Research Journal of Computer Systems and Engineering
ISSN: 2230-8571, 2230-8563
Volume 02 Issue 01 - 2021 (January to June)
Page 01:05

Biometric Image Analysis in Enhancing Security Based on Cloud IOT Module in Classification Using Deep Learning- Techniques

Dr. Vishal Goar
Associate Professor,
Govt. Engineering College Bikaner (Rajasthan)
https://orcid.org/0000-0002-2267-6912

Article History

Received: 22 January 2021
Revised: 14 April 2021
Accepted: 19 May 2021

Abstract

In several industries, like internet banking and secure file storage, biometric authentication is expanding. Spoof fingerprint detection is a crucial component utilised to identify accurate fingerprint analysis. This research proposes novel technique in biometric image analysis based on secure cloud internet of things (IoT) by classification with segmentation using deep learning techniques. here the input image has been collected as biometric image using cloud IoT module and processed for noise removal, smoothening and normalization. The processed image has been segmented using histogram equalization with mask convolutional neural network. The experimental analysis is carried out in terms of accuracy, precision, recall, F_1 score and RMSE. When compared to existing methods, this suggested solution shows a 2.5% reduction in mistake rate.
Keywords: biometric image analysis, secure cloud, internet of things, classification, segmentation.

1. Introduction:

With the advent of smart homes and lifestyles, many industrialised nations are becoming entirely automated. One of the most efficient ways to use or unlock any smart gadget in the environment is through biometric authentication. Additionally, wealthy nations are experiencing a lot of fingerprint spoofing. Therefore, the only method of preventing spoofing is liveness detection [1]. The integration of liveness detection will allow for the detection of any functional information or the individual's living moment. Handwritten signatures are now digitalized and preserved for use in automatic document verification and authentication procedures thanks to the development of electronic scanning technologies [2]. The majority of signatures consist of horizontal, vertical, and curved strokes with multilingual words that mostly provide the signer's name and last name as the description of himself or herself, signifying their approval or presence on the document [3].

2. Related works:

Much more complicated features can be obtained using this type of layered structure, which has better representational capacity. In study [4], low-dimensional codes were learned using restricted Boltzmann machines (RBMS), which perform significantly better than PCA. The stacked denoising autoencoders approach was also proposed in study [5] and utilised for handwritten recognition. These deep learning techniques [6] are being used in a wider range of fields, including artificial intelligence

[8], natural language processing [7], and visual tasks. Deep learning techniques have also started to be used to solve certain classic fingerprint recognition issues, including orientation field estimation and minutiae extraction [9, 10].

3. System model:

This section propose novel technique in biometric image analysis based on secure cloud internet of things (IoT) by classification with segmentation using deep learning techniques. here the input image has been collected as biometric image using cloud IoT module and processed for noise removal, smoothening and normalization. The processed image has been segmented using histogram equalization with mask convolutional neural network. Figure 1 shows overall architecture

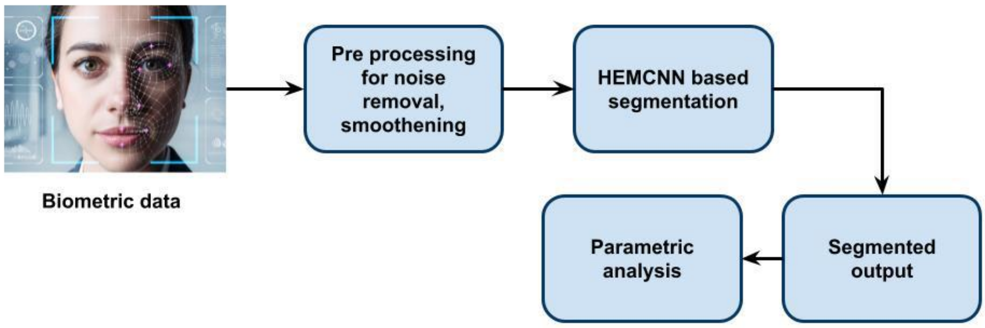


Figure 1: Overall architecture

The RGB to grey conversion process is used to first convert the input colour image to grayscale. We use picture scaling to adjust each image's size to [128*128] in order to make all the database photos the same size. By making the ridge borders more distinct, mean shift filtering is utilised to segment the images. This procedure separates the fingerprint ridges from the valleys, making it simple to spot ridge edges.

3.1 Histogram equalization with mask convolutional neural network based segmentation with mask convolutional neural network:

A widely common method for enhancing the contrast of photographs is histogram equalisation (HE). The dynamic range of an image—defined as the ratio between its brightest and darkest pixel intensities—determines how contrasty it is given by eq. (1).

$$S_k = C(r_k) = \sum_{i=0}^{k} p(r_i) = \sum_{i=0}^{k} \frac{n_i}{n} \qquad (1)$$

Assume that fm 0 and L-1 and that it represents the mean of the picture f. The image is divided into two sub-images, fL and fU, based on the input mean fm eq. (2).

$$f = f_L \cup f_U$$

$$f_L = \{f(i,j) \mid f(i,j) \leq f_m, \forall f(i,j) \in f\}$$

$$f_U = \{f(i,j) \mid f(i,j) > f_m, \forall f(i,j) \in f\} \qquad (2)$$

Be aware that the sub-image fU is formed of fm+1, fm+2,..., fL-1, while the sub-image fL is composed of f0, f1,..., fm. Continue by defining the subhistogramsfL and fU's respective probability density functions as eq. (3)

$$P_L(f_k) = \frac{n^k{}_L}{n_L} \qquad (3)$$

and where k − 0,1, … … … , m, and by eq. (4)

$$P_U(f_k) = \frac{n^k U}{n_U}$$

$$L_{\text{loc}}\,(t'', v) = \sum_{i\in(x,y,w,p_1)} \text{smooth}_{L_1}\left(t_i^{\mu} - v_i\right). \qquad (4)$$

$$smooth_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases}$$ (smooth s L_1 Loss Function of the Regressor)

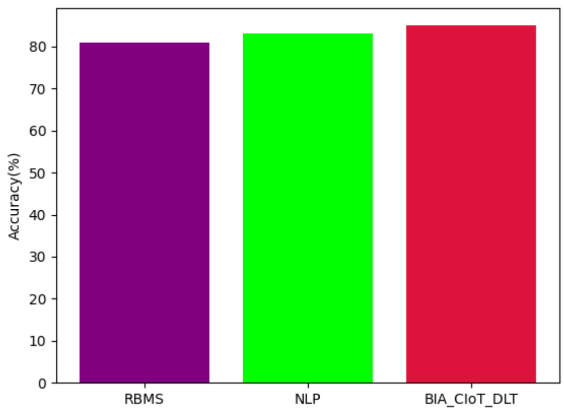
The speed increases by up to 150% when the aforementioned three are trained simultaneously, but the accuracy is unaffected. By using image-centric sampling as a guide, stochastic gradient descent and back-propagation can be employed to train the region proposal network.

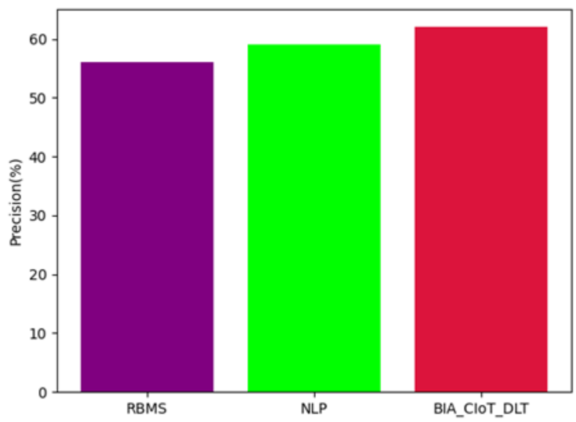
4. Performance analysis:

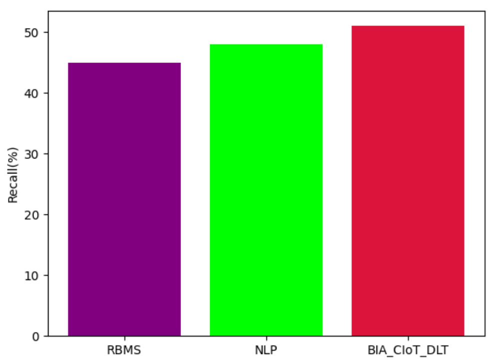
The evaluation of separate systems and the fully integrated system are listed in this section. An Intel Core i7 processor and 8 GBs of RAM are used in the Lenovo U31-70 PC used for the experiment.

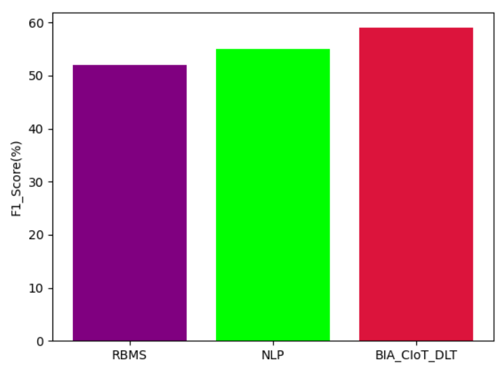
Table 1: Comparative analysis between proposed and existing technique

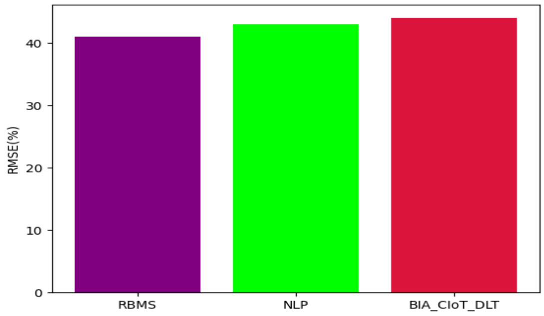
Parameters	RBMS	NLP	BIA_CIoT_DLT
Accuracy	81	83	85
Precision	56	59	62
Recall	45	48	51
F1_Score	52	55	59
RMSE	41	43	44











Above table-1 shows comparative analysis between proposed and existing technique for various biometric dataset based on DL methods. Parametric analysis is carried out in terms of accuracy, precision, recall, F-1 score and RMSE. Above figure- 4 (a)- (d) shows comparative analysis between proposed and existing technique for SDUMLA-HMT dataset. Here proposed technique attained accuracy 91%, precision 72%, recall 62%, F-1 score 65%. Existing technique KNN attained accuracy 82%, precision 63%, recall 55%, F-1 score 61%; while LSTM attained accuracy 88%, precision 65%, recall 58%, F-1 score 63%. One metric for measuring classification model performance is accuracy. Informally, accuracy is percentage of predictions that our method correctly predicted. Accuracy is defined as follows in formal language: Accuracy is the quantity of accurate forecasts. sum of all projections. How frequently an algorithm successfully classifies a data point can be determined, for example, by looking at the accuracy of the algorithm. The percentage of projected data points that really occurred is known as accuracy. One measure of a ML methods effectiveness is precision, or standard of a successful prediction the model makes. Ratio of overall number of true positives to total number of positive forecasts is known as precision. F1-score combines precision and recall of a classifier into one metric by computing their harmonic means. It is mostly used to evaluate the performance of two classifiers.

5. Conclusion:

This research propose novel technique in biometric image analysis based on secure cloud internet of things (IoT) by classification with segmentation using deep learning techniques. here the input image has been collected as biometric image using cloud IoT module and processed for noise removal, smoothening and normalization. The processed image has been segmented using histogram equalization with mask convolutional neural network. the experimental analysis is carried out in terms of accuracy, precision, recall, F_1 score and RMSE. Using unsupervised machine learning and deep learning approaches, we may employ more level 3 features in future studies, such as pores, ridges that are just beginning to emerge, and scars, to evaluate the effectiveness of fingerprint identification systems.

Reference:

[1] Li, J.; Schmidt, F.; Kolter, Z. Adversarial camera stickers: A physicalcamera-based attack on deep learning systems. In Proceedings of the International Conference on Machine Learning, Long Beach, CA, USA, 10–15 June 2019; pp. 3896–3904.

[2] Selvaraju, R.; Cogswell, M.; Das, A.; Vedantam, R.; Parikh, D.; Batra, D. Grad-CAM: Visual Explanations From Deep Networks via Gradient-Based Localization. In Proceedings of the 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 22–29 October 2017

[3] Zhou, B.; Khosla, A.; Lapedriza, A.; Oliva, A.; Torralba, A. Learning Deep Features for Discriminative Localization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016

[4] Chattopadhay, A.; Sarkar, A.; Howlader, P.; Balasubramanian, V.N. Grad-CAM++: Improved Visual Explanations for Deep Convolutional Networks. arXiv 2018, arXiv:1710.11063v3.

[5] He, K.; Gkioxari, G.; Dollar, P.; Girshick, R. MASK RCNN. arXiv 2018, arXiv:1703.06870v3

[6] Minaee, S., Abdolrashidi, A., Su, H., Bennamoun, M., & Zhang, D. (2019). Biometrics recognition using deep learning: A survey. *arXiv preprint arXiv:1912.00271*.

[7] Cheng, L.; Liu, X.; Li, L.; Jiao, L.; Tang, X. Deep Adaptive Proposal Network for Object Detection in Optical Remote Sensing Images. arXiv 2018, arXiv:1807.07327.

[8] Yang, X.; Sun, H.; Fu, K.; Yang, J.; Sun, X.; Yan, M.; Guo, Z. Automatic Ship Detection in Remote Sensing Images from Google Earth of Complex Scenes Based on Multiscale Rotation Dense Feature Pyramid Networks. Remote. Sens. 2018, 10, 132.

[9] Cheng, G.; Zhou, P.; Han, J. Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Images. IEEE Trans. Geosci. Remote Sens. 2016, 54, 7405–7415.

[10] Sobhaninia, Z., Rafiei, S., Emami, A., Karimi, N., Najarian, K., Samavi, S., &Soroushmehr, S. R. (2019, July). Fetal ultrasound image segmentation for measuring biometric parameters using multi-task deep learning. In *2019 41st annual international conference of the IEEE engineering in medicine and biology society (EMBC)* (pp. 6545-6548). IEEE.