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Development of novel signature architecture for signature recognition

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Abstract

The aim of this research paper is to propose a novel signature recognition system that utilizes deep learning techniques to accurately identify the name of a person based on their handwritten signature. The proposed architecture involves the use of a convolutional neural network (CNN) for feature extraction and a neural network for classification.

Experiments were conducted on the GPDS synthetic Signature dataset [1] to evaluate the performance of the model. The results of the experiments showed that the proposed system achieved an impressive training accuracy of 99.98% and a validation accuracy of 84.53%

Subject Classification (2020): *68T07, 68T45, 68T05, 68U10.*

Keywords: *Signature recognition, Convolutional neural network, VGG16, GDPS, Machine learning.*

1. Introduction

There is a growing need for an efficient online method for signature recognition in today world. Handwritten signatures are widely used for person authentication as they are considered to be a reliable method for verifying a person's identity. Deep learning and machine learning

This experiment was performed at Poornima Institute of Engineering & Technology Jaipur, India. It is conducted at deep learning lab financed by AICTE MODROB. This experiment was performed using a Quadro RTX 8000 GPU.

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techniques have shown promise in creating highly accurate systems for signature verification and recognition [2].

The objective of this experiment is to propose a signature recognition model that can accurately identify the name of the person who signed a legal document [11]. When a signature is detected on a legal or administrative document, the system will immediately recognize the signatory based on their signature, and reveal their name. The system will be able to scan and transform the signatures on checks, legal documents, and administrative documents for easy identification of the signatory

2. Background

In the current digital age, there is a growing need for automated processes that can facilitate users in various sectors. The use of automated handwritten signature verification and recognition has been identified as a crucial area that requires attention. In many instances, individuals are required to be physically present to validate their signature, which can be a challenging task [11].

To address this challenge, this study proposes an automatic signature recognition system that leverages artificial intelligence-based identification techniques. The aim of this study is to develop a system that can perform recognition tasks without the need for person presence, which can enhance the efficiency and convenience of signature verification and recognition.

The proposed system will utilize advanced machine learning and deep learning algorithms to accurately identify and verify handwritten signatures. This will enable the system to recognize the signatory's identity and authenticate their signature with high accuracy and reliability [10].

Overall, the development of an automatic signature recognition system using artificial intelligence-based identification techniques has significant implications for various sectors, including banking and legal industries. This will eliminate the need for individuals to be physically present for signature validation, and enable them to carry out transactions and other activities with greater ease and convenience [1]. The proposed system has the potential to revolutionize the way in which signature verification and recognition is carried out, and will pave the way for greater efficiency and security in various sectors.

3. Literature Review

Wijesoma, Mingming, and Yue [1]. Dynamic two sets have been used and ten shape related features were used in first set and 14dynamic features were used in second set. RMS speed, acceleration, Time duration of positive or negative velocity, pen down time ratio and direction based dimensions were used for classification. Training set consist of 410 genuine signatures of 41 authors where each author 15 genuine signatures were recorded. Testing set had 820 genuine signatures with 410 forged signatures. EER was 82%.

Wu, Lee, and Jou [2]. Fourier analysis was used. For verification task cestrum coefficients were mined. Fourier transformation was applied and Dynamic similarity was used for classification task. Training set consisted 270 genuine signatures from 27 authors and testing set consisted 570 genuine and 650 forged signatures of 27 authors. FRR was 4% and FAR was 8%.

Xuhua, et al. [3]. To extract features Genetic Algorithm was used and for signature verification fuzzy logic approach was implemented. Curvature and geometric and based features were used with Fuzzy logic for classification. Training set was made of 45 genuine signatures of one author and 45 forged signatures of 19 authors. Testing set consisted 75 genuine signatures of 1 author and 90 forged signatures of 19 authors. FAR was 8% and FRR was 5%.

Yang, Widjaja, and Prasad [4]. HMM-LR demonstrated better capability in acquiring features. It was able to accept variability of signature image. Directions of pen movement was used as features and Hidden markov model was used as classifier. Full dataset of 496 signatures from 31 authors had been collected. False Rejection rate was 75% and FAR was 44%. D.-Y.

Yeung et al. [5]. Task 1 included positions and second task included pen Position, inclination and pen pressure as characteristics. HMM was used as classifier. For the first task position information taken from PDA was used. Second task used features like position of pen, pen inclination, and pressure information. Training set included 800 genuine signatures, 800 skilled forged signatures, from 40 authors. Each author has made 20 samples. Test 1 used 600 genuine and 1200 skilled forged signatures in testing phase. Test 2 was done 600 genuine signatures and 1200 random forged signatures. Test 1 ERR was 84% (Task1) EER was 89% (Task 2). Test 2 EER was 79% (Task1) and EER was 51% (task2).

Zhang, Nyssen, and Sahli [6]. In this experiment global, local, and function features were used. For dissimilarity measure Mahalanobis distance was used. Corner extraction and corner matching was done. At the last elastic matching algorithm was implemented. Position parameters were used and HMM was used as classifier. Full dataset of 306 signatures and 302 forged signatures were used. FRR was 8% and FAR was 0%.

Zou et al. [7]. This experiment used local shape analysis, to originate spectral and tremor features from Geometric features. To combine similarity values a weighted distance was used. Full dataset of 1000 genuine signatures and 10000 forged signatures was used. FRR was 30% and FAR was 0%. Speed, Pressure, Direction based and Fourier transformation was used as features and Membership function was used as classifier.

Qu, Saddik, and Adler [8]. Stroke based features were used. membership function acted as classifier. Signature time, RMS speed, pressure on paper, direction based dimensions were used. Membership function classifier is used. Testing dataset used 60 forged and genuine signatures. FRR was 67% and FAR was 67%.

Yoon, Lee, and Yang [9]. Computing time polar coordinate was used to reduce normalization error. Modelling and verification were HMM was used to acquire appearances of time series data. Position parameters were used and HMM was classifier. 100 authors 1500 signatures of have been taken into account in training dataset and testing dataset included 500 signatures of 100 authors. Equal error rate was 2%.

Moud, Sharma, and Kushwaha [10], Dilara Gumusbas and Tulay Yildirim paper objective is to assess Network of Capsule and the CNN model for signature image for identification. Features were extracted directly from Convolutional neural network. Network got 98,8% accuracy for 64x64 image of signature and accuracy of 98,6% of 32x32 signature resolutions, convolution Neural Network got accuracy of a 51,4% and 54,7% for same signature images.

4. Problem Statement

Handwritten signature recognition is a challenging task due to the intra class variation between signatures, it makes difficult to distinguish between legitimate signatures skilled forged signature. However, there are several techniques and models that can be used to improve the accuracy of signature recognition

Overall, there is still scope for research and improvement in the field of handwritten signature recognition. By combining different techniques and models, and by exploring new approaches. It is possible to achieve higher accuracy and better performance in this important application.

5. Methodologies

As shown in Table 1, the proposed architecture for signature recognition used VGG16 network, with the weights of VGG 16 layers were fine-tuned to enhance performance. It includes 13 convolutional layers with varying kernel sizes and 5 max pool layers with a filter size of 2x2. Rectified Linear Unit (ReLU) activation function is used in each convolution layer. The classification is done using 5 dense layers with 4096 neurons each, and an output layer with 4000 neurons using SoftMax function. The input size of the image is 224x224x3, and the training is done in batches of 32. A total of 96000 images of size 224x224x3 are used, out of which 76000 are used for training and 20000 are used for validation. Image augmentation techniques such as flipping, jittering, cropping, and color normalization are used in preprocessing. SGD momentum learning algorithm is implemented. The dimensions extracted from the neural network are used as input for image classification.

Table 1

Architecture Diagram

Type of Layer	Shape of output	Number of parameters
VGG 16 Layers	None, 7, 7, 512	14714688
Flatten	None, 25088	0
Dense	None, 4096	102764544
dense_1	None, 4096	16781312
dense_2	None, 4096	16781312
Dense hidden_layer	None, 4096	16781312
Dense classification_layer	None, 4096	16781312
Dense output_layer	None, 4000	16388000

Total number of parameters: 200,992,480

Total number Trainable parameters: 186,277,792

Total Number Non-trainable parameters: 14,714,688

5. Dataset

The research employed the publicly accessible GDPS synthetic dataset. It comprises data from 4000 artificial individuals. Each individual has 24 authentic signatures and 30 forgeries of their signature, which were generated using diverse modeled pens.

6. Result and Discussion

Feature are extracted through Convolutional neural network. Extracted features were used for signature classification. It has been shown Figure 1 that Neural network has exhibited 99.98 % Accuracy on training data and 84.53% on validation data.

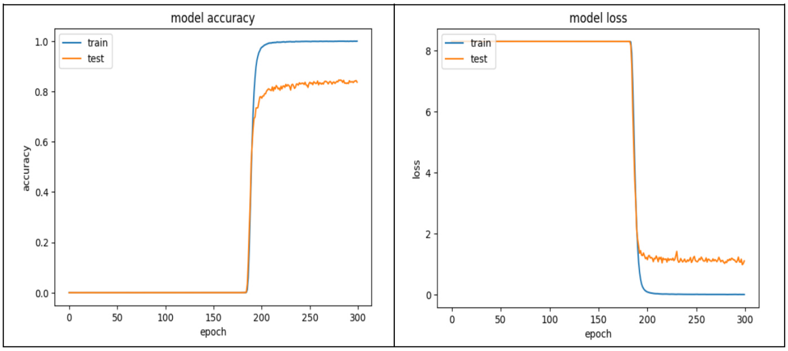

Figure 1

Model Loss and accuracy

7. Conclusion

The proposed approach for signature identification involves using a novel architecture that combines a convolutional neural network for characteristic extraction and a neural network for classification. The CNN is used to take out features from the images of signatures, which are then fed into the neural network for classification. The results show that the neural network achieved 99.98% accuracy on the training data and 84.53% accuracy on the validation data.

8. Future Scope

There is scope of research to improve in validation accuracy. Other regularization mechanism can be adopted to improve validation accuracy. Other Pre trained Neural network can also be used for feature extraction.

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