Signature Verification Using Deep Learning

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***Abstract*-- Even though people moving to digital documents with digital signature for authentication, most of the areas such as land records, agreement between parties, legal certificates, identification cards etc., uses only handwritten signature. Verifying signatures is an important one because a fraudulent signature would affect the real owner too much. Hence, recognizing genuine signatures becomes essential to avoid such frauds. To recognize the signature, deep learning technique is used in this work since it produces highest accuracy and it does not require too much preprocessing. A convolutional neural network (CNN) based deep learning model is mostly used for image processing, classification, and segmentation. As CNN algorithm learns more than KNN, SVM etc., CNN is used in this work for better classification. The CNN based models such as VGG16, Inception v3, CNN - with three and four convolution layers are trained for this classification. The dataset is created by collecting signatures from 10 different users with 50 signatures each. Out of 500 signatures, 400 is taken for training and 100 is used for testing. Among these four models Inception V3 produced highest accuracy of 95% with preprocessed images whereas the same model produced only 88% when unprocessed images are given as in input.**

Key Words: Signature verification, Classification, CNN, VGG16, INCEPTION V3.

I. INTRODUCTION

Machine learning is the result of humans inventing a brilliant approach to simplify complex issues by training a computer to act like a human brain. The capacity of CNNs to build an inside portrayal of a two-dimensional image is one of their benefits. This allows the model to learn position and scale invariant data, which is crucial when working with images. Deep learning is a type of machine learning that is modeled based on how people learn specific types of information. Because it involves statistics and predictive modeling, it is extremely useful for data scientists. The two sorts of profound learning approaches are counterfeit neural organizations (ANNs) and mimicked neural organizations (SNNs). Their name and structure are inspired by the human brain, and they function similarly to organic neurons. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) are the three most important kinds of neural networks.

CNNs are a sort of deep, feed-forward artificial neural network that is utilized to break down visual aids to AI. As demonstrated in figure 1, convolution, max pooling, dropout, and dense layers are applied. A multilayer perceptron form is used in the CNN, which requires relatively little preprocessing. These biologically inspired computational models surpass prior types of artificial intelligence by a factor of 10 in standard machine learning tasks. The Large Scale Visual Recognition Challenge is one of the enormous scope concerns (LSVRC). Convolutional Neural Networks (CNNs)- based calculations that gain from the beginning accomplish cutting edge precision on the image net issue. The purpose of this project is to utilize a typical CNN to classify 10 users' genuine signatures. The Large Scale Visual Recognition Challenge is one of the enormous scope concerns (LSVRC). Convolutional Neural Networks (CNNs)- based innovation is being gained from the beginning. A total of 50 valid signatures are available to each user. 400 test images and 100 train images are included in our distinctive learning set. After the images have been changed over to twofold, commotion is taken note. On the image net issue, ues accomplishes best in class precision. That noise is reduced using CV masking.

II. LITERATURE SURVEY

In the framework of Handwritten Signature Verification using Binary Particle Swarm Optimization (BPSO), author Rafael M O Cruz [1] investigated the presence of overfitting when performing feature selection (HSV). In the HSV context, Sig-Net is a 2048-dimensional state-of-the-art Deep CNN model for feature representation. Some of these dimensions may contain duplicate information in the dissimilarity representation space generated by the writer-independent (WI) approach's dichotomy transformation (DT). The GPDS-960 dataset was used in this study. Experiments in this work indicate that while looking for the most discriminant representation, this technique avoids overfitting. Maergner Graphs [2] described two new graph-based offline signature verification algorithms: key point graphs with approximated graph edit distance and inkball models. They described the methods, suggested improvements in terms of processing time and accuracy, and presented experimental findings for four benchmark datasets. The proposed methods outperform the competition in a variety of benchmarks, demonstrating the power of graph-based signature verification.

S Tsang's[3] told that signature verification was the most widely used way for verifying a person's identity in the field of behavioral biometrics. Convolutional Neural Networks were used to extract information from pre-processed real and fake signatures in this article.CEDAR, the BHSig260 signature corpus, and UTSig are among the publically available datasets used in this study to test the proposed approach. Based on explainable deep learning (DCNN) and a novel local feature extraction technique, Hsin Hsiung Kao [4] suggested an off-line handwritten signature verification system. To train their algorithm and determine if a questioned signature is authentic or false, they used the open-source dataset Document Analysis and Recognition (ICDAR) 2011 SigComp.They achieved precision of 94.37% to 99.96 percent in their testing dataset, with a false rejection rate (FRR) of 5.88 percent to 0% and a false acceptance rate (FAR) of 0.22% to 5.34%.

Author Soleimani [5] proposed a deep multitask learning-based metric for offline signature verification system. Deep Multi Task Metric Learning (DMML), a unique classification method for offline signature verification is presented in this work. DMML used multitasking and transfer learning techniques to train a distance measure for each class while also teaching other classes. Unlike prior algorithms that only examined the training samples of that class for confirming questioned signatures, DMML coordinates information from the likenesses and contrasts between the real and forged examples of different classes. They compared the proposed method to SVM, writer-dependent, and writer-independent Discriminative Deep Metric Learning methods using Histogram of Oriented Gradients (HOG) and Discrete Radon Transform (DRT) features (UTSig, MCYT-75, GPDSsynthetic, and GPDS960GraySignatures). DMML beats other systems in authenticating real signatures, competent forgeries, and random forgeries, according to the findings of their testing.

The author Bouamra et al. [6] main goal is to increase the capabilities of automatic signature verification systems so that they can work in a real-world setting by training them with only positive specimens and no fake sample. The classification is done with the One-Class Support Vector Machine and the evaluations are done with the GPDS960 database, which is one of the largest offline signature corpuses ever generated (OC-SVM). Experiments show that the suggested technique can detect competent forgeries even when the training set only contains a single reference signature.

Author Zhang et al. [7] had the option to accomplish new most elevated correctness for both on the online and offline written by Chinese person acknowledgment (HCCR) on the ICDAR-2013 contest information by joining the conventional standardization coordinated bearing feature map (directMap) with the deep convolutional neural network (convNet). They additionally show that, regardless of the way that directMap + convNet can accomplish the best outcomes and beat people, author transformation is as yet supportive for this situation. To lessen the discrepancy between training and test data on a specific source layer, a novel adaption layer is proposed. Unsupervised adaptation is a viable option. By introducing an adaptation layer into the pre-trained convNet, it could adapt to unique handwriting styles of specific writers, significantly enhancing recognition accuracy.

Author Moises Diaz [8] proposed a method based on a sequence of nonlinear and linear modifications that mimic the spatial cognitive map and intrapersonal variability of the human motor system while signing. By artificially augmenting a training sequence, the duplicator is put to the test, proving that the performance of four state-of-the-art off-line signature classifiers utilizing two publicly available databases has increased on average as if three additional real signatures were acquired.Oliveira et. al. investigated signature verification system [9]with set of algorithmically produced feature descriptors for a subset of graphometric characteristics. The static properties height-to-width ratio of an image, the symmetry of the signature, baseline alignment and spacing were taken into consideration. To conquer the absence of dynamic data in static signature images, Shih Yin Ooi [10] proposed a functioning structure dependent on a mix of Discrete Radon Change, Principal Component Analysis, and probabilistic neural networks (PNN). At the image level, the proposed approach seeks to identify forgeries from authentic signatures. Both their private signature database and MYCT, a public signature database, are subjected to stringent verification. Arbitrary, relaxed, and proficient frauds of their own data set all had equivalent error rates (EER) of 1.51%, 3.23%, and 13.07% respectively. With 10 training samples with the MYCT signature database, suggested technique achieved an EER of 9.87%.

The utilization of Deep Convolutional Neural Networks to prepare interpretations from signature pixels for Offline Handwritten Hafemann et al. [11] suggested a signature verification system and established a significant constraint: the neural network inputs must be of a certain size, although signature sizes vary widely between individuals. The system is trained with the GPDS dataset while eliminating the limitation of a most extreme size for the signs to be examined. At the point when talented falsifications from a subset of clients are accessible to include learning, higher resolution(300 or 600dpi) can further develop execution, while lower goals (around 100dpi) can be utilized if by some stroke of good genuine signature are utilized. The research proposed by M. Diaz et al.[12] utilized handwritten signature as a biometric trademark. The authors reviewed the literature on handwritten signatures over the preceding ten years, focusing on the most intriguing study domains and aiming to elicit prospective future research directions in this field. Authors V. Nguyen and M. Blumenstein [13] proposed the chain code histogram, which is derived from the directional information retrieved from the signature contour to construct a grid-based feature extraction technique. By applying 2D Gaussian channel to the grids containing the chain code histograms, the system had the option to accomplish an average error rate (AER) of 13.90% while limiting the False Acceptance Rate (FAR) for arbitrary frauds to 0.02%.

This research proposed by J. F. Vargas et al. [14] was an off-line approach for verifying handwritten signatures. At the global image level, it uses statistical texture features to measure the image's gray level changes. The local binary pattern and the co-occurrence matrix are analyzed and used as features. A histogram can also be used to reduce the impact of diverse signers' ink pens on the final product. An SVM model was trained using genuine samples and random forgeries, and then evaluated using random and competent forgeries with two dataset: MCYT-75 and GPDS-100 Corpuses.

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III. MATERIALS AND METHODOLOGY

Artificial neural networks are calculations derived by the design and capacity of the human brain, and Deep Learning is a subfield of AI that deals with them. Computerized reasoning is a trendy expression for a method that permits computers to mirror human thinking. All of this is made possible through machine learning, which is a collection of algorithms trained on data.Convolutional Neural Networks (CNNs) are a sort of profound deep learning neural network that is utilized to recognize visual information. Every convolution neural network has layers such as convolution layer, pooling layer, flattening layer, dropout layer, and dense layer, and they're also known as space invariant artificial neural networks (SIANN) or shift invariant. ANN (Artificial Neural Network) and RNN (Recurrent Neural Network) are examples of deep learning algorithms.

IV. PROPOSED ARCHITECTURES

For signature verification, two CNN models (with 3 layers and 4 layers) and two pre-trained models (VGG16 and Inception V3) with transfer learning are implemented.

A. CNN MODEL WITH THREE CONVOLUTION LAYERS:

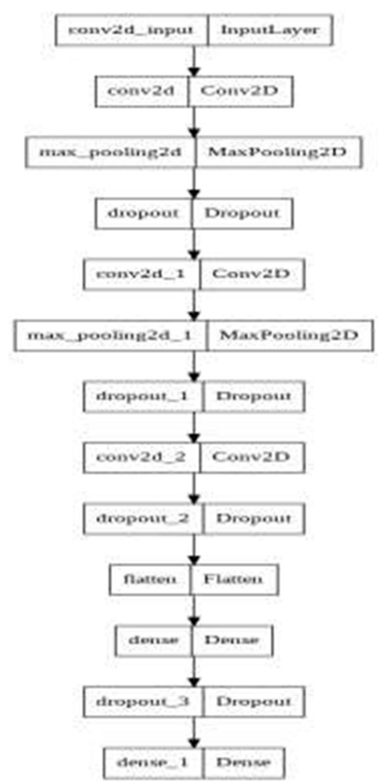

Fig 1. CNN with 3 layers architecture

This model consists of three convolution layers as shown figure 1. The first level of the convolution layer, with a filter size of 3x3 is applied to input image. To incorporate non-linearity into the Convolutional Neural Network, ReLu activation is employed, followed by a max pooling and dropout layer, and the same is done for the next two layers, i.e. convolution layer followed by max pooling and dropout. The image is flattened into a one-dimensional array and moved to the completely connected layer going through three convolution layers.

B. CNN MODEL WITH FOUR CONVOLUTION LAYERS:

This CNN model consists of four convolutional layers. To stabilize the training process, each image will be processed through two convolution layers that are separated into tiny batches using batch normalisation. The convolution layer with filter is 3x3 in size, with a ReLu actuation layer, trailed by a maximum pooling and dropout layer, and afterward a similar cycle is rehashed prior for moving to the completely associated layer. There are 512 parameters in the first fully connected layer, which has been reduced to 10 by adding batch normalisation and dropout layers.

C. VGG16:

VGG16 is a convolutional neural network configuration used in various profound learning image classification whose architecture is shown in Figure 2. VGG16 is trained with Imagenet dataset which has 1000 classes with 10 million images. By applying transfer learning method to VGG16 pretrained model to verify the Signature of 10 different users is achieved. This model consists of 16 layers with 3x3 size filters which uses sequential model which means that all the layers are connected in sequence. At the end it has two fully connected layer followed by Output layer with Softmax activation having 10 outputs, each output activation represents one user signature. All the hidden layers used RELU activation function. When applying preprocessed images as input to the model, it produced 94% as accuracy whereas produced only 76% for unprocessed input images.

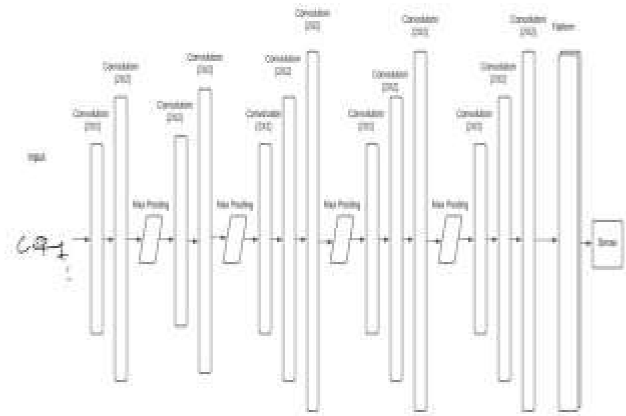

Fig 2 VGG16 architecture

D. INCEPTION V3 :

This is CNN based pre-trained model used for classification and segmentation. It is also trained with ImageNet dataset for classifying 1000 different images. Using transfer learning, this model is modified to classify the user signatures. It is a deep neural network consists of 48 layers. By applying label smoothing approach, factorization of convolutions and auxiliary classifiers, it produced only very less error rate. This model used 5x5 convolution kernel and RMSProp optimizer. Output layer of this model is removed and add a new output layer to produce 10 different signature classifications. This model produced 94% as training accuracy and 88% as validation accuracy when giving the images without applying preprocessing whereas, 97% as training accuracy and 95% as validation accuracy when giving preprocessed images were given as an input.

V. DATA SET DESCRIPTION

The dataset (Figure 3) for this technique is made up of signature images from roughly 100 test and 400 train images which are captured using a 48 megapixel camera. These images have a resolution of 128x128 pixels. All of these signature images were collected from ten individuals and organised into ten groups, each with 50 signature images.

Fig 3. Unprocessed dataset

VI. DATA PREPROCESSING

In data preprocessing, feature extraction is a technique for reducing noise in data and cleaning it up for further processing by extracting only the essential features in an image that the model needs to train. For the signature dataset, the following steps for feature detection and extraction are used. The images are fed into the open cv function, which preprocesses them as original, sharpened, binary, and invert masked images.

Fig 4 Preprocessed images

We sharpened the edges of the image in the signature dataset to make the binary translation more precise, as shown in the above figure 4. The images are transformed to binary images after sharpening. After converting the image to binary, masking is used to remove only the noiseless region of the image, and the result is obtained by inverting the masked image.

VII. RESULTS AND DISCUSSION

Accuracy is the parameter that is used to evaluate the model. The percentage can predictions the correct prediction of the data is known as accuracy. It's simple to calculate by dividing the total number of forecasts by the number of right guesses. The results are shown in Table 1.

$$Accuracy = \frac{True\ Negative + True\ Positive}{True\ Positive + False\ Positive + True\ Negative + False\ Negative}$$

The figure 5 illustrates that loss of the CNN with 3 layers model when training and testing. The loss is reduced when number of epoch is increased while training as well as testing.

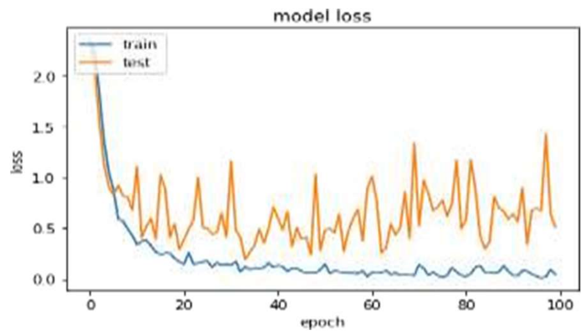

Fig 5. Loss of CNN with 3 layer model

The figure 6 illustrates that accuracy of the CNN with 3 layers model. The accuracy is increased when number of epoch is increased while training as well as testing. During 100 epoch it produced 95% accuracy.

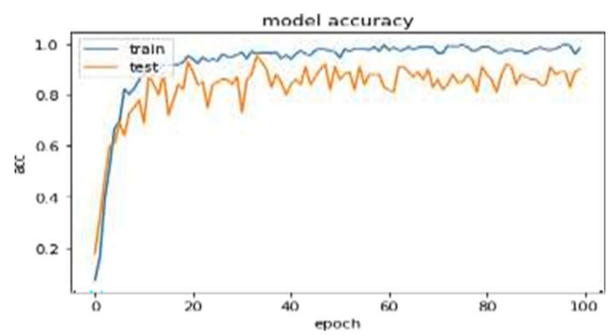

Fig 6. Accuracy of CNN with 3 layer model

Table 1 Training and validation accuracy comparison

MODELS	Without Preprocessing		With Preprocessing	
	Training Accuracy	Validation Accuracy	Training Accuracy	Validation Accuracy
CNN with 3-layer	93%	85%	96.25%	95%
CNN with 4-layer	91%	77%	96.50%	93%
VGG16	92%	76%	96.50%	94%
INCEPTION V3	94%	88%	97%	95%

Figure 7 represents the performance of different models Without and With Pre-processed dataset.

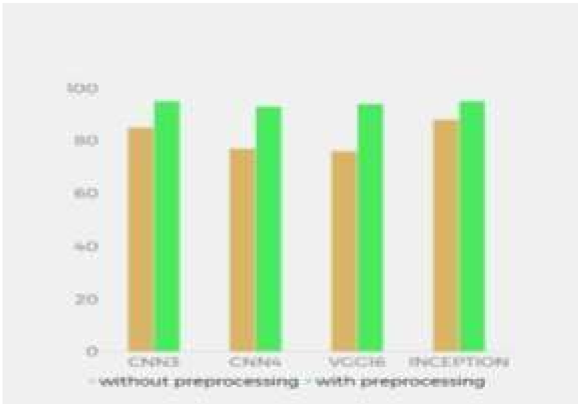

Fig 7. Accuracy of the Models without and with Pre-processed dataset

Figure 8 represents the test and validation accuracy of several models given in which has 0.001 learning rate and 100 epochs were run in CNN with 3 convolution layers gives an accuracy of 95% and CNN with 4 convolution layers gives an accuracy of 93% and in VGG16 it gives an accuracy of 94% and 95% is obtained in inception V3.

Fig 8 Train and validation accuracy of models with Preprocessed dataset

VIII. CONCLUSION

The purpose of this research is to use the models VGG16, Inception V3, and CNN with three and four layers to validate signatures. In those models, VGG16 and CNN with three layers had a 94% accuracy, whereas Inception v3 and CNN with four layers had a 93% accuracy.

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