



Offline Signature Verification using Python

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Abstract— *Every person has his/her own unique signature that is used mainly for the purposes of personal identification and verification of important documents or legal transactions. There are two kinds of signature verification: static(offline) and dynamic(online). Static verification is the process of verifying an electronic or document signature after it has been made. Offline signature verification is not efficient and slow for a large number of documents. To overcome the drawbacks of offline signature verification, we have seen a growth in online biometric personal verification such as fingerprints, eye scan etc.*

In this project , offline signature verification using Convolutional Neural Network (CNN) is proposed. CNN is a type of neural network model which allows us to extract higher representations for the image content. CNN takes the image's raw pixel data, trains the model, then extracts the features automatically for better classification . The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision also it has the highest accuracy among all algorithms that predicts images.

Keywords— *Offline signature, Image processing, Convolutional Neural Network , Artificial Neural Network , Authentication, Accuracy and Security.*

I. INTRODUCTION

In a world which is progressing towards innovation, signature actually assumes the most crucial part in ID of a specific individual. As years cruise by, instances of phony is likewise expanding in an incredible number. Hence, signature check framework is request of an opportunity to further develop the confirmation interaction and give secure means to approval of authoritative archives. The mark confirmation frameworks help to separate between the first and phony marks.

This section presents data about advancements utilized in project that are Image Processing and Convolutional Neural Network.

1.1.1 Image Processing

Image processing is a strategy to play out certain procedure on a picture, to get an improved picture or to extricate some valuable data from it.

1.1.2 Artificial Neural Network

Artificial Neural Network is an endeavor to reproduce the organization of neurons that make up a human cerebrum so the PC will actually want to learn things and settle on choices in a humanlike way.

1.1.3 Convolutional Neural Network

A convolutional neural organization (CNN) is a kind of counterfeit neural organization utilized in picture acknowledgment and handling that is explicitly intended to deal with pixel information.

II. LITERATURE SURVEY

The survey paper we have studied is tabulated as follows:

Sr. N0	Ref. No, Author and Year	Work Done By Author	Findings by Author	Conclusion
1.	KESANA MOHANA LAKSHMI, TUMMALA RANGA BABU [1] "AN EFFICIENT ALGORITHM FOR HAND WRITTEN SIGNATURE RECOGNITION USING TRANSFORM BASED APPROACH WITH IMAGE STATISTICS"	implemented an efficient framework for off line signature recognition system by utilizing NSCT framework	Extensive simulation analysis disclosed that the proposed methodology achieved superior performance over the conventional retrieval system by achieving higher mAP and mAR	performing texture features extraction by computing spatial dependence matrix and utilized NSCT algorithm for multi-scale decomposition and directionality.
2.	A. B. Jagtap and R. S. Hegadi [2] "Offline Handwritten Signature Recognition Based on Upper and Lower Envelope Using Eigen Values"	Both the envelopes are fused by performing union operation and their covariance is computed	The feature set consists of features such as large and small Eigen values computed from upper envelope and lower envelope and its union values	These features set are coupled with support vector machine classifier that lead to 98.5% of accuracy

3.	D. Morocho , A. Morales, J.Fierrez , and R. VeraRodriguez [3] “Towards human assisted signature recognition: Improving biometric systems through attribute based recognition”	work explores human-assisted signature recognition including a baseline performance of human recognition of signatures and the analysis of manual attribute-based signature recognition.	Present a crowdsourcing experiment to establish the human baseline performance for signature recognition tasks and a novel attribute based semi-automatic signature verification system inspired in FDE analysis.	FDE analysis give better understanding of output
4.	R. Sa-Ardship and K. Woraratpanya [4] “Offline Handwritten Signature Recognition Using Polar-Scale Normalization”	They has reviewed offline signature verification schemes in their paper. They have considered the Artificial Neural Network Technique	the adaptive variance reduction algorithm is proposed to retain	These problems can be considered for improving the system
5.	Vinayak Jadhav, Nikhil kadam, Paresk Keluskar, Ayyaj Khan[5] “Artificial Neural Network Based Signature Verification”	paper presents a method of offline signature verification using artificial neural network approach	For implementation of above this paper uses Feed Forward Neural Network (FFNN) using Error Back propagation algorithm for recognition and verification of signatures of individuals	For verification of signatures some novel features needs to be extracted. The extracted features are used to train a neural network using error back propagation training algorithm

III. Implementation Methodology

1.1 Proposed System

In this project, we center around removing preprocessed information from the data set to prepare and test the organization utilizing brain network methods to characterize a signature as certified or fabrication. The acknowledgment and check of disconnected signature tests utilizing counterfeit brain network is pertinent as it follows a worldview which models human learning designs.

Data Acquisition/Signature Database

The signature database is gathered from MCYT-75 disconnected signature corpus data set. Every signature is finished utilizing a WAMCOM Intuous inking pen. In which 15 certifiable and 15 imitation signature tests are given for every one of 75 clients in data set. The imitation mark in the MCYT data set is the combination of irregular, straightforward and gifted falsifications.

- a) Training Stage - A training stage consist of following two steps
 - i. Retrieval of a signature image from a database.
 - ii. Neural network training.
- b) Testing Stage - A testing stage consists of following two steps
 - i. Retrieval of a signature to be tested from a database.
 - ii. Checking output generated from a neural network.

The methodology begins by examining pictures into the PC utilizing fringe gadgets, then changing their quality through picture upgrade, trailed by highlight extraction and brain network preparing, lastly checks whether a signature is real or fake.

The general engineering of our unique acknowledgment framework follows: Signature securing, Preprocessing, Feature extraction, and Classification. Offline signatures are made on papers. By and large in any picture handling application preprocessing is expected to eliminate adjustment, from the first info picture. Any normal scanner with sufficient resolution can be used as an image attainment device for offline operation. Signatures are scanned in gray, using following equation as: (1) Gray colour = $(0.299 * \text{Red}) + (0.5876 * \text{Green}) + (0.114 * \text{Blue})$



Scaling Let H be the height of the inputted image & W be the width of the inputted image. We can fit the image uniform at $100 * 100$ pixels by using the following equation as:

$$(2) X_{\text{new}} = (X_{\text{old}} * 100) / H; \text{ Where } X_{\text{new}} \& X_{\text{old}} \text{ are calculated \& original X coordinate}$$

$$(3) Y_{\text{new}} = (Y_{\text{old}} * 100) / W; \text{ Where } Y_{\text{new}} \& Y_{\text{old}} \text{ are calculated \& original Y coordinate.}$$

Sound Reduction Images are defiled due to coming from translating blunders or boisterous channels. A picture additionally gets corrupted on account of the impeding impacts because of light and different articles

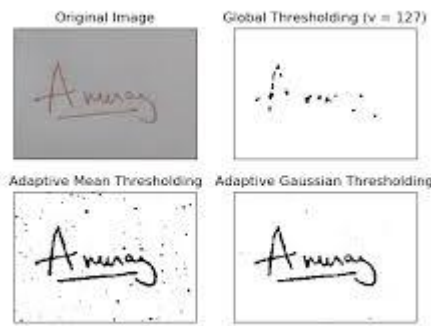
in the environment.

Background Elimination- We involved Thresholding strategy for recognize the signature from the background. In proposed application, we are worried in dim items on light foundation and subsequently a limit esteem T entitled as the brilliance edge is reasonably picked and applied to picture. After the Thresholding, the pixels of the mark would be 1 and different pixels which have a place with the background would be 0.

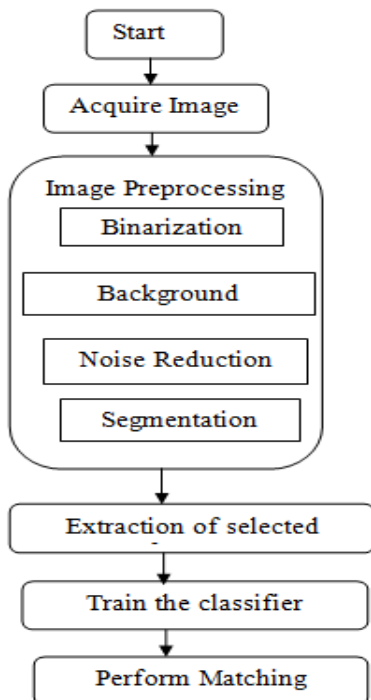
The brightness threshold can be chosen such that it satisfies the following conditions;

Suppose image pixels $f(x, y)$ then, If $f(x, y) \geq T$ Then $f(x, y) = \text{Background}$

Else $f(x, y) = \text{Object}$



1.2 Architecture



1.3 Working

In this project, we first train all the signature images. These trained and tested images are saved in the training and testing folder. Then it gets the image name and path as input from the user and starts verification on it step by step using Convolutional neural networks. In this process, first image preprocessing happens. In image preprocessing binarization, segmentation is done. The extracted image is then used to train the classifier, and if it matches, it produces a genuine output; otherwise, it produces a fraudulent output.

IV. OUTPUT

```

# Network Parameters
n_hidden_1 = neurons # 1st layer number of neurons
n_hidden_2 = 7 # 2nd layer number of neurons
n_hidden_3 = 30 # 3rd layer

train_avg, test_avg = 0, 0
n = 10
for i in range(1,n+1):
    if display:
        print("Running for Person id",i)
        temp = ('0'+str(i))[-2:]
        train_score, test_score = evaluate(train_path.replace('01',temp), test_path.replace('01',temp))
        train_avg += train_score
        test_avg += test_score
    if display:
        print("Number of neurons in Hidden Layer-", n_hidden_1)
        print("Training average-", train_avg/n)
        print("Testing average-", test_avg/n)
        print("Time taken-", time()-start)
return train_avg/n, test_avg/n, (time()-start)/n

evaluate(train_path, test_path, type2=True)

Enter person's id : 001
Enter path of signature image : real/001001_001.png
Genuine Image

Out[16]: True

In [ ]:

In [ ]:

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learning_rate = rate
training_epochs = epochs

# Network Parameters
n_hidden_1 = neurons # 1st layer number of neurons
n_hidden_2 = 7 # 2nd layer number of neurons
n_hidden_3 = 30 # 3rd layer

train_avg, test_avg = 0, 0
n = 10
for i in range(1,n+1):
    if display:
        print("Running for Person id",i)
        temp = ('0'+str(i))[-2:]
        train_score, test_score = evaluate(train_path.replace('01',temp), test_path.replace('01',temp))
        train_avg += train_score
        test_avg += test_score
    if display:
        print("Number of neurons in Hidden Layer-", n_hidden_1)
        print("Training average-", train_avg/n)
        print("Testing average-", test_avg/n)
        print("Time taken-", time()-start)
return train_avg/n, test_avg/n, (time()-start)/n

evaluate(train_path, test_path, type2=True)

Enter person's id : 002
Enter path of signature image : real/001001_001.png
Forged Image

Out[35]: False

In [ ]:

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V. CONCLUSION

In this paper, we presented different formulations for learning representations for offline signature verification. Analyzing the above results shows that Convolutional Neural Networks are better for the classification of signatures. The intuition to classify between genuine signatures and forgeries (regardless of the user) by learning the visual cues has improved the accuracy. The significant improvement in the accuracy is also due to the new architecture inspired by GoogleNet, which worked more widely than going deeper. Hence, from the above experimental results, it is clear that the InceptionSVGNet Architecture is more efficient in identifying patterns in images by using the wider networks. This pattern will continue for future work, with researchers proceeding to investigate better feature sets (using Deep Learning networks) and approaches to improve arrangement with a limited number of tests. Techniques based on ensembles of classifiers, specifically methods for dynamic choice, are likewise encouraging in this field.

VI. REFERENCES

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