Offline Verification of Signature Using CNN

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Abstract*— Now a day's signature is becomes a most important biometric authentication technique. In banks or at the other necessary documents, signature plays an important role to authenticate the person. In this technique, we are going to present a deep learning approach for offline signature verification to prevent the fraud signatures by fake peoples. We are going to do deep learning with the help of Convolution Neural Network (CNN). In this study, we are going to collect dataset of different signatures from the different angles. Signature is taken as an input in the form of image. For signature recognition, it is important to make structural and some geometrical calculation getting to extract special features from the signatures then we train a man-made neural network on these features from different signers. Finally, the extracted features from the tested signature are compared with the previously trained features and that we know the signer.

***Keywords*— Biometric, Deep Learning, CNN, Neural Network, Signer.**

I. INTRODUCTION

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. The inevitable side-effect of signatures is that they can be exploited for the purpose of feigning a document's authenticity. Hence the need for research in efficient automated solutions for signature recognition and verification has increased in recent years to avoid being vulnerable to fraud.

Signature verification can be considered a special case of pattern recognition. Like in any pattern recognition problem, in signature verification distinctive features can be extracted from a set of original signatures. However, Approaches to signature verification fall into two categories: On-line and Off-line. There are two types of signatures, offline (static) and online (dynamic). Online signatures have higher distinctive features but offline signatures have fewer distinctive features. So offline signatures are more difficult to verify. In addition, the most important drawback of offline signatures is that they cannot be signed with the same way even by the most talented Signer.

Offline signatures, which legally impose financial and moral liabilities, are an authentication technique that is still widely used today especially in legal documents, banking and commercial transactions. Hence, offline signatures are frequently misused by malicious people and used for fraud. To prevent fraud and malicious intentions signature verification is used. With the development of machine learning, new algorithms present promising solutions that can be used for signature verification. For these reasons, signature verification is one of the most important problems remains to be solved in machine learning methods nowadays. The most important drawback of offline signatures is that they cannot be reproduced in the same way.

In this study we will take the dataset of the different signatures. We will take signature as an input in the form of image. After taking signature as an input next step is feature extraction. Signature is separated according to the features. After extracting the features, matching process is done. According to the matching result is implemented. And final output is recognition of signature.

Main motivation of the system is to provide security to the signatures which are widely used in legal documents, banking and commercial transactions. Normally it is difficult to identify the signature of the particular user at the time of verification of the documents. At that time, there is a need to identify the fake signatures from the documents. So there must be some system or application which would help banking system and some other systems like commercial transaction to detect the fake signature. There are many devices in market are available for signature check up, But there are many limitations regarding their maintenance due to their heavy cost, size of instruments. This system is also helpful to provide more security at the time of all transactions and also at the time some property issues.

Many of the systems were introduced in the developed countries where the infrastructure is working perfectly. In most cases, the systems are adapted to work in developing countries. To reduce some of these problems there is need to approach the remote detection from a ground-up approach to suit the basic minimal conditions presently available in developing countries.

A simple signature verification system design can be approached by the number of parameters it can detect. In some instances, by verifying one parameter several readings can be calculated.

As we know that, the population of country is growing day-by-day and fraud issues are becoming one of the major factors that lead to spend lot of expenditure. To verify the signatures of user on regular basis is getting harder. So, using this system we are trying to provide security by using offline signature verification technique. One major advantage is in reduction of expenditure and frauds. Bank system can find out fraud signatures after verifying signatures. By using a trending technology, we can verify signatures offline.

II. LITERATURE SURVEY

Elias N. Zois , Dimitrios Tsourounis , Ilias Theodorakopoulos , Anastasios L. Kesidis, and George Economou, during this paper, a feature extraction method for offline signature verification is presented that harnesses the facility of sparse representation (SR) so as to deliver state-of- the-art certify attainment in number of signature datasets like CEDAR, MCYT-75, GPDS, and UTSIG. Beyond the accuracy improvements, number of major parameters allied to SR; likeselected configuration, dictionary size, sparsity level, and positivity priors are analysis. Besides, it's evinced that secondorder statistics of the sparse codes may be a powerful pooling function for the formation of the worldwide signature descriptor. Also, a radical evaluation of the consequences of preprocessing is introduced by an automatic algorithm so as to pick the optimum thinning level. Finally, a segmentation strategy which employs a special kind of spatial pyramid tailored to the matter of SR is presented in conjunction with the enhancing of the produced descriptor on relevant areas of the signature as arrive from the binary robust invariant scalable key-point identify mechanism.

Victor L. F. Souza, Adriano L. I. Oliveira, Robert Sabourin, in this work it is investigated whether the use of these CNN features provide good results in a writer- independent (WI) HSV context, based on the dichotomy transformation combined with the utilization of an SVM writer-independent classifier. The praised attainment within the Brazilian and GPDS datasets indicate that (i) the proposed approach outperformed other WI-HSV steps from the literature, (ii) within the worldwide threshold scenario, the proffer approach was ripe to outperform the writer-dependent method with CNN features within the Brazilian dataset, (iii) in an user threshold scenario, the results are almost like those obtained by the writer-dependent method with CNN features.

Muhammed Mutlu Yapıcı, Adem Tekerek, Nurettin Topaloglu, during this study, we proposed a Deep Learning (DL) based offline signature verification method to stop signature fraud by malicious people. The DL method used in the study is the Convolution Neural Network (CNN). CNN was designed and trained separately for 2 different models such one Writer Dependent (WD) and therefore the other Writer Independent (WI). The experimental outcome showed that WI has 62.5% of success and WD has 75% of success. It is predicted that the achievement of the obtained outcome will increase if the CNN step is supported by adding another feature extraction steps.

Elias N. Zois, Ilias Theodorakopoulos, Dimitrios Tsourounis, in this work, sparse dictionary learning and coding are for the first time employed as a means to provide a feature space for offline signature verification, which intuitively adapts to alittle set of randomly selected genuine reference samples, thus making it attractable for forensic cases. In this context, the K-SVD dictionary learning algorithm is used so as to make a writer oriented lexicon. For any signature sample, sparse representation with the utilization of the writer's lexicon and therefore the Orthogonal Matching Pursuit algorithm generates a weight matrix; features are then extracted by applying easy average pooling to the new sparse codes. The act of the proposed scheme is demonstrated using the favored CEDAR, MCYT75 and GPDS300 signature datasets, delivering state of the art results.

Wang Kai, Liu Jingzhi, Xu Shun, Wang kai, Gan Zhichun, In this paper, we study a fast and computationally efficient sparse representation classification scheme for battlefield textual information in which the block sparsity of sparse coefficients is exploited. A novel sparse approximation algorithm tailored for this low complexity classification method is proposed. Experiment output show that our classification algorithm that leverages the canny structure of the textual information outperforms plain canny representation classification procedures in all classification accuracy an computationally efficiency.

A. Hamadene and Y. Chibani, In this paper, we propose a one-class writer-independent system using feature dissimilarity measures (FDM) thresholding for classification and a reduced number of references. The proposed system involves the use of Contourlet Transform (CT) based directional code co-occurrence matrix (DCCM) feature generation method. The verification is achieved through a WI threshold which is automatically selected employing a new signature stability criterion. The proposed writer independent concept is besides addressed through the mixture of different writers' datasets in both design and verification stages. Experimental results show the effectiveness of the proposed system in spite of the strict verification protocol using the one class concept, a singular threshold for accepting or rejecting a questioned signature, the reduced number of writers and therefore the limited number of reference signatures.

Shih-Chung, Hsu, Chung-Lin, Huang, This paper proposes an object verification method in two different views by using sparse representation. The proposed method contains three major modules. First, we train the sparse matrix by using K-Singular Valued Decomposition (K-SVD) and therefore the maximum correlation training sample selection. Second, we project the training samples onto the sparse matrix to get the parse vector training set. Third, we combine two training sets of the same/different objects from two different views to generate positive/negative hybrid sparse vector sets for SVM classifier training. Our contributions in this paper are (1) proposing a better dictionary representation learning than original K-SVD learning, and (2) developing an optimal sparse representation for object verification with very good accuracy. In the experiment, we show that our method has the better accuracy than the other methods.

Mrs. Madhuri R.Deore, Mrs. Shubhangi M. Handore, The signature identification can be offline or online. We apply the image processing technique for offline signature recognition here no dynamic feature are available in offline identification. A brief survey on various off-line biometric identification & verification schemes is represented this paper.

Amit Kishore Shukla, Pulkit Mohan, Gaurav Ojha, Manoj Wariya, the target of this paper is to process the hand written signature and verify it. For verifying the signatures of a particular person, we have taken n samples of Genuine Signature, signed by that person on a piece of paper. Further we scanned the paper containing the set of signatures. Now we've extracted each of the real signatures of the person and stored it in separate file of the format .bmp. The extraction of the signatures within the last step has been in minimum area to supply accurate area of the signing of signature. We could have matched the signature of each person with the other signature but usually it is almost impossible to produce exactly the same set of signatures. We would verify the signatures on the subsequent parameters allowing a percentage of error in it. Permissible boundary, Hand pressure, Euclidian distance, Center of cylinder generated from minimum spanning tree, Delaunay triangulation of the signature, Angle between base line and center of gravity.

Unnila A. Jain, Prof. Nitin N. Patil, This paper presents current approaches to off-line signature verification with the goal of surveying the most beneficial techniques that are available. This investigation also will introduce techniques which will significantly boost the achieved classification accuracy rate. This paper presents a comparative study of varied approaches of offline signature verification too

H. Firouzi, M. Babaie-Zadeh, A. Ghasemian Sahebi, C. Jutten, during this paper an extension of the sparse decomposition problem is taken into account and an algorithm for solving it's presented. In this extension, it is known that one of the shifted versions of a signal has a sparse representation on an over complete dictionary, and we are looking for the sparsest representation among the representations of all the shifted versions of. Then, the proposed algorithm finds simultaneously the quantity of the specified shift, and therefore the sparse representation. Experimental results emphasize on the performance of our algorithm.

III. PROPOSED METHODOLOGY

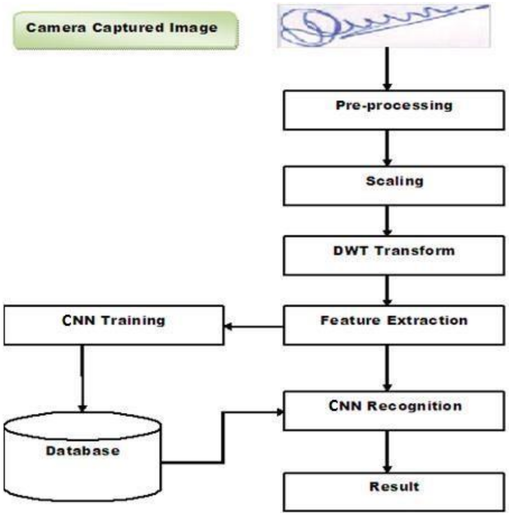


Fig.1. System Architecture

The proposed system is as shown in fig.1. It consist of various activities. First the camera captured input image is taken for processing and after pre-processing with basic image operation same image is mapped to CNN trained model to get the prediction of which user the image is and if signature is authorized or not.

The proposed system is designed to help these organizations, which are depending on the signatures to complete the documentation and transactions. The basic ideology is integrating the principle of CNN with the input signature image to verify and identify accurate result of signatures.

To overcome the problems faced in existing system we are going to implement our system. In this system we are going to use CNN algorithm to get correct output. In this system we are going to minimize the human interpretation error. By using this system, it should be easy to find out the frauds and duplicates signature easily.

A. Algorithm:

CNN is the basic algorithm used in the project which is as follows,

1. Classify dataset under labeled folders with signature samples as CNN is supervised algorithm
2. Read dataset and prepare dataset in one file as pickle or numpy.
3. Read features of all images and label (here name of dataset folder) of it using following functions,
   a. Conv2D
   b. Maxpool2D
   c. Relu activation for layers
   d. Sigmoid activation for dense layer
   e. Binary Crossentropy for loss calculation
4. Store it in model file
5. Get input image
6. Read features of input image
7. Compare features of stored features
8. Show label as prediction of nearly matched features.

B. Mathematical Model:

Let S be the closed system defined as, S = {Ip, Op, A, Ss, Su, Fi}
Where, Ip=Set of Input, Op=Set of Output, Su= Success State, Fi= Failure State and A= Set of actions, Ss= Set of user's states.

- Set of input=Ip={username, password}

- Set of actions =A={F1,F2,F3,F4,F5,F6} Where,

  - F1= Authentication of user

  - F2 = input the signature image

  - F3 = system detect the object this image

  - F4 = Perform operation Image Processing and Machine Learning

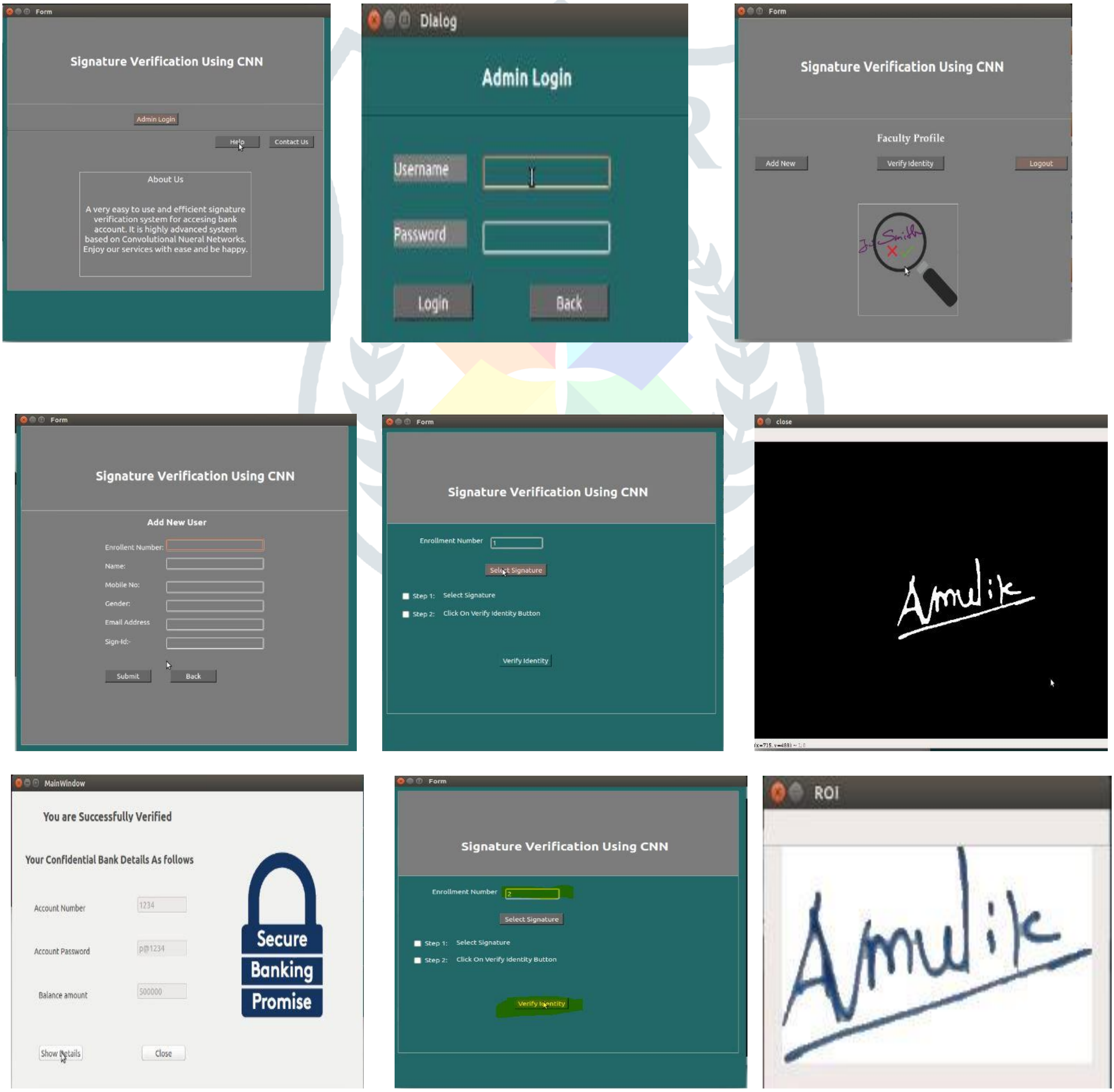
  - F5= Detecting of various sources

  - F6= This result show and stored the database

- Set of user's states=Ss={registration state, login state, selection signature image, classified image, logout}
- Set of output=Op={Show results}
- Su=Success state={Registration Success, Login Success
  }
- Fi=Failure State={Registration failed, Login failed}
- Set of Exceptions= Ex ={Null Pointer Exception while registration state, Record Not Found (Invalid Password) while login state , Null Values Exception while showing state}

IV. RESULT AND DISCUSSION

In the proposed system, we will be using supervised CNN approach which further will improves the accuracy of the prediction. CNN is proved for better accuracies with supporting to the deep learning methods. It is also complemented with the light weight library in python for image processing as OpenCV which help us to detect signs on paper automatically and improves the speed of execution



Comparative results of existing and proposed system is as follow,

Parameters	**Existing System**	**Proposed System**
Automatic signature detection	No	Yes
Use of OpenCV	Somewhat	Yes
CNN	No	Yes
Improved speed	No	Yes
Light Weight	No	Yes

Table 1: Comparative Results

With reference to Table 1 it is clear that we overcome various problems in existing system and our approach works efficiently.

V. CONCLUSION

Neural networks have demonstrated their success in many applications due to their ability to solve some problems with relative ease of use and the model-free property they enjoy. One of the main features, which can be attributed to CNN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate response.

Application of Convolution Neural Network (CNN) to the above mentioned problem has attained increasing importance mainly due to the efficiency of present day computers. In addition, the times of simulation and testing in the CNN application are minimal. And the verification system based on CNN is able to learn different kinds of signature datasets, by using only geometrical offline features.

VII. REFERENCES

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