Acta Scientific COMPUTER SCIENCES

Volume 4 Issue 10 October 2022

Research Article

An Iris Recognition System Using Enhanced Convolution Neural Network

Adegboye Olujoba James[1]* and Awodoye Olufemi Olayanju[2]

[1]Department of Computer Science, The Federal Polytechnic, Ilaro, Ogun State, Nigeria

[2]Department of Computer Engineering, Ajayi Crowther University, Oyo State, Nigeria

***Corresponding Author:** Adegboye Olujoba James, Department of Computer Science, The Federal Polytechnic, Ilaro, Ogun State, Nigeria.

Received: July 26, 2022

Published: September 14, 2022

Abstract

The paper aimed at developing an enhanced Convolution Neural Network based system to recognize iris features. The enhancement was done using Gravitational Search Algorithm (GSA) due to its advantages over other algorithms. Four hundred and fifty (450) Iris image were acquired from CASIA (vi) iris dataset. Without changing the images, the original iris images were resized to 200 by 200 pixels. Sixty percent of the acquired images (270) were used for training and forty percent (180) were used for testing. Processes such as iris segmentation, normalization, feature extraction and template matching were carried out within. On the basis of recognition accuracy, false positive rate, sensitivity, specificity, and average recognition time, the effectiveness of the existing CNN and GSA-CNN on both trained and recognized iris was evaluated. The effectiveness of the performance metrics was evaluated using a confusion matrix. it was inferred from the performance of both algorithms that the GSA-CNN model gave an increased 2.11% recognition accuracy, 2.22% specificity, 0.74% sensitivity and a decreased FPR of 2.22% over the CNN model at 0.75 threshold value. GSA-CNN outperformed CNN using the said metrics therefore we recommend that our proposed system can be used to handle security challenges in Banks, Schools, the Military, Medicine and any security-threat prone Organizations than CNN.

Keywords: CASIA; Confusion Matrix; Convolution Neural Network; Gravitational Search Algorithm; Iris

Introduction

The need for accurate identification of people has evolved over time for the purpose of security and identity supervision. Infallible characteristics of a person, such as fingerprints, facial traits, sutures, ear and iris patterns, have been used in numerous accurate and practical procedures created for this purpose. Due to their accuracy and precision, these biometric approaches have acquired acceptance and appeal. Iris recognition is one of these methods that is growing in popularity. Because of its textural qualities, the human iris can be uniquely identified. The radial and longitudinal muscles that dilate or constrict the pupil in response to variations in light are what give the iris its texture. A reasonably vivid image of iris shows rings, pustules, undulation and stripes forming a peculiar pattern [11]. Iris is more reliable and stable for identification because it has a unique feature which does not change with age. Iris is steady and fixed from the age of roughly one year onwards for the duration of life. Iris recognition is very efficient method of biometrics and error rate is very less according to statistics [4]. Among all biometric characteristics, iris pattern has been revealed as one of the most reliable biometric traits to distinguish among different persons [3].

Eye iris network pattern recognition technology is the common name for iris recognition. Information from iris is mapped using the human iris network features. This serves as a unique identity card that can be automatically recognized when utilized with computer technology and imaging techniques [6].

A group of learning techniques known as deep learning try to model data using intricate architectures that combine several non-linear transformations. The concept of Deep Learning comes from the study of Artificial Neural Network. The neural networks that are combined to create deep neural networks are the fundamental building blocks of deep learning [5]. In the areas of sound and image processing, such as iris detection, speech recognition, computer vision, automated language processing, and text classification, these techniques have significantly advanced research (for example spam recognition). Prior to the advent of deep learning for computer vision, learning was based on the extraction of relevant variables, or features, but these approaches require a great deal of expertise for image processing. Convolutional neural networks (CNN), which LeCun, Bottou, Bengio, and Haffner proposed in 1998, have revolutionized image processing and eliminated the need for manual feature extraction. In the case of images with three RGB color channels, CNN acts directly on matrices or even tensors. Image classification, image segmentation, object recognition, and iris recognition now frequently use CNN.

The Newtonian gravity law, which governs the interaction of masses, served as the inspiration for the gravitational search algorithm (GSA), a stochastic population-based meta-heuristic. Based on the law of gravity and the interactions between masses, it is an optimization algorithm. An increasing number of algorithms have been developed over time that are motivated by observations of natural events. These algorithms are effective alternatives to other methods for tackling challenging computational issues, according to a number of studies [9].

Review of related works

[2] proposed an architecture based on the combination of CNN and Softmax classifier to extract discriminative features from the input image without any domain knowledge, where the input image represents the localized iris region, and then classified it into one of N classes. In addition, a discriminative CNN training scheme based on a combination of back-propagation algorithm and mini-batch AdaGrad optimization method was proposed for weights update. When compared to Wavelet transform, scattering transform, Local Binary Pattern, and Principal Component Analysis, the performance of the system performed better on three public datasets collected under different conditions, achieving a Rank-1 identification rate of 100 percent on all the databases used and a recognition time of less than one second per person.

[8] investigated how state-of-the-art pre-trained CNNs performed on iris recognition and demonstrated that the pre-built CNN features, although originally trained for classifying generic objects, are also very good at representing iris images, successfully extracting discriminative visual features, and achieving promising recognition results on two iris datasets.

By employing a Fully Convolutional Network (FCN) and a Multi-scale Convolutional Neural Network, [10] bypass the time-consuming task of manual segmentation and feature extraction (MCNN). Four steps of fully automated processing were carried out. In the paper, a method based on vision deep neural networks was suggested, where the first and last phases were combined with deep neural networks that automatically execute feature extraction, segmentation, and classification. The use of many deep networks operating at various scales (size of the input) and having their outputs combined is also suggested. On three databases, the approach demonstrates recognition accuracy of 95.63 percent, 99.41 percent, and 93.17 percent with FRR of 4.27 percent, 0.49 percent, and 6.73 percent.

Methodology

Figure 1: The Structure of iris recognition system.

The iris dataset was obtained. The iris image had noise and other undesirable components eliminated. The iris region of the eye image was located by using the Hough transform. An accurate representation with constant dimensions was produced using

Daugman's Rubber Sheet Model. Dimensionality reduction and feature extraction both used Principal Component Analysis. Finally, the GSA-CNN classifier was used to do classification and matching.

After going through a few image processing steps, these obtained images were used for the training and recognition stage to test approaches like CNN and GSA-CNN.

Input image size

The 200 x 200 pixel image size was used to study this. A zero padding (of 1 pixel) was solely provided to the input layer in order to regulate the spatial size of the input and output volumes.

Matching and classification

CNN fine-tuned by GSA classifier was used after feature extraction. On the basis of recognition accuracy, false positive rate, sensitivity, specificity, and average recognition time, the effectiveness of the existing CNN and GSA-CNN on both trained and recognized iris was evaluated. Using a confusion matrix, the performance metrics' efficacy was assessed. "True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN)" are all contained in it.

The number of items for the tuple that was successfully classified as positive is in TP. The amount entries for tuples that are projected to be positive but are actually negative are contained in FP. The number of expected and actual negative tuples is known as TN. The number of tuples that are positive but were expected to be negative is known as FN. Also, the sensitivity, specificity, false positive rate and accuracy were calculated using these terms:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} X\ 100\% - - - - - (3.1)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} X\ 100\% - - - - - - - - (3.2)$$

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{TN} + \text{FP}} X\ 100\% = 1 - Specificity - - - - - (3.3)$$

$$\text{Overall Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} X\ 100\% - - - - - - - (3.4)$$

$$\text{Average recognition time} = \frac{\text{Total Recognition Time}}{\text{Number of recognized Iris images}} - - - -(3.5)$$

Meanwhile the Gravitational Search Algorithm with the followings steps was adopted and used for pruning:

- **Step 1:** Initializing the agents
- **Step 2:** Best fitness computation and fitness evolution
- **Step 3:** Calculating the gravitational constant (G)
- **Step 4:** Calculating the agent masses
- **Step 5:** Calculating the Accelerations of the Agent
- **Step 6:** Agent positions and speed
- **Step 7:** Recurring steps 2 through 6 until the maximum number of iterations, steps 2 through 6 are repeated.

The position of the relevant agent at the provided dimensions is computed as the global solution of that specific problem, whereas the best fitness value at the final iteration is computed as the global fitness.

$$\text{Kbest} = \text{H}_{\text{GSA}}$$

The best convolution weight is selected based on the minimum error value. The minimum error value convolution weight is selected as the best convolution weight in equation

$$\text{H}_{\text{best}} = \text{error\_min}\ (\text{Kbest})$$

H_{best} gives the best convolution weight obtained from our method. Then compare the error values obtained from all the convolution weight and then select the convolution weight with minimum error as the best convolution weight.

Training strategies

In each training iteration, the optimization strategy completely ignored the connections between the individual nodes with the highest fitness values in order to prevent neural networks from overfitting the training set. By avoiding interdependencies from developing between the nodes, this technique reduces the complex co-adaptations of the nodes. The trimmed nodes are excluded from both forward and reverse passage. In that training cycle, the input data are used to train the reduced network that has been left. As a result, after training a neural network with n nodes, a set of (2n) potentially "thinned" neural networks with shared weights was produced. This lowers the computational complexity of the CNN architecture by enabling the neural network to avoid overfitting, learn more robust features that generalize well to new data, and accelerate the training process.

Procedure using GSA-CNN

The Procedural steps in achieving the training and classification processes are as follows:

Figure 2: Proposed System Architecture.

- **Step 1:** Forward Pass
- **Step 2:** The output deviation of the kth neuron in the output layer O is back propagated.
- **Step 3:** Enter deviation in the output layer's kth neuron
- **Step 4:** K^{th} neuron's weight and bias fluctuation in output O
- **Step 5:** K^{th} neuron's output bias in hidden layer H
- **Step 6:** k^{th} neuron input bias in hidden layer H:
- **Step 7:** A former layer in front of k neurons in the hidden layer H, with weight and bias variations in rows x and y of the m^{th} feature pattern.

Network architecture

The optimum network architecture is found when the parameters of the training approach (such as learning rate, number of epochs, etc.) are established. According to the literature, selecting a network architecture is still a difficult decision that depends on the application. The number of layers to use in converting the input image to a high-level feature representation, as well as the number of convolution filters in each layer, are the major factors to consider when determining the ideal CNN design. Therefore, by altering the number of convolutional and pooling layers, as well as the number of filters in each layer, several CNN configurations employing the suggested training methods may be tested. The proposed system design is depicted in figure 2.

Results and Discussion

Dataset

Four hundred and fifty (450) Iris image were acquired from CASIA (vi) iris dataset. The implementation of iris expression recognition utilizing a 200 by 200 pixel resolution was tested using the CNN and GSA-CNN models. Using the performance metrics of sensitivity, specificity, false positive rate, recognition accuracy, and computation time, the system was put to the test. Utilizing the aforementioned square dimension pixel resolution at various threshold levels, all performance indicators were examined. Two hundred and seventy (270) iris images were used for training which equals 60% of the total dataset and one hundred and eighty (180) iris images which equivalent to 40% of the total dataset were used for testing.

Discussion of results

It was observed using performance metrics such as false positive rate, sensitivity, specificity, recognition time and recognition accuracy that threshold values 0.10, 0.12, 0.18, 0.23 and 0.25 generated the same output, the threshold values 0.29, 0.31, 0.33, 0.35 and 0.36 generated the same output, the threshold values 0.38, 0.40, 0.42, 0.44 and 0.45 generated same output, the threshold values 0.47, 0.50, 0.60, 0.65, 0.75 and 0.76 generated same output and the threshold values 0.85, 0.88, 0.90 and 0.96 returned. No values after testing for both CNN algorithm and enhanced CNN i.e. GSA-CNN algorithm, hence we decided to select the threshold values of 0.25, 0.36, 0.45 and 0.75.

Threshold	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (sec)
0.25	24.44	97.78	75.56	92.22	1202.81
0.36	17.78	97.04	82.22	93.33	1160.83
0.45	11.11	96.30	88.89	94.44	1160.44
0.75	6.67	95.56	93.33	95.00	1162.83

Table 1: Experimental Results for GSA-CNN at 200 x 200-pixel resolution.

Comparison results between CNN and GSA-CNN

Table 3 illustrated a combined result of CNN and GSA-CNN at the threshold value of 0.75 with respect to all metrics at 200 x 200-pixel resolution. All result obtained in table 3 presume that GSA-CNN model has the lowest recognition time compared with the corresponding CNN model irrespective of threshold value.

Algorithm	Threshold values	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (sec)
GSA-CNN	0.75	6.67	95.56	93.33	95.00	1162.83
CNN	0.75	8.89	94.82	91.11	92.89	1286.65

Table 3: Comparison of CNN and GSA-CNN resolution at 0.75 threshold value.

Similar to this, the study compared the 200 x 200 dimensional sizes of the CNN and GSA-CNN models for recognition accuracy, sensitivity, false positive rate, and specificity. It found that the GSA-CNN model performed better than the CNN model in terms of accuracy, specificity, and false positive rate. The recognition accuracy of 95.00% was gotten with GSA-CNN and CNN model had accuracy of 92.89%, the GSA-CNN model has a specificity of 93.33%, false positive rate of 6.67% and sensitivity of 95.56% at 1162.83s while the CNN model has a specificity of 91.11%, false positive rate of 8.89% and sensitivity of 94.82% at 1286.65s respectively.

Discussion based on performance metrics

The outcome demonstrated that there is a considerable fluctuation in performance metrics as threshold value increases, with the optimum outcome for GSA-CNN and CNN being at the threshold value of 0.75 for all metrics (false positive rate, specificity, sensitivity, and accuracy). Therefore, the performance of these techniques is dependent on the threshold value. The outcomes based on the performance metrics suggest that the GSA-CNN model provided an increase of 2.11% recognition accuracy, 2.22% specificity, 0.74% sensitivity and a decreased FPR of 2.22% over the CNN model at 0.75 threshold values. Consequently, in terms of FPR, recognition accuracy, specificity, and sensitivity, GSA-CNN surpassed CNN.

The result achieved in this study is as a result of good and stable convergence that was observed for GSA-CNN and CNN with interpolated output. Hence, GSA-CNN improves the performance in iris recognition system. Based on the aforementioned findings, the GSA-CNN is superior to CNN in terms of accuracy, specificity, and sensitivity, with fewer false positives. As a result, GSA-CNN outperformed CNN in terms of accuracy, sensitivity, specificity, and false positive rate.

Statistical analysis

The results were analyzed for accuracy, false positive rate, sensitivity, and specificity between GSA-CNN and CNN approach utilizing inferential statistical analysis using paired sampling t-test. To ascertain the level of relevance in the use of the methodologies, the test was conducted. Table 4 displays the findings from the analysis performed with SPSS. At a 5% level of significance, the paired sampling t-test was used to compare the null hypothesis (H0), according to which there is no significant difference between the GSA-CNN and CNN techniques, with the alternative (H1). The definition of the hypothesis is:

- H0: The GSA-CNN and CNN techniques are not significantly different from one another.
- H1: The GSA-CNN and CNN techniques differ significantly from one another.

From table 4, the p-value for accuracy, FPR, sensitivity and specificity are 0.001, 0.005, 0.000 and 0.005 respectively. The p-value depicts statistical significance at . There was a substantial difference between the GSA-CNN and CNN approaches, according to a 95 percent confidence level test of significance of the accuracy, FPR, sensitivity, and specificity. The alternative theory is therefore accepted. The GSA-CNN technique beat CNN in terms of accuracy, FPR, sensitivity, and specificity, and the t-test result supports this claim. Summarily, the combination of CNN and GSA techniques gave a significant improved performance over CNN technique.

Parameter	T	Degree of freedom (df)	p-value	Comment
Accuracy	14.576	3	0.001	Significant
FPR	-7.340	3	0.005	Significant
Sensitivity	889.000	3	0.000	Significant
Specificity	7.340	3	0.005	Significant

Table 4: Summary of Result of T-test for GSA-CNN and CNN technique.

Conclusion

The paper evaluated the essential features of CNN and GSA-CNN iris recognition system. Two hundred and Seventy (270) iris images were trained and One hundred and Eighty (180) images were used to test each of the three techniques at different threshold value. According to the experimental findings, GSA-CNN surpassed CNN in terms of recognition computation time, accuracy, sensitivity, specificity, and FPR. Given this, a GSA-CNN-based iris recognition system would result in a more trustworthy security surveillance system than CNN. When developing a system for iris identification that is truly robust, high recognition accuracy and computing efficiency must not be sacrificed. With regard to the performance of each GSA-CNN and CNN; GSA-CNN based iris recognition system can be used to handle security challenges in Banks, Schools, the Military, Medicine and any security-threat prone Organizations than CNN.

It is advised that:

- Future research should examine how well GSA-CNN performs in comparison to other classifiers like SVM and HMM.
- To maximize the effectiveness of GSA-CNN, an appropriate evolutionary search algorithm, such as Ant Colony Optimization (ACO), Evolutionary Programming (EP), Genetic Programming (GP), Differential Evolution (DE), and Artificial Immune Systems (AIS), may be taken into consideration.

Bibliography

1. Alaslani M G and Elrefaei L A. "Convolutional Neural Network Based Feature Extraction for Iris Recognition". *International Journal of Computer Science and Information Technology (IJCSIT).* Egypt: Cairo 10.2 (2018): 65-78.

2. Al-Waisy AS., *et al*. "A multi-biometric iris recognition system based on a deep learning approach". Article in Pattern Analysis and Applications. UK: Bradford (2017).

3. Bowyer KW., *et al*. "Image Understanding for Iris Biometrics: A Survey". *Computer Vision and Image Understanding* 110.2 (2008): 281-307.

4. Chandel GS and Bhargava A. "Identification of People by Iris Recognition". *IJCSNS International Journal of Computer Science and Network Security* 14.3 (2014): 77-80.

5. Ciresan Meier., *et al*. "Multi-column deep neural network for traffic sign classification". *Neural Network* 32(2011):333-338.

6. Godara S and Gupta R. "Comparison of Different Neural Networks for Iris Recognition, Network and Complex Systems". India: Kota 324010. 2.4 (2012): 9-14.

7. LeCun Y., *et al*. "Gradient-based learning applied to document recognition". *Proceedings of IEEE* 86 (1998): 2278-2324.

8. Nguyen K Fookes., *et al*. "Iris Recognition with Off-the-Shelf CNN Features: A Deep Learning Perspective". Special Section on Visual Surveillance and Biometrics: Practices, Challenges, and Possibilities 6 (2018): 18848-18855.

9. Rashedi E., *et al*. "Binary gravitational search algorithm". *Natural Computing* 9.3(2010): 727-745.

10. Tobji R., *et al*. "Efficient Iris Pattern Recognition method by using Adaptive Hamming Distance and 1D Log-Gabor Filter". (*IJACSA) International Journal of Advanced Computer Science and Applications* 9 (2018): 662-669.

11. Yaser DK., *et al*. "Iris Recognition using Image Moments and K-means Algorithm". *The Scientific World Journal* (2014).