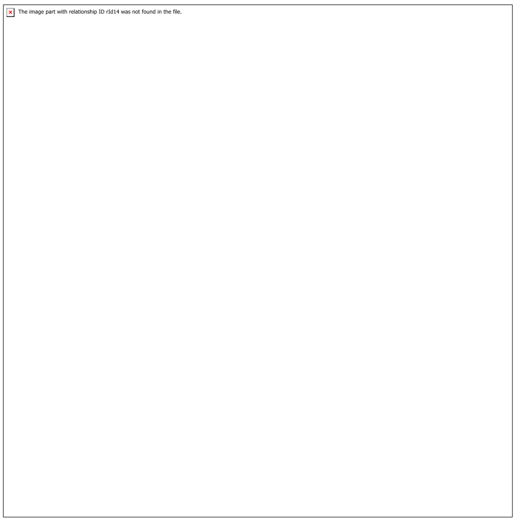


Fig: Performance plot Fig: Template of training state



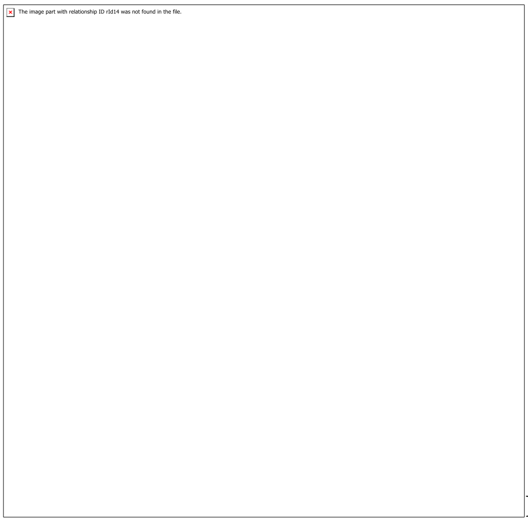


Fig:
Template of regression plot

Fig: Neural Network Training

RESULTS

Depending on the matched or not –matched results are displayed. By both subjective and objective analysis we can say that proposed method is better compared to state of art techniques. Confusion matrix is plotted as per the final results to get detailed study. GUI is prepared to get easy analysis.

Select Testing Image

CONCLUSION

In this project we present a simple approach to offline signature verification, where the signature is written on a paper and transferred into an image format or captured using tablet/mobile. Matlab toolboxes are successfully used for 2 major objectives as, one is pre-processing on input data to get final modified input. Second is based on deep learning using auto encoders and softmaxlayer. GUI is prepared to get easy understanding of application.

REFERENCE

1. Handwritten Signature Recognition: A Convolutional Neural Network Approach

2. Dynamic Signature Verification System Based on One Real Signature

3. Y. Akbar, M. J. Jalili, J. Sadri, K. Nouri, I. Siddiqi, and C. Djeddi. 2018. A novel database for automatic processing of Persian handwritten bank checks. Pattern Recognition 74 (2018), 253–265.

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Systems with Applications 107 (2018), 182–195.

5. Dynamic Signature Verification System Based on One Real Signature

6. Off-line signature verification based on geometric feature extraction and neural network classification

7. A Perspective Analysis of Handwritten Signature Technology