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Development of signature recognition system using VGG16

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Abstract

The goal of this research is to locate a signature recognition system that can replace individual presence in the process of handwritten signature recognition. It has been discovered that an automatic signature recognition system that does not require a person's physical presence is necessary throughout corona duration. In this article more accurate signature recognition model employing VGG 16 pre- trained models is proposed. Novel Convolution neural network has exhibited 83% validation accuracy on the GPDS synthetic Signature dataset[1].

Subject Classification: *68T07 Artificial neural networks and deep learning.*

Keywords: *Signature recognition, CNN, VGG16, GDPS, ML.*

1. Introduction

Movement was restricted during the lockdown. It made it challenging for the financial, administrative, and banking sectors to authenticate and identify signatures of people without their physical presence. An online method for signature recognition was considered necessary. It has been noted that deep learning and machine learning may be used to create

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This research was conducted at Deep Learning lab at Poornima Institute of Engineering & Technology in Jaipur, India, financed by AICTE MODROB, used for experiment. This experiment was run using a Quadro RTX 8000 GPU.

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effective systems with high accuracy for signature verification[2]. This method will automatically recognize the name of the person who signed a check on piece of paper or any legal document. Once a signature has been detected on paper, the signatory will immediately be recognized based on the signature. The signatory's name will be revealed when the person has been identified. A check, legal document and administrative document's signature will be scanned and transformed.

2. Background

Many challenges faced by various industries, such as banking and insurance, due to movement restrictions during the COVID-19 lockdown. It was found an automatic signature recognition system using artificial intelligence is necessary as physical presence is not possible during lockdown. The study aims to find a system that can perform verification tasks without requiring a person's presence.

3. Literature Review

Xiao, et. al., [1999] proposes signature verification using direction grid- based features and a selective attention mechanism to address the variability within signature classes. The approach uses a multi-layer perceptron neural network as a classifier. The study reports a FRR of 6% and false acceptance rate (FAR) of 9% for skilled forgeries. For case 1, the FRR was 2%, and for case 2, the FAR for skilled forgeries was 17%. The dataset used in the study included genuine samples only for case 1 as the training set and genuine samples as well as artificial forgeries for case 2 as the training set. The testing phase included 350 genuine signatures, 158 skilled forged signatures, and 230 random forged signatures.

Bovino, et. al., [2003] stroke-oriented features were extracted from signatures using position, velocity, and acceleration measures. The DTW (Dynamic Time Warping) algorithm was used as a classifier to distinguish between genuine and forged signatures. The training dataset contained 45 genuine signatures from 15 authors, with each author providing three signatures. The testing dataset included 750 genuine signatures and 750 forged signatures. The approach achieved an equal error rate of 4%, indicating a good performance in distinguishing between genuine and forged signatures.

Lecce, et. al., [2000] Three experts have been used for signature authentication. Shape features were castoff by first expert speed features and regional analysis were used by second and third expert. Majority voting strategy adopted for decisions. Shape based features have been used DTW was used as classifier. FRR was 2%and FCR 0.55%. .

Huang, et. al., [2003]. Online signature verification was done through left-to-right HMM. features of velocity and pressure were used and DTW was used as classifier. 4600 signatures were used in full database. Equal Error rate 4%. 4600 signatures were used in full database.

Igarza, et. al., [2003] HHM was used on features like pen movement on large dataset. Direction of pen movement was used as features and Hidden Markov model was used as classifier. Equal error rate was 5%. 3750 genuine and forged signatures were used. 150 author's signatures have been recorded. Each user has given 25 signatures.

Jain, et. al., [2002] Spatial and temporal information was used. Three dissimilarity values were considered: the min, avg and the max of all dissimilarity values. Velocity, Curvature based features were used and String matching was used for classification. FRR was 3% and FAR was 7% using common threshold. FR was 8% and FCA was 6% using writer dependent threshold. Dataset was small. And 1232 signatures were used of 102 authors.

Kashi, et. al., [1997] . Hidden Markov Model classified genuine/ forged signatures achieving a 5% Equal Error Rate using 542 genuine and 325 forged signatures.

Lee, et. al., [2004] Geometric extreme based DP technique was used. Global features and a DP approach was used for segment matching. And BPN for signature verification. Pen Position, velocity of AVE, pen ups, negative/positive time duration. Total time taken for signing and features based on direction have been used. Neural network has been used as classification. Equal Error rate was 0.98%. 6790 signatures were used of 271 authors.

Li, et. al., [2004]. Principal component analysis was used for signature verification. Position velocity was used as feature and Principal component analysis was used as classifier. Equal error rate 5, 00%. Training set consist of 405 genuine signatures of 81 authors and testing set consist of 405 genuine and 405 forged signatures of 81 persons. ,

Morita, et. al., [2001] Initially template was generated from genuine signatures of persons then distance between input signature and template was calculated by DTW. Position of pen, pressure and inclination was used as features and DTW was used for classification. Training set consist of 205 signatures and testing set had 861 genuine signatures and 1921 forged signatures. EER was 3%.

Muramats, et. al., [2003] Discrete wavelet transformation was used to decompose online signature signals into sub bands, and high-frequency signals were extracted. The direction of pen movement was used as features for the Hidden Markov Model classifier. The model achieved an EER of 2.78% in testing, with a dataset of 1683 genuine and 3170 forged signatures.

4. Problem Statement

There is challenge of finding a suitable dimension vector for offline signatures in the research on signature recognition. There is importance of identifying optimal descriptors to use as inputs for the recognition model. Identifying the key features that best characterize signatures is a challenging task. Despite several tests done on signatures using hand-crafted features, no experiment has produced real-world applicable outcomes.

5. Methodologies

Signature recognition model is used to verify identity of person who has made signature. In this experiment VGG 16 Pre trained model along with custom dense layers have been used in CNN for feature extraction. Extracted features were used as input for Random Forest classifier and KNN for classification. Table 1 shows the architecture of Neural network used for experimenttation

- Input image size was 224x224x3, and training was done in batches of 32
- Soft Max function was used at the output layer for signature recognition
- A total of 22,000 images of size 224x224x3 were used, out of which 17,2000 were used for training, and 20000 images were used for validation
- Stochastic Gradient Descent (SGD) momentum was used as the learning algorithm.

5. Dataset

The GDPS synthetic dataset is a publicly available dataset that can be used for signature verification research. It consists of 4000 synthetic individuals, each with 24 genuine signatures and 30 forgeries of their

Table 1

Architecture diagram

Layer (type)	Output Shape	Param #
vgg16	7, 7, 512	14714688
flatten	25088	0
dense	4096	102764544
dense_1	4096	16781312
dense_2	4096	16781312
hidden_layer	4096	16781312
classification_layer	4096	16781312
output_layer	4000	16388000

signature. The forgeries were created using different modeled pens, adding to the variability in the dataset.

6. Result and Discussion

The Figure 1 Accuracy Model describes an experiment result that was conducted to determine the best optimization technique and machine learning algorithm for signature recognition using the VGG16 CNN architecture. Features were extracted from the VGG16 model and used as input for the machine learning algorithm. Classification accuracy was used as the primary metric to evaluate the performance of the algorithms, which is calculated by dividing the number of correct predictions by the total number of predictions made.

The formula is given below to calculate accuracy.

Classification Accuracy = True positive +True negative/Total samples

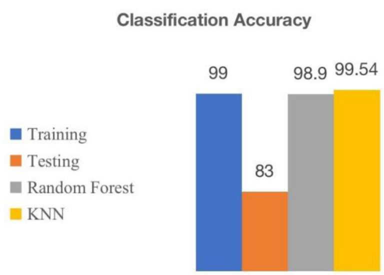

Figure 1

Accuracy of Models

7. Conclusion

The experiment involved extracting features from a pre-trained VGG16 neural network and developing different models under the same conditions. The results show that the nearest neighbor classifier achieved the best performance with an accuracy of 99.54% on test data, while the neural network had an accuracy of 99.0% on training data and 83% on validation data.

8. Future Scope

Signature Recognition is open for research with scope of improvement in validation accuracy. Other regularization mechanism can be adopted to improve validation accuracy. Online features can also be combined with offline features for classification. Other Pre trained Neural network can also be used for feature extraction.

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