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OFFLINE SIGNATURE VERIFICATION USING CONVOLUTION NEURAL NETWORK

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ABSTRACT

In this work, signature forgery is detected/classified using Convolution Neural Network (CNN). 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. For the problem of tedious and low degree of automation of manual document inspection, put forward a method for handwritten forged signature detection based on convolutional neural networks. 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.
Offline handwritten signature verification is widely used important form of biometrics. It is a challenging task due to time-variant nature of signature. To address the above difficulty, a new approach is proposed in this paper to compute the features of signatures. The proposed approach is divided into two parts: 1) writer-independent approach, 2) writer-dependent approach. Writer-independent approach is utilized for fine-tuning of VGG16 convolutional neural network (CNN). In writer dependent approach, this fine-tuned CNN is utilized to extract the features from the signature. The signature is passed through this fine-tuned CNN and the vector obtained at first fully connected.

Keywords:
Convolution Neural Networks, Forensic Science, Forgery Detection, Support Vector Machine.

1. INTRODUCTION

Biometrics is defined as an automated use of 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 a 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, 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.

Signature Verification

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.

Depending on the signature acquisition method used, automatic signature verification systems can be classified into two groups: online (dynamic) and offline (static). A static signature image, generally scanned at a high resolution (e.g. 600 dpi), is the only input to offline systems. Verification of signatures found on bank cheques and vouchers are among important applications for offline systems. An example set of offline signatures is shown in Figure 1.1. In addition to the signature image, time dimension is also available for dynamically captured signatures that are acquired using pressure sensitive tablets or smart pens.

These input devices sample the signature at a high frequency, resulting in a time ordered sequence of signature's trajectory points. An example online signature capturing device is shown in Figure 1.3. Each point is associated with a corresponding acquisition time

stamp and a location coordinate, besides other dynamic features such as pressure and pen inclination angles that can be captured subject to the hardware used. Online signature verification is generally used for access control and electronic document authentication types of applications. Due to the differences in the input, preprocessing, feature extraction and classification methods used; online and offline systems show significant variations in their approaches, specifically in representation, preprocessing and matching steps. Offline signature verification can be said to be more challenging compared to online signature verification.While variations among a user's signatures and easy to forge signatures pose a challenge in both cases, dynamic information available in online signatures make the signature more unique and more difficult to forge. In particular, imitating both the shape and dynamic information of an online signature seems to be difficult except for very simple signatures. In contrast, it is possible in some real life situations, for an impostor to trace over a genuine offline signature and obtain a high quality forgery.Furthermore, the availability of the signature's trajectory also makes it easier for online verification systems to align two signatures and detect differences. Higher accuracies obtained in online systems also inspired researchers to recover the dynamic information from static images with some success [3].Applying special techniques, such as conoscopic holography [4], can reveal stroke order and pressure applied by a pen during handwriting. However, these are bulky and very expensive equipment's and the process is inefficient in time and difficult to automate. Furthermore, it may fail with certain paper and pen types; thus such an approach is impractical in the context of automatic signature verification. Signature authentication scenarios are also twofold: while forensic examiners are interested in verifying the identity of the signer of a document, many companies such as banks are interested in identity control with online or offline signatures, for routine operations. In the latter case called, high throughput and instant response is desired.

The system performance is generally reported using the False Rejection Rate (FRR) of genuine signatures and the False Acceptance Rate (FAR) of forgery signatures. Other measures such as the Equal Error Rate (EER), the error rate where both FAR and FRR are equal or the Distinguishing Error Rate (DER) which is the average of FAR and FRR are also commonly reported. Reported EER can be expressed as DER, however reported individual FAR and FRR when calculated as DER cannot be expressed as EER.

Other evaluation measures include FRR at a certain fixed FAR and the Receiver Operator Characteristics (ROC) curve which is a graphical plot relating true accept rate (1- FRR) and FAR, obtained at varying acceptance thresholds. In real life, a forgery may be signed by an imposter who knows about the target user's signature and who may have even studied it with determination to break into the system.

On the other extreme, it may also be the case that the imposter does not know the target user's signature or even his/her name. In some intermediate cases, the imposter may only know about the name of the target but not the signature shape. These differences in information about the signature to be forged or the acquired skill level of the forger are important when evaluating a signature verification system: an uninformed or unskilled forgery is much easier to detect compared to a more skilled one.

In parallel with real life scenarios, research databases define two types of forgeries: a skilled forgery refers to a forgery which is signed by a person who has had access to some number of genuine signatures and practiced them for some time. Often, the imposter is simply one of the enrolled users who have been asked to forge the signature of another user, since finding real imposters is not feasible.

Similarly, a random forgery is typically collected from other people's real signatures, simulating the case where the impostor does not even know the name, nor shape of the target signature and hence uses their own in forgery. In this paper, as in the literature, when the term "forgery" is used without further qualifications, it may refer to a skilled or random forgery.

Motivation

Signature images have variations in terms of pen thickness, embellishments found in strokes, translation or relative position of strokes, rotation, scaling even within the genuine processed. Sample genuine (first three columns) and their corresponding skilled forgery (last column) signatures from GPDS dataset.

2. LITERATURE SURVEY

Offline signature verification is a well-researched topic, where many different approaches have been studied. A series of surveys covering advances in the field are available [6–14]. A more up to date overview of proposed works is detailed in a recent work by Coetzer [15]. Here, we review some of the recent research on offline signatures.

Locating the region of interest: The first step before utilizing further applications such as verification or recognition is to extract the signature region of interest from a document. This step is generally skipped in the works that concentrate on biometric applications of signatures thanks to the public offline signature databases.

However, there are a few studies in the literature that concentrate on signature localization. In most of the cases of real life scenarios, original documents containing the signatures are available. Signature region is extracted and then verification is preceded.

Relation between handwriting and signature is analyzed by Bouletreau et al. [16]. A method is applied both to handwriting and signature classification that is based on their fractal behavior. The fractal dimension is a measure of the degree of irregularity or of fragmentation of a set, or the measure of the complexity of the studied set.

Different properties related to writing and signature styles are extracted by the help of the method. Properties include cursive writings, legible writings, and separated writings. This method provided an evidence of the independence between the behaviors of the writer when he signs and when he writes.

Such independence is reported to have a potential source of enriching information within the context of signature authentication, where the signatures and writings are used as independent identifiers.

Signature region extraction from documents is the main focus of the work by Chalechale et al. [17]. A document image database containing 350 documents signed by 70 different persons who have Persian or Arabic cursive signatures is used. The content of the images includes a variety of mixed text of Arabic, Persian and English alphanumeric with different fonts and sizes, a company logo, some horizontal and vertical lines and a cursive signature.

The signature region was found correctly in 346 cases (98.86%) and the signature was extracted completely in 342 cases (97.71%). This is due to the fact that some cursive signatures have several disjoint parts while the algorithm focuses on neighboring connected parts.

Recently, a novel method for automated localization of handwritten signatures in scanned documents is proposed by C¨ucelo˘glu and O˘gul [18]. The framework is based on the classification of segmented image regions using a set of representative features. The segmentation is done using a two-phase connected component labeling approach.

Distinguishing signature and non-signature segments are learnt over a SVM classifier. The experiments on a real banking data set have shown that the framework can achieve a reasonably good accuracy to be used in real life applications.

Determining the signature type: Embellishments, also called flourish, can be defined as the strokes that often begin or end a signature, changing the shape or bounding box significantly. Signatures may be grouped by a signature verification system, based on the complexity of the signature which itself depends on trajectory length and overlap; or the amount of flourish on the signature, in order to handle separate groups differently.

Alonso et al. categorize signature according to the amount of embellishments in a signature [2]. Users are categorized according to the type of their signatures as simple flourish (C1), complex flourish (C2), simple flourish.

Signature verification methods based on the concept of fuzzy sets and different fuzzy membership functions have also been developed in the literature. In, geometric features, as a family of shape factors, and the coding of information related to the dynamics of the signature, have been used to characterize signature images.

A fuzzy technique has then been adapted to combine these two types of information for off-line signature verification. In the studies presented in a signature image has initially been preprocessed using binarization, size normalization, and thinning methods. The thinned image has then been partitioned into a number of sub-images to compute features consisting of angle information.

A fuzzy system based on the Takagi–Sugeno (TS) model and an exponential membership function has further been used for the signature verification task. The TS model with structural parameters takes into account the local variations in the characteristics of the signature. The membership functions constitute weights in the proposed modification of the

TS model to provide better results. A method based on the spectral analysis of a directional gradient density function and a weighted fuzzy classifier has been proposed for off-line signature verification in.

The outline of a signature image was initially extracted and the frequency spectrum was then computed using a directional gradient density function as the feature set. A weighted fuzzy classifier based on a triangular membership function was adapted for the verification of forgeries.

An overview of the signature verification methods, which exist in the literature, is provided in Table I. From the literature reviewed, it is noted that there has been significant progress in the off-line signature verification domain.

However, despite the progress in the area over the past decades, it remains an open research problem [1, 2]. In addition to the limitations mentioned in Table 1, some general challenges in the area of off-line signature verification that still attract many researchers for further investigation in this field are indicated as follows: i) high intra-class variability in handwritten signatures of every individual compared to the physiological biometrics, such as fingerprints or iris of the individual, ii) low inter-class variability between genuine signatures and skilled forgeries of every individual, iii) the existence of only genuine signatures as partial knowledge for training off-line signature verification systems, iv) limitations in the amount of signature data available for training off-line signature verification systems in real scenarios, as during the enrolment process users often provide only a few samples of their signatures, and v) the presence of signatures written in different scripts.

Furthermore, with particular reference to fuzzy-based signature verification methods, we noted that only a few related papers have been reported in the literature despite the progress achieved in the signature verification field.

Moreover, the membership functions and also the russification processes used for signature verification are mostly based on the exponential and Gaussian membership functions, which provide a probability very close to zero for a sample that deviates much from the mean in the Gaussian as well as in the log-space models.

This would mean a very large negative number is added to the accumulation probability result. That is a big penalty for the cases where handwritten genuine signatures are roughly written by genuine authors. In the present research work, we mainly focus on the problem of inter-/intra-class variability of handwritten signature.

Signature region extraction from documents is the main focus of the work by Chalechale et al. [17]. A document image database containing 350 documents signed by 70 different persons who have Persian or Arabic cursive signatures is used. The content of the images includes a variety of mixed text of Arabic, Persian and English alphanumeric with different fonts and sizes, a company logo, some horizontal and vertical lines and a cursive signature. The signature region was found correctly in 346 cases (98.86%) and the signature was extracted completely in 342 cases (97.71%). This is due to the fact that some cursive signatures have several disjoint parts while the algorithm focuses on neighboring connected parts.

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Robustness to variations: Genuine signatures contain many variations with respect to illumination, rotation, translation, scaling, pen thickness, embellishments and noise (such as lines or scripts) is an important issue in an image-based biometric.

In a work by Nguyen et al., two signatures (query and a reference) are first aligned using rigid or non-rigid alignment and compared based on basic global features extracted from the whole signature (e.g. width/height ratio or pixel density).

This alignment is hoped to compensate for rotation, translation and scaling variations. Ferrer et al. analyze the robustness of offline signature verification to different influencing factors. The novel part is adding different levels of noise to signature images, simulating real bank checks. Baseline verification method follows from [3]

Local derivative pattern feature gives the best result of 15.35% EER with 10 references using GPDS-300 database which is a superset of GPDS-160. In case of adding the maximum level of noise level, EER reaches to 16.43%. Ganapati and Rethinaswamy present a person- dependent off-line signature verification using fuzzy techniques in image contrast enhancement, feature extraction and verification based on similarity measure.

3. EXISTING SYSTEM

In this 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. The block diagram of existing model is shown below.

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The proposed method includes four main steps: a) preprocessing, b) feature extraction, c) creation of an interval valued symbolic model for each individual, and d) computation of similarity values and the final decision. An overview of our proposed signature verification method is shown in Fig. 4.1. Each step of the proposed method is detailed in the following subsections.

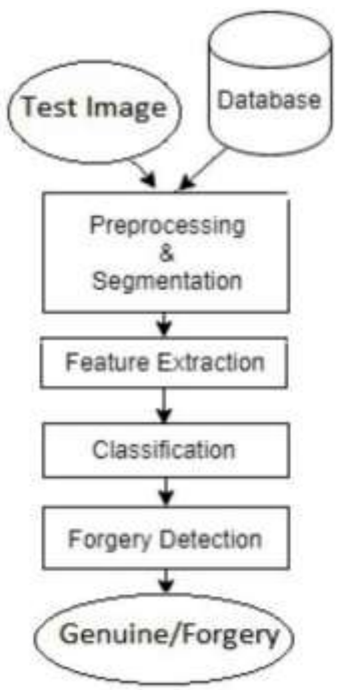

Fig 3.1: An overview of existing method

Pre-processing

Similar to most pattern recognition problems, preprocessing plays an important role in signature verification systems as well. Signature images, even genuine signatures of an individual, include significant variations in terms of size, rotation/slant, pen thickness, etc.

Therefore, the preprocessing step, prior to the application of feature extraction methods, is employed on the images to make the images noise-free and have transition invariant features.

To do so, first, a histogram-based threshold technique is applied to convert the digitized grey-scale signature images to two-tone images. A mean filter is also employed on the signature images to remove noise. The input images are then cropped to find minimum bounding boxes of the signature images.

The cropped signature images of size M × N are then used for feature extraction. Under-sampled bitmap images have been used in the literature for pattern recognition. In this research work, we have further considered the under-sampled bitmap for feature extraction, since the under-sampled version of an image can be considered as a low resolution version of the image whilst keeping the whole visual appearance of the original one. To compute the under-sampled bitmap, the input image is divided into a number of non-overlapping blocks of similar size, say b × b.

The number of black pixels in each block is then counted and represents the block intensity. This generates a matrix of size M/b × N/b with each element being an integer in the range 0 to the size of the no overlapping block. Dividing these values by the size of the block and multiplying the results by 255 provides an under sampled grey image where all pixel values are normalized between 0 and 255. A pictorial representation of the techniques involved in the pre-processing step.

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 [10, 15].

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 inclu-
-ding such elements as the amount of pressure and speed changes, pen-holding, ink distribution, etc

Disadvantages in existing method

- Choosing “good” kernel not easy
- Low accuracy
- It takes a large time
- Difficult to understand the final model

4. PROPOSED SYSTEM

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 diff iculties: 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.

The data is acquired from the Kaggle. 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:

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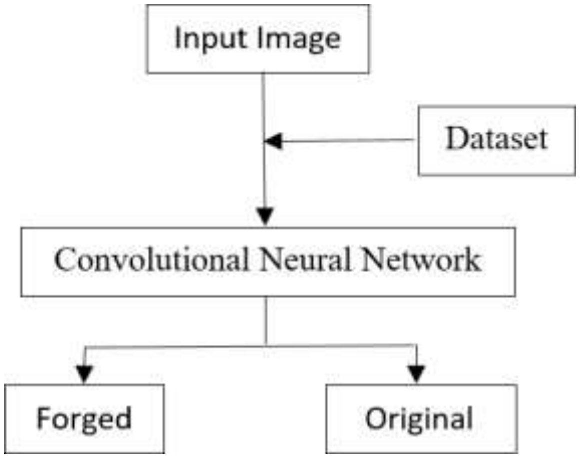

Fig 4.1: Block diagram of proposed method

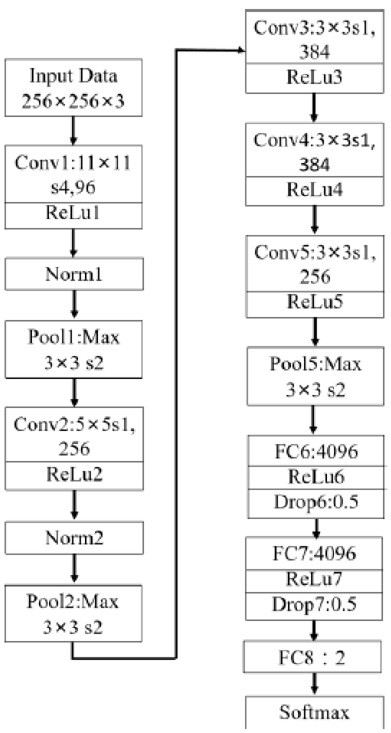

Fig 4.2: Architecture of proposed method

Pre-Processing and segmentation

Signatures are introduced to the system as scanned images of 200 dpi resolution. Images' size is normalized and Segmentation is achieved by binarization. Thinning algorithm is applied on signatures.

Pre-processing and segmentation performed on a signatures using thinning algorithm shown in below example:

Fig 4.3: Image before thinning and Image after thinning

Feature Selection

Most existing models in the literature use explicit feature extraction, including geometric [9], graph metric [10], directional [11], wavelet [12], shadow [13], and texture [14] features. Only in recent years has feature learning been explored [15].

We feed in raw pixels to our network, letting the CNN learn the relevant features for signature verification. 2.3. Competing Models The signature verification literature includes several examples of Hidden Markov Models, Neural Networks [17], Support Vector Machines [19], and other machine learning models.

In 2012, Khalajzadeh et al. [16] used CNNs for Persian signature verification, which is the only report of CNNs being used in the offline signature verification literature.

Unfortunately, the paper includes very little information about their methodology (i.e. forgery exposure, writer dependence).

Based on their explanation, we assume their model is trained on forgeries and genuine signatures for all IDs, and thus can be compared with our work in our main experiment. There results only report an average of 99.86 for validation performance, and mean squared error, making it difficult to fully compare our model to theirs.

Convolution neural network

Convolutional Neural Networks (CNNs) have proven successful in recent years at a large number of image processing-based machine learning tasks. Many other methods of performing such tasks revolve around a process of feature extraction, in which hand-chosen features extracted from an image are fed into a classifier to arrive at a classification decision. Such processes are only as strong as the chosen features, which often take large amounts of care and effort to construct.

By contrast, in a CNN, the features fed into the final linear classifier are all learned from the dataset. A CNN consists of a number of layers, starting at the raw image pixels, which each perform a simple computation and feed the result to the next layer, with the final result being fed to a linear classifier.

The layers' computations are based on a number of parameters which are learned through the process of backpropagation, in which for each parameter, the gradient of the classification loss with respect to that parameter is computed and the parameter is updated with the goal of minimizing the loss function.

Exactly how this update is done and what the loss function is are tunable hyper parameters of the network, discussed in more detail below. For more details on backpropagation, see [5]. 3.2. VGG Architecture The architecture of a CNN determines how many layers it has, what each of these layers is doing, and how the layers are connected to each other. Choosing a good architecture is crucial to successful learning with a CNN.

For our main training tasks, we used the VGG-16 CNN architecture [6]. This network contains a total of 16 layers with learnable parameters. These layers are of the following types: Fully Connected Layers: Fully connected layers apply an affine transformation to their inputs. Mathematically, a fully-connected layer from n inputs to h outputs works as follows:

In a fully-connected layer, every output depends on every input according to the weight matrix W, a learnable parameter. Outputs also depend on a bias term b which is learnable but doesn't depend on the inputs. ReLU Nonlinearity:

$f(X) = WX+b$

The Rectified Linear Unit is a commonly used activation function after fully-connected layers. This layer applies the following mathematical operation to input X:

$f(X) = \max(X,0)$

Here, the maximum is taken elementwise. ReLU layers do not have any learnable parameters. ReLU is commonly used in modern neural networks instead of other possible activation functions such as sigmoid and tanh for several reasons. One reason is that their computation is very simple, saving time during training that would be spent computing exponentials for sigmoid and tanh.

ReLU neurons also do not become saturated at high input values, meaning their gradient does not vanish to zero when receiving such values. This allows the neurons to

continue learning in 2scenarios where other activation functions would have vanishing gradients.

However, because the gradient of a ReLU neuron is 0 for negative inputs, it's also possible for these neurons to stop learning in cases where their input never produces positive values. Softmax Nonlinearity: The Softmax nonlinearity appears in the final layer of the neural network and computes final class scores that will be fed into the loss function or outputted during testing. It has no learnable parameters.

These scores have an interpretation as the neural network's estimated probabilities for each class. Note that all the output values produced by the Softmax function add to one. Mathematically, the ith class probability f(x)i is computed as follows:

$$f(x)_i = \frac{e^{x_i}}{\sum e_j^x}$$

Using Softmax to compute class scores is an attractive option because of its ease of interpretation. Convolutional Layers: Convolutional layers process an input image by sliding a number of small filters across each possible region and outputting the dot product of the filter and the image at each region.

They are similar to fullyconnected layers, but with restrictions on which input neurons are connected to which outputs. Specifically, outputs are only connected to inputs of a small region, and all weights for each filter are tied together rather than being allowed to be learned independently.

The learnable parameters for a convolutional layer are the weights of each filter and one bias value for each filter. Convolutional layers lend themselves naturally to understanding of images, in which we often want to extract features by looking at small areas of an image, where we don't care exactly where in the image the feature is. For example, a face is still a face regardless of where in the image it is. Our architecture uses 3x3 filters, with more filters used per layer as the network gets deeper.

Max Pooling Layers: Max pooling layers reduce the size of an image by combining 2x2 regions of the input into a single output value. For each 2x2 region of input, the output value is simply the max value of those 4 input pixels.

This layer has no learnable parameters. This layer cuts both the width and height of the image in half as it goes to the next layer. In networks with max pooling layers, the input width and height decrease as the image is forwarded through the network, and the number of filters (depth) tends to increase.

This corresponds to processing the image at a higher level of abstraction in which features correspond to larger region of the input image. Dropout Layers: Dropout layers are a non-deterministic nonlinearity used in many modern neural networks.

A dropout layer takes in a number of inputs and for each input, sets it to 0 with probability p and leaves it unchanged with probability (1-p). During test time, dropout layers instead behave deterministically and multiply all input values by (1p), the average value which they were multiplied during training. The dropout value p is a tunable hyper parameter for the network.

Dropout can be interpreted as a form of regularization, as using dropout during training forces the network to have many ways of computing a correct result rather than just one. This keeps the network from relying too heavily on any single connection

Advantages

- Manual feature is not required
- CNN performance well.
- In CNN we does not so much of time for feature selection
- Choosing “good” kernel easy
- High accuracy
- It takes a short time compare to existing method
- easy to understand the final model

Applications

- Forensic science
- Criminal department
- CBI

Investigation purpose and etc..

5. RESULTS

Example of the forgery signature using convolution neural network shown in below figure.In this we can take the sample signatue as the input and also taken another signature(same persons handwritten signature (or) forgery signature for the input signature) and next click the validate signature key it shows the signature fake (or) geniune.

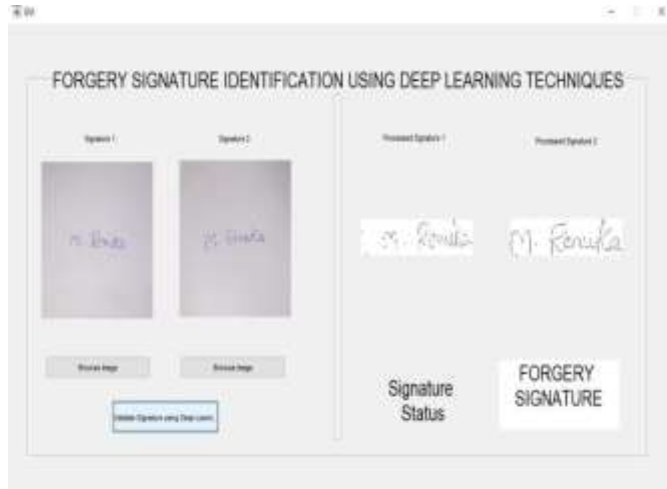

Fig 5.1: Example for forgery signature

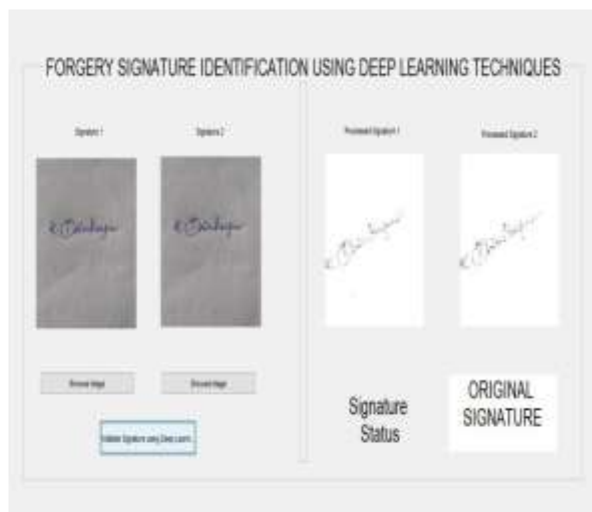

Fig 5.2: Example for original signature

In this example we can see the original type of signature shown in below.In this we cantake the sample signatue as the input and also taken another signature(same persons handwritten signature (or) forgery signature for the input signature) and next click the validatesignature

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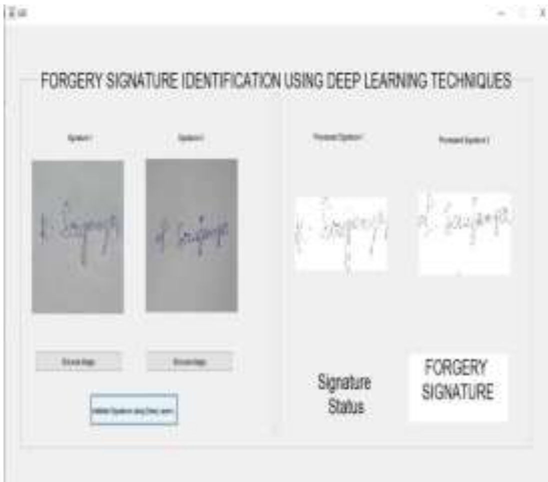

Fig 5.3: Example for forgery signature

In this example we can see the forgery type signature shown in below.In this we can take the sample signatue as the input and also taken another signature(same persons handwritten signature (or) forgery signature for the input signature) and next click the validatesignature key it shows the signature fake (or) geniune.

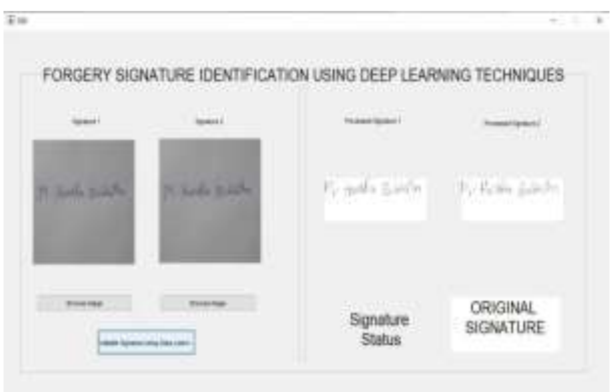

Fig 5.4: Example for original signature

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6. CONCLUSION

In this investigation, 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, resulting in performance little better than a naive baseline due to the inherent difficulty of this task.

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.

- For future work, Access to more resources would allow us to achieve better performance on our main task. Specifically, being able to train on a larger dataset with more signature examples.
- For future work, preprocessing of dataset may not have been sufficient and further

operation in data cleaning and preprocessing will ensure enhanced outcomes.

- For future work, Data for training was collected hard copy format which limits the capability of collecting large number of traing data. So, the collection with improved technique such as with electronic signature capturing device can facilities large number of sample collection in comparatively less time.
- For future work, the proposed systems with some advancements can be extended for automatic verification of checks in the banking systems and registration offices.
- For future work, the proposed system combined wit with other domains such as Block chain for high security, IoT, etc.
- For future work can design a system combination of online and offline signature systems.

For future work, May also aim to develop advanced and sophisticated models for feature extraction which eventually increases the accuracy of overall system

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