SAVEETHA ENGINEERING COLLEGE AUTONOMOUS

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TNEA CODE 1216

OFF-LINE HANDWRITTEN SIGNATURE VERIFICATION USING DEEP LEARNING

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ABSTRACT :

- ✓ Signature verification is a biometric technique used in the identification of one's signature.
- ✓ Mainly in recognition of signature in bank cheques.Signature verification is used based on the examination of a singleknown sample.
- ✓ Many existing pieces of research are there, yet few attempts have been made to perform the verification on a single reference sample.
- ✓ In this work, we propose an offline handwritten signature verification method based on a deep learning method (deep convolutional neural network, DCNN) and a BRISK-based feature extraction approach. From the experimental results, we get higher accuracy in our testing dataset.

LITERATURE SURVEY

YEAR	AUTHOR	TITLE	PROS	CONS	COMMENTS
2022	Okawa, Manabu	Online Signature Verification Using Locally Weighted Dynamic Time Warping via Multiple Fusion Strategies	Remote Access And Improved User Convenience	Reference of large data set and updating data base	Uses dynamic signature verification system to confirm the writer's identity.
2021	Patil, Punam R, Bhushan V. Patil	A Review-Signature Verification System Using Deep Learning	Higher Possibility Of Identifying Fraud Signature	The dynamic information of the signature is lost	This proposed method is independent on signature datasets, though experimental results .
2020	Malik, Jameel	Deepairsig: End-to-end deep learning based in-air signature verification	Accuracy of 79.02%	The extraction and selection of comprehensive signature features is necessary	It is created using an accurate convolutional neural network (CNN) based 3D hand pose estimation algorithm.
2019	Ren, Yanzhi	Signature verification using critical segments for securing mobile transactions	Higher Positive Signature Verification Rate	The Low Quantity Of Available Signature Samples vs the high Number Of Extracted Features	Our system identifies and exploits the segments which remain invariant within a user's signature to capture the intrinsic signing behavior embedded in each user's signature.
2011	Karouni, Ali, Bassam Daya, Samia Bahlak	Offline signature recognition using neural networks approach	Little Time Of Verification	Insufficient data is a major problem to compare with original signature	Then artificial neural network (ANN) was used to verify and classify the signatures

Existing system :

- A wavelet-based feature extractor
- Handcrafted feature extraction methods
- The local binary patterns (LBP) and uniform local binary patterns (ULBP) as their texture-based feature extraction method
- Meta-learning approach
- A one-class support vector machine (OC-SVM) classifier

Drawback of Existing System :

- Less accuracy
- Still need a large number of samples to train their system

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Proposed System :

- In this project, an off-line handwritten signature verification method based on an explainable deep learning method (deep convolutional neural network is proposed, DCNN) and Binary Robust Invariant Scalable Key-points (BRISK) feature extraction approach used
- DNN (Deep Neural Network) is a type of machine learning that mimics the way the brain learns. It's been used for a variety of tasks

Signature verification system :

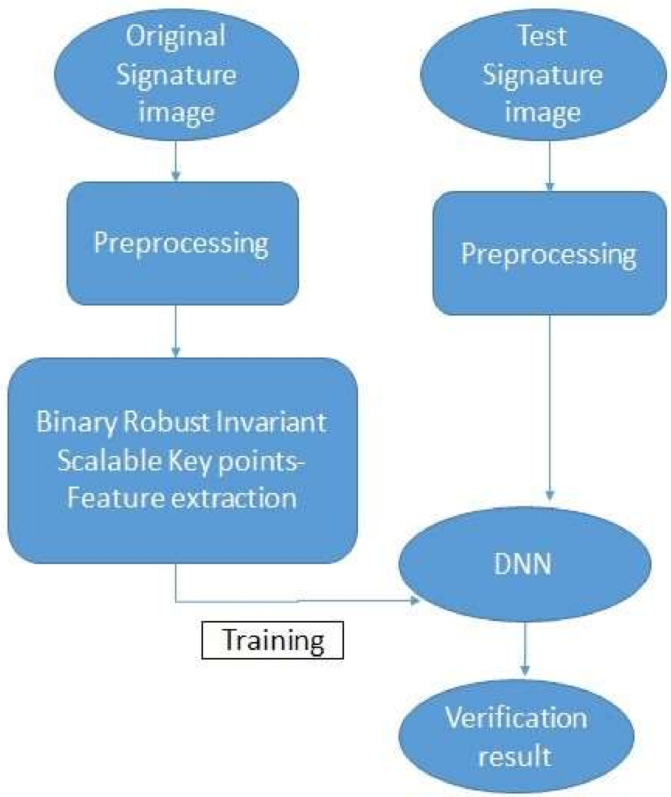
- In offline scheme, signatures are nothing but 2D images which are generated by scanning it or captured it from cameras.
- Off-line signature process is complex task due to the absence of dynamic geometry of signatures.
- Difficulty also comes in the fact that due to different modern and unconventional writing styles, it is harder to segment signature strokes.
- The nature as well as the different pattern of pen may also affect the nature of the signature obtained.

CNN-CONVOLUTIONAL NEURAL NETWORK:

- A convolutional neural network (CNN) is a class of deep learning networks that has achieved state-of-the-art performance in many computer vision areas, such as image classification, pattern recognition, object detection, etc. Typically, CNN consists of three main types of components: convolutional layer, pooling layer, and fully-connected layer
- The convolutional layer uses multiple convolution filters (or convolution kernels) to extract the higher-level features from the low-level information, such as detecting the edges, corners, connection points, and other features from input images. Since multiple convolution filters will dramatically increase the size of the feature map and accompanied by tedious calculations, we use the pooling layer to reduce the feature map size and thus leads to a faster convergence rate for networks.

- all of the multi-dimensional feature maps are converted into a one-dimensional feature vector and input to the fully-connected layer.
- The fully-connected layer is basically a regular multilayer perceptron (MLP) and is used to generate class predictions for the further classification task
- In this project, we use VGG19 architecture in our experiments, since both architectures are well-designed and have shown their great ability in ImageNet competition.

FLOW CHART:


Original Signature image
Test Signature image
Preprocessing
Preprocessing
Binary Robust Invariant Scalable Key points-Feature extraction
DNN
Training
Verification result

Feature extraction :

Binary Robust Invariant Scalable Key points

- The key concept of the BRISK descriptor makes use of a pattern used for sampling the neighborhood of the key point
- The strength of gradient between pairs is computed
- In BRISK, identify the characteristic direction of each key point to allow for orientation-normalized descriptors and hence achieve rotation invariance which is key to general robustness

BRISK :

- Binary Robust Invariant Scalable Key-points (BRISK) is characterized by the fact that computations are significantly less complex, its use distance rather than Euclidean distance and it is faster than the Fast algorithm and the SURF algorithm
- BRISK is a new algorithm designed to identify key points that match the description by evaluating this algorithm shows that the performance of high quality compared to calculations less complex. In addition, the algorithm BRISK has faster implementation than the SurF algorithm.
- we can see that they consist of a binary series and the comparison tests between the points are simple and that the neighborhood points are in specific circles with one center and equal spacing. BRISK is easily scalable for faster execution by reducing the number of sampling-points in the pattern at some expense of matching quality, which might be affordable in a particular application.
- using sub-image blocks as the training and verification data can effectively prevent a small number of local features from dominating the whole CNN and BRISK system

OUTPUT:

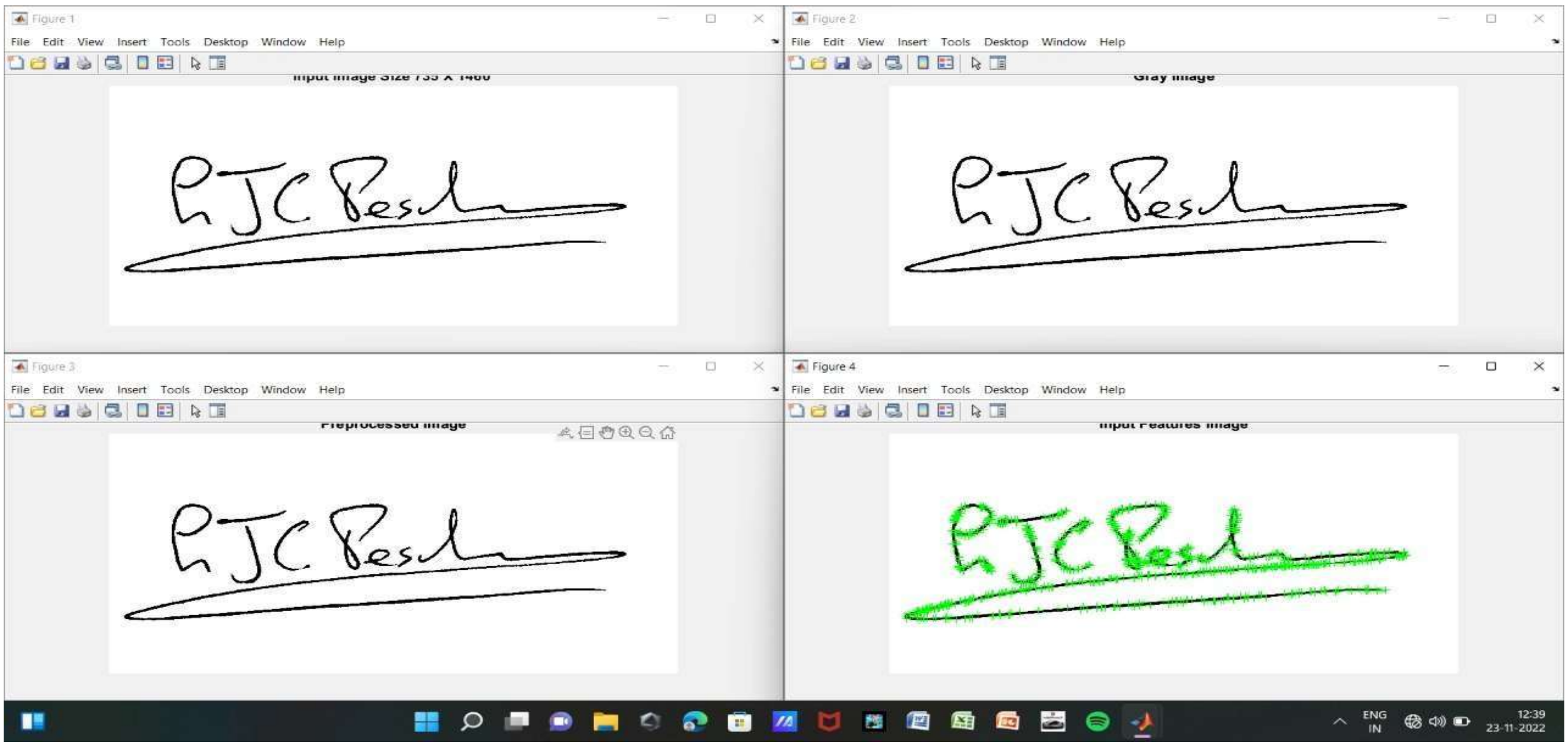


Figure 1
File Edit View Insert Tools Desktop Window Help
Figure 2
File Edit View Insert Tools Desktop Window Help
Gray image
Figure 3
File Edit View Insert Tools Desktop Window Help
Preprocessed image
Figure 4
File Edit View Insert Tools Desktop Window Help
Input Features image
ENG
IN
12:39
23-11-2022

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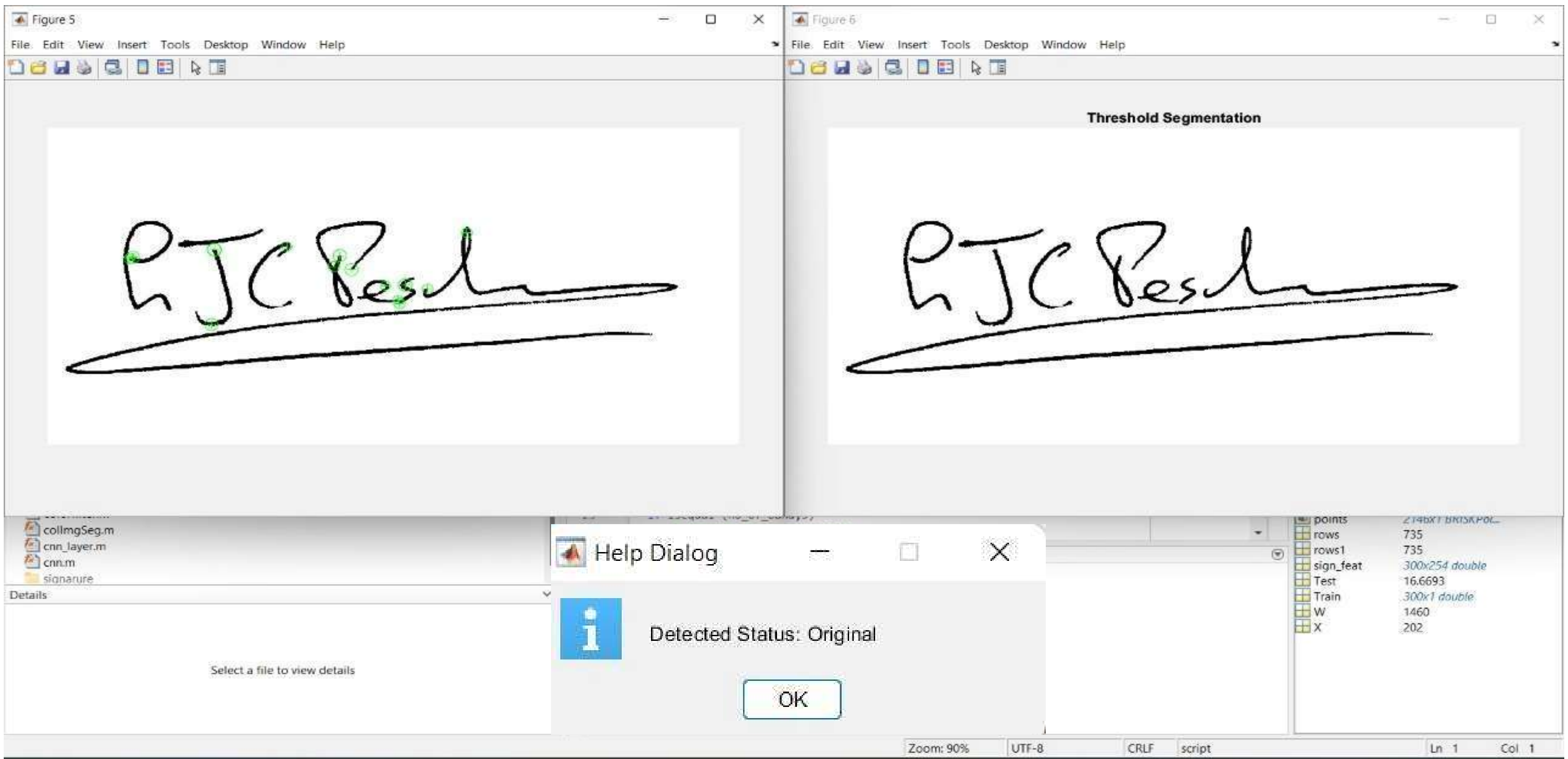

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Conclusion

- In this project, we propose an off-line handwritten signature verification method by using single known sample and based on a deep CNN network and BRISK algorithm.
- We ensure the reliability of the experimental results through a series of methods, including preprocessing (removing background noise), designing controlled groups for different sample sizes and network architectures, and applying visualization techniques (to provide interpretability of the model).
- The experimental results indicate that it is possible to perform automatic signature verification by single known sample.