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HANDWRITTEN SIGNATURE VERIFICATION USING SIAMESE NEURAL NETWORK

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***Abstract*—Nowadays, most cases for verification are done using biometrics, but certain alternatives still use physical signatures such as Banks and Document signing. In this paper, we compare signatures and verify whether the given signature matches with the original signature or is a forgery. This is done using Artificial Neural Networks, which is a part of artificial intelligence and has brought in a lot of solutions to real world complex problems that need extensive study and research for arriving at a solution which is difficult to do so with the help of standard conventional techniques that does not make use of sophisticated algorithms. Convolutional Siamese Network, which is one part of the Artificial Neural Network, is the technique used here for signature verification. We will see how this is done by first understanding what a Siamese network is and then explaining about the various steps involved in the signature verification process such as uploading dataset, pre-processing, training, testing and finally the implementation part which tells us if the signature is authentic or forged.**

***Keywords*—Convolutional Siamese Network, Artificial neural network**

I. INTRODUCTION

In the modern world, deep learning has expanded the research for better solutions and applications which has helped develop better technology in various fields that affects our day-to-day life. Convolutional Siamese Network, being a subset of machine learning that is based on Artificial Neural Networks, which is quite a complex model, helps us analyse and compare the signatures in a sequential and methodical way. We can understand the working of the Siamese network in the following steps: There will be two signature networks, which is actually a twin Convolutional Neural Network (for two separate signatures) with ReLU (Rectified linear units) as the input layer. The twin CNNs will have similar weights and configuration. The ReLU introduces non linearity that helps with faster computation.

Starting from the input layer, pooling of layers takes place to reduce the dimensions of the layer step by step. Common entities will be grouped into one single entity which makes unnecessary duplicates redundant and reduces the dimensions of the layer. The next section of the paper contains related work followed by methodology, results and finally the conclusion.

II. RELATED WORK

Nowadays, Deep Learning, which is an intricate part of machine learning, is used in research work and also in many practical real-life situations which although, is complicated to understand, makes our everyday life better, safer and comfortable with its applications. One such concept related to our topic Handwritten Signature Verification, is used in [1], which proposes an offline handwritten signature verification method using a single known genuine signature, an explainable deep learning method (deep convolutional neural network, DCNN) and unique local feature extraction approach.

There are various other such learning techniques used in this domain, such as Boosted Tree, Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) with respect to number of signers and sample size as given in [2]. In this case, the signature verification process is divided into three phases, such as Data collection, Feature Extraction and Classifier usage.

There have been various types of Convolutional Neural Network techniques, which is also one of the Deep Learning techniques that comes under Artificial Neural Networks (ANN), that have been derived from the base concept, such as shallow Convolutional Neural Network (sCNN) as shown in [4], Convolutional Siamese Network (CSN), which we have used in our signature process verification system. There are other similar techniques such as Deep Multi Task Metric

Learning (DMML) as shown in [8], Otsu method and morphological operations as shown in [7], which makes use of Median Filter to reduce noise and help extract the signature from the image. Before applying all these techniques, the samples usually undergo a pre-processing stage, where extra space, noise can be removed and filters added to help in the extraction and verification process.

III. METHODOLOGY

A. Dataset

The dataset used here is CEDAR which consists of 2644 signatures, each batch consisting 24 original signatures and 24 forged signatures from 55 users each. In the later stage, processing of this dataset is done batchwise, where we identify the distance between the original and forged images for each batch respectively. The reason to choose CEDAR as the dataset is because highest accuracy is obtained when trained and tested with CEDAR, as shown in Table 1.

	GPDS Synthetic	GPDS300	Hindi	Bengali	CEDAR
GPDS Synthetic	77.76	62.65	63.77	66.65	79.13
GPDS300	52.61	76.83	63.01	69.00	94.82
Hindi	52.78	55.78	84.64	60.65	59.57
Bengali	52.66	52.98	64.57	86.81	50.00
CEDAR	54.26	55.79	55.61	64.15	100

Table 1: Testing and Training results

B. Pre-processing of signature

Pre-processing is the step where filters and other functions are added to extract the signature part in the best possible way, so that they can be used in the comparison and verification process. Pre-processing of images can involve removing the noise, removing extra content from image, blurring, resizing, inverting and adding other filters for studying and analysing the image.

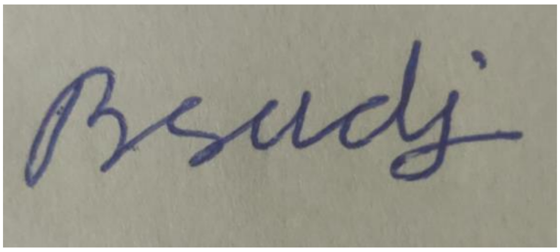

Fig 2: A sample signature image

In batch processing, since we need signatures of similar sizes, resizing of the signature is done to maintain a uniform size that helps with better comparison. This resizing of images is done using the bilinear-interpolation technique. Next step in pre-processing involves applying a special filter called Adaptive Threshold, giving the sample image a scanned effect, which is effective in the signature comparison and verification process.

Fig 3: Applying Adaptive threshold

Finally, inverting the image, we bring in 0 and 1 values to images in the form of black and white making the signature part white (1) and the background dark (0). This way, the signature part can be highlighted ignoring the rest of the image.

Fig 4: Inverting image to complete pre-processing

C. Training the Dataset

Convolutional Siamese network is the neural network model used to train the dataset. During the process of training, the twin convolutional neural network for two signature networks undergoes optimization and dimensional reduction with help of Rectified Linear Units, which introduces non linearity and undergo max pooling that helps reduce the dimensions of the neural network.

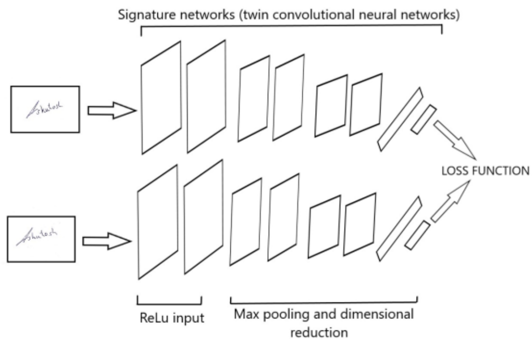

Fig 5: Signature networks of two signature samples

After maximum reduction possible, the vector space of the two networks is combined using a loss function to get a loss value which helps deduce the distance between the signatures in the testing process.

D. Comparison and verification

This step involves uploading sample signatures and comparing them with any other signature to check whether the signature taken for comparison is an authentic signature or a forged signature. Here, we upload three signatures in the front end and take any signature of our choice to compare and identify whether the signature is authentic or not.

$$L(s_1, s_2, y) = \alpha(1-y) D_w^2 + \beta y \max(0, m-D_w^2) \text{——}(1)$$

Eqn 1: Loss function for comparing signatures

Here, shown above is the loss function for combining the two signatures and comparing them. Here, s_1 and s_2 are the two signature samples taken, y is a variable that helps us identify if the two signatures are of the same class or not, α and β are the two constants having margin as unity. We also have an important factor, which is the Euclidean distance denoted by D_w. The Euclidean distance is calculated using the formula $f(s_1 ; w_1) - f(s_2 ; w_2)$, where the f is the embedded space and w_1, w_2 are the weights of the signatures respectively in the layer of the Convolutional Neural Network chosen. Here, we keep a threshold value for comparison. If the distance calculated of the sample signature is less than and close to or equal to the threshold value, then the signature is authentic. If the distance value exceeds the threshold value or if it is not anywhere near the threshold value, then the signature is a forgery or a wrong signature (signature chosen for comparison need not be similar to the one with which you are comparing). This way, we can verify whether the signature is authentic or not.

IV. RESULTS

Here, the training of the dataset is done batch wise and the distance metric is calculated during this process. Once the sample signatures are taken for verification, the distance metric is compared with a constant threshold value, which helps us determine if the signature is authentic or not. The distance metric mentioned here is the Euclidean distance that is embedded in the loss function as shown below.

$$Dw = f(s1;w1) - f(s2;w2) \text{—}(2)$$

Eqn 2 : Euclidean distance

It is found that applying adaptive threshold to the signature sample during the last stage of pre-processing has played a vital role in the signature verification process and the results or the distance value obtained during the verification helps in better classification of the signature, as to whether it is an authentic signature or a forged signature. The accuracy of this signature verification system after applying it to the cedar dataset was found out to be 80% after the testing process.

V. CONCLUSION

In this paper, we have applied the concept of Convolutional Siamese Network, which is a part of Artificial Neural Network, which makes use of twin Convolutional Neural Networks in the signature verification process. This model helps train the dataset and learns the pattern of various signatures that helps to detect if the signature is authentic or not. There is a lot of scope in the future for using frameworks like these for prediction and verification purposes. Models like this help bring about more competition and research in this field to develop a better neural network model, for training and testing on datasets or real time data that help find solutions for many real-world problems.

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