INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

Received: 17-02-2023

Accepted: 12-03-2023

Published: 02-05-2023

Citation: Salvadi SR, Rao DN, Vathsal S (2023) Visual Mapping for Gender Identification from Facial Images using BAM and DON. Indian Journal of Science and Technology 16(17): 1295-1301. https://doi.org/10.17485/IJST/v16i17.349

* **Corresponding author**.

reddymallashobarani2@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Visual Mapping for Gender Identification from Facial Images using BAM and DON

Shoba Rani Salvadi[1]*, D Nagendra Rao[2], S Vathsal[3]

1 Research scholar, Jawaharlal Nehru Technological University, Hyderabad, Telangana, India
2 Professor and Principal, Abhinav-Hitech College of Engineering, Moinabad, Telangana, India
3 Retired DRDO Scientist

Abstract

Objective: To Develop an intelligent and innovative method to categorize the Gender by focusing facial images. **Method:** We integrate the characteristics of Bidirectional Associative Memory (BAM) and Deep Octonion Networks (DON) to enhance the Gender detection in real time applications. The developed hybrid model is called Visual Mapping of BAM and DON (VMBAD). To validate the projected system, we make use of 4000 images and 126 different subjects as a data set to train the proposed approach and simultaneously compare our results with the existing methods using the same data set. **Findings:** The projected technique improves the performance of the system by 3 -5 % in terms of sensitivity, accuracy, and precision when compared with the existing approaches (vide figures 4-7). **Novelty:** The designed method enhances both the accuracy and precision of image by nearly 4% and 2% respectively when compared with the reported work.

Keywords: Artificial Intelligence; Bidirectional Associative Memories; Gender Identification; Deep Octonion Networks; Deep Quaternion Networks

1 Introduction

Many methods of gender detection have been suggested to improve the identification. However, no or very less attention was given toward a hybrid model of image algorithm and storage to improve the training of the desired identification system. Because conventional methods of artificial intelligence and image processing algorithms were employed to verify the depth of the image, as a result, some methods reduce overall output due to more delay and some experienced storage problems. To overcome the storage gap and analyze images more deeply, a model has been suggested that not only mitigates the gaps but also improves the performance of the identification system.

In the present environment, there has been a rise in the usage of hyper complex values in digital signal processing to study complex signals[(1)]. Many commonly used algorithms, ranging from simple real-valued to hyper complex algorithms are employed[(2–4)] to analyze the image characteristics. In[(5–8)] the authors exploit octonion linear canonical transform and Quaternion based algorithm to investigate the mathematical analysis of an image signal. Takahashi et al[(9)] suggested Remarks on Octonion–valued Neural Networks to control the Robot applications. Cariow and

Cariowa,[10] proposed a quaternion-valued linear convolution algorithm to decrease the arithmetic complexity. In this study the author's make use of notion that quaternion multiplication can be expressed as a matrix-vector product in the synthesis of the procedure mentioned. For the classification of data Wu et al[11] employed general outline for DON and the fundamental building elements of DON to initialize the weight and normalization of octa- norm algorithm. Rasheed et al[12] presented a gender identification model based on complete face, however the authors didn't consider changing image characteristics and it may not be valid in a real time application. Rani and Pushpalatha[13] presented an approach to improving the application of IOT using a distributed mining algorithm. However, this may not be helpful to recognize the gender.

Garai et al[14] suggested· A method to identify the gender based on Gate technology. However, this is a binary classification problem, whereas age estimation is a regression problem and may not be the optimum solution for real time applications. Abirami et al[15] employed CNN to identify the age and sex from same face, since the approach showed less accuracy and precision and didn't meet the requirement of gender identification in real time applications. The authors of[16–18] suggested an Artificial intelligence based methods to analyze age group and gender of a human the methods have more delay and reduces overall throughput. Swaminathan et al[19] proposed a technique in which numerous Machine Learning Classification Procedures on Facial image has been considered to identify the gender. However, due to additional features of machine learning, the algorithm has become more complex, which reduces the overall performance of the desired system. Xiao et al[20] proposed a fractional-order octonion-valued to improve gender identification property. However, the system is too multifaceted and compact the overall performance of the system.

In this paper, visual mapping of Bidirectional Associative Memory and Deep Octonion Networks have collectively employed to optimize the gender identity and is called Visual Mapping of BAM and DON (VMBAD). Bidirectional Associative Memory improves the access speed and storage capacity of the desired system. Moreover, the Deep Octonion Network Algorithm utilizes the benefits of Bidirectional Associative Memory by analyzing the image very deeply to enhance the Gender determination process from a facial image in the Augmented Reality (AR) data base.

The remaining sections of the paper is systematized as section 2 describes the proposed approach. Section 3 enlightens about results and discussion, and finally the conclusion of the paper has been presented in section 4.

2 Methodology

2.1 Proposed Approach

The heart of the proposed approach is the Octonion values and can be calculated as

$$O_V = \sum_{i=0}^{7} x_i e_i \in 0 \tag{1}$$

Where '0' indicates the Octonion sum 'x_i' $\in$ R and represents the real sum, in addition to this

$e_0 = 1$ and $e_{i,}i = 1, 2, 3 \ldots, 7$ represents the seven pretended entities to model the rule and has to follow equation (2)

$$\begin{cases} e_i^2 = -1 \\ e_i e_j = -e_j e_i \quad \forall i \neq j \neq k : 1 \leq i, j, k \leq 7 \\ (e_i e_j)\, e_k \qquad = -e_i\,(e_j e_k) \end{cases} \tag{2}$$

The above-mentioned analysis only finds characteristics of the image and didn't provide any storage to compare the end result. So, to eliminate the storage dilemma in Octonion analysis we introduced an octonion-valued bidirectional associative memory to enhance the gender probability detection.

2.2 Bidirectional associative octonion-valued memories

The bidirectional Associative memory is commonly used in neural networks to store the training algorithms and the processor compatible with the memory unit. In this paper the bidirectional Associative memory is employed to store the entire training data of an image and enhances the probability of gender detection using Octonion approach.

Once the octonion data are stored using bidirectional associative memories, it must be retrieved for identification of gender. The identification process is carried out by one of the methods of Octonion approach called deep octonion network.

2.3 Deep octonion networks

In this we make use of numerous mathematical models such as batch normalization module, convolution module and octonion initialization technique of Octonion networks to analyze the image and improves the performance of the designed system.

Batch normalization is used to reduce the internal covariate shift and simultaneously improves the speed up deep network training. While as convolution module is used to create octonion multiplications that allows each octonion to interact with the image's linear depth to enhance the probability of gender detection. Finally, the octonion initialization technique is employed to compare the between the input image and the output image.

Figure 1 represents the architectural block diagram of the proposed approach. Here Weight initialization is employed to condense the octonion input, and it is followed by the filter Bank operation, in which Octonion BN specifies a batch normalization of the octonion input. Then the normalized input is given to the VMBAD for further processing of image to acquire high resolution and accuracy. Finally, the output of VMBAD is moved to the output stages i.e. pooling, Flatten and Dense) to speed up the training, quality improvement and classify the data.

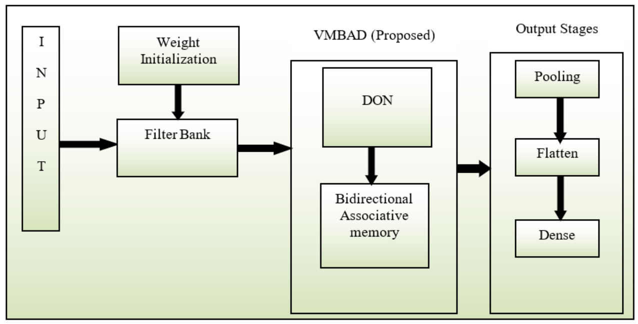

Fig 1. A proposed architecture model

3 Results and Discussion

We are training the final model with deep octonion networks, stochastic gradient descent, and the cross-entropy loss function. To validate the proposed approach, we examined more than 4,000 samples in the Application Requester (AR) database of over 126 different subjects, along with some collected images to identify the gender. We have chosen 26 images of each participant in different emotions, and the reduced pixel size i.e. 20 x 20, has been employed to improve the probability of gender detection.

Figures 2 and 3 represents the Sample photos from the AR database and collected images respectively.

Fig 2. Sample of Database images

Table 1 represents the learning rate of the designed model with respect to epochs, the value of Nester Momentum is set at 0.9 to achieve the desired values of stability and speed.

In each of the network's epochs, different learning rates have been used to make the network more stable. The learning rate is set at 0.01, since it rises by a factor of 10 for the next 40 evaluations and enhances the performance of the proposed system.

The performance of the proposed method is enhanced when compared with the current state of the art (see Figures 4, 5, 6 and 7) by considering well-known parameters such as accuracy, precision, sensitivity, and F-score. These parameters can be

Fig 3. Sample of collected images

Table 1. The learning rate

Learning-rate	Epoch
0.1	(20, 60)
0.01	(0, 20)
0.01	(60, 80)
0.001	(80,110)
0.0001	(110, 120)

mathematically represented as

$$Accuracy\ (A_C) = \frac{M_A + M_B}{M_A + M_B + M_C + F_D} \tag{3}$$

$$Precision\ (P) = \frac{M_A}{M_A + M_B} \tag{4}$$

$$Sensitivity\ (S) = \frac{M_A}{M_A + F_D} \tag{5}$$

$$F - Score = F_S = \frac{2 * P * S}{P + S} \tag{6}$$

In equations, the male is represented by 'M_A', the male but predicted as female is Represented as 'M_B', the female but identified as male is represented as 'M_C' and finally, the female is represented as 'F_D'.

In the experimental analysis we chose different training and testing ratio such as 70 %- 30% and 60% - 40% to get the desired output. Figures 4, 5, 6 and 7 represents the response of various existing and proposed approach, in terms of Sensitivity, Accuracy, Precision and F- score. It has been observed from figure Figures 4, 5, 6 and 7 that the proposed approach showed enhanced response when compared with the existing approaches.

The execution time of the proposed model with different layers for various ratios is Presented in Table 2 .

From Table 2 it has been clearly observed, when the architecture layer is less the execution time is also less, i.e. 101.24s for 70:30 and 91.44s for 60:40. So it is clearly demonstrates that the layer plays an imperative role in the execution time of the proposed model, which authenticates the suggested model

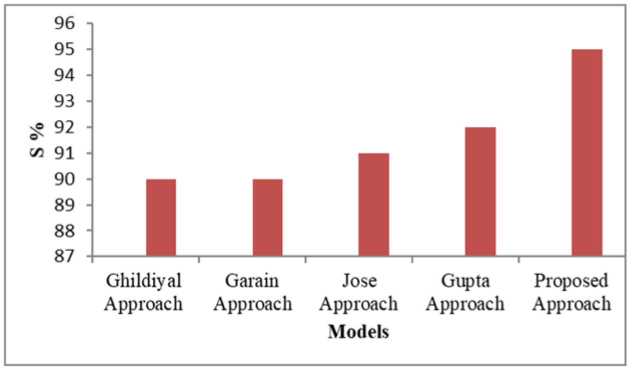

Fig 4. Comparison of presented model Versus Existing models in terms of Sensitivity

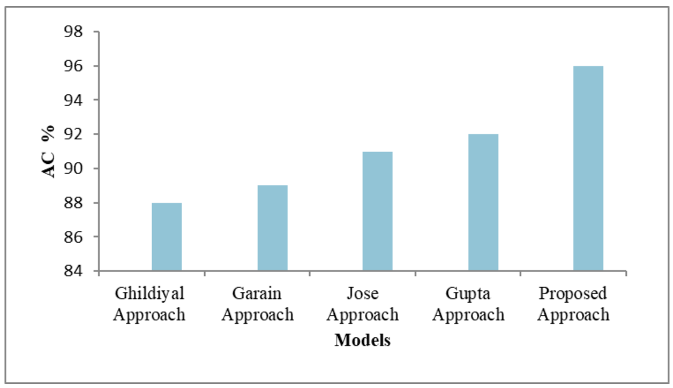

Fig 5. Comparison of presented model Versus Existing models in terms of Accuracy

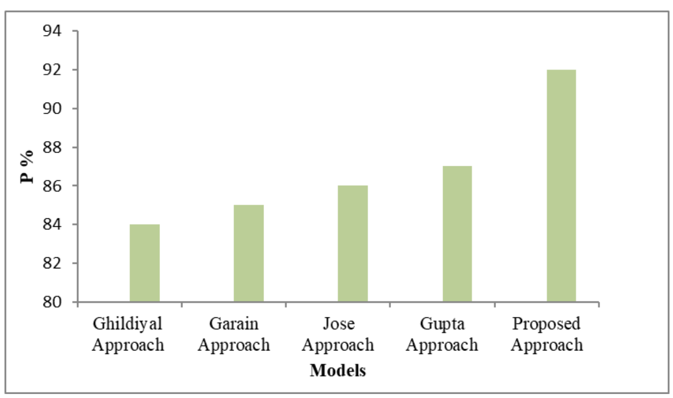

Fig 6. Comparison of presented model Versus Existing models in terms of precision

Table 2. Execution time of the Proposed Pre-trained model for various ratios

S.No	Architecture	70%-30%	60%-40%
1	25:100:40:3	119.80	112.26
2	25:50:20:3	115.79	107.65
3	8:16:10:2	101.24	91.44
4	8:6:4:2	84.27	84.04

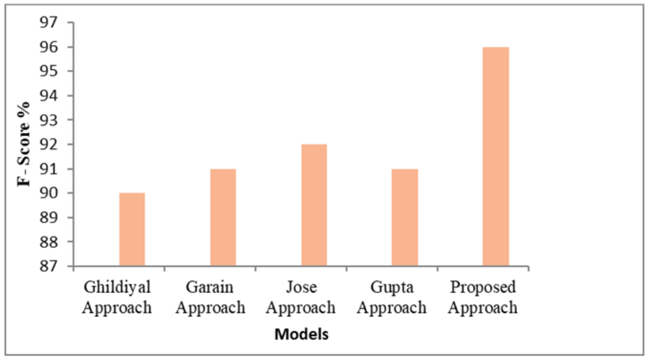

Fig 7. Comparison of presented model Versus Existing models in terms of F-Score

Finally, from the above analysis we examined that the design process is simple and effectual; furthermore, the probability of detection of a gender in the given system is more when compared with the current art of work. Also, the designed system does not require additional hardware as the presented approach used combined properties of DON and BAM which is the significant attractiveness of the proposed approach.

4 Conclusion

The presented approach created a very useful and innovative algorithm to identify the gender from the facial image. The algorithm also takes care of execution time and saves the energy of the desired system. Furthermore, additional memory has been provided to the presented approach by combining the properties of DON and BAM. This makes the storage system compatible with the processor, and no extra hardware is required for the proposed system. This property of the proposed system enhances the processing speed of the desired system and can reduce the cost. Also, the proposed approach improved the overall performance of the system by 5%. The proposed approach will also provide a base for the image and signal processing research community to enhance the gender detection process.

References

1) Comminiello D, Scarpiniti M, Parisi R, Uncini A. Frequency-domain Adaptive Filtering: from Real to Hypercomplex Signal Processing. In: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE. 2019;p. 7745–7749. Available from: https://doi.org/10.1109/ICASSP.2019.8683403.
2) Labunets VG, Smetanin JG, Chasovskikh VP, Ostheimer E. Hypercomplex Algebras as Unified Language for Image Processing and Pattern Recognition Part 1. Cliffordean Models of Multichannel Images. In: Innovation and Discovery in Russian Science and Engineering. Springer International Publishing. 2020;p. 3–19. Available from: https://doi.org/10.1007/978-3-030-37514-0_1.
3) Wang C, Hao Q, Ma B, Wu X, Li J, Xia Z, et al. Octonion continuous orthogonal moments and their applications in color stereoscopic image reconstruction and zero-watermarking. *Engineering Applications of Artificial Intelligence*. 2021;106:104450. Available from: https://doi.org/10.1016/j.engappai.2021.104450.
4) Schwarzenberg P, Figueroa A. Textual Pre-Trained Models for Gender Identification Across Community Question-Answering Members. *IEEE Access*. 2023;11:3983–3995. Available from: https://doi.org/10.1109/ACCESS.2023.3235735.
5) Gao WBB, Li BZZ. The octonion linear canonical transform: Definition and properties. *Signal Processing*. 2021;188:108233. Available from: https://doi.org/10.1016/j.sigpro.2021.108233.
6) Cariow A, Cariowa G, Majorkowska-Mech D. An Algorithm for Quaternion-Based 3D Rotation. *International Journal of Applied Mathematics and Computer Science*. 2020;30:149–160. Available from: https://doi.org/10.34768/amcs-2020-0012.
7) Jose JA, Kumar CS, Sureshkumar S. Region-Based Split Octonion Networks with Channel Attention Module for Tuna Classification. *International Journal of Pattern Recognition and Artificial Intelligence*. 2022;36(07):2250030. Available from: https://doi.org/10.1142/S0218001422500306.
8) Chouhan SS, Kumar R, Sarkar S, Das S. Multistability analysis of octonion-valued neural networks with time-varying delays. *Information Sciences*. 2022;609:1412–1434. Available from: https://doi.org/10.1016/j.ins.2022.07.123.
9) Takahashi K, Fujita M, Hashimoto M. Remarks on Octonion–valued Neural Networks with Application to Robot Manipulator Control. In: IEEE International Conference on Mechatronics (ICM). IEEE. 2021;p. 1–6. Available from: https://doi.org/10.1109/ICM46511.2021.9385617.
10) Cariow A, Cariowa G. Fast Algorithms for Quaternion-Valued Convolutional Neural Networks. *IEEE Transactions on Neural Networks and Learning Systems*. 2021;32(1):457–462. Available from: https://doi.org/10.1109/TNNLS.2020.2979682.
11) Wu J, Xu L, Wu F, Kong Y, Senhadji L, Shu H. Deep octonion networks. 2020. Available from: https://doi.org/10.1016/j.neucom.2020.02.053.
12) Rasheed J, Waziry S, Alsubai S, Abu-Mahfouz AM. An Intelligent Gender Classification System in the Era of Pandemic Chaos with Veiled Faces. *Processes*. 1427;10(7):1427. Available from: https://doi.org/10.3390/pr10071427.

13) Rani RM, Pushpalatha M. Generation of Frequent sensor epochs using efficient Parallel Distributed mining algorithm in large IOT. *Computer Communications*. 2019;148:107–114. Available from: https://doi.org/10.1016/j.comcom.2019.09.006.
14) Garain A, Ray B, Singh PK, Ahmadian A, Senu N, Sarkar R. GRA_Net: A Deep Learning Model for Classification of Age and Gender From Facial Images. *IEEE Access*. 2021;9:85672–85689. Available from: https://doi.org/10.1109/ACCESS.2021.3085971.
15) Abirami B, Subashini TS, Mahavaishnavi V. Gender and age prediction from real time facial images using CNN. *Materials Today: Proceedings*. 2020;33:4708–4712.
16) Abdolrashidi A, Minaei M, Azimi E, Minaee S. Age and gender prediction from face images using attentional convolutional network. 2020. Available from: https://doi.org/10.48550/arXiv.2010.03791.
17) Ghildiyal A, Sharma S, Verma I, Marhatta U. Age and Gender Predictions using Artificial Intelligence Algorithm. *3rd International Conference on Intelligent Sustainable Systems (ICISS)*. 2020;p. 371–375. Available from: https://doi.org/10.1109/ICISS49785.2020.9316053.
18) Gupta SK, Nain N. Review: Single attribute and multi attribute facial gender and age estimation. *Multimedia Tools and Applications*. 2023;82(1):1289–1311. Available from: https://doi.org/10.1007/s11042-022-12678-6.
19) Swaminathan A, Chaba M, Sharma DK, Chaba Y. Gender Classification using Facial Embeddings: A Novel Approach. *Procedia Computer Science*. 2020;167:2634–2642. Available from: https://doi.org/10.1016/j.procs.2020.03.342.
20) Xiao J, Guo X, Li Y, Wen S, Shi K, Tang Y. Extended analysis on the global Mittag-Leffler synchronization problem for fractional-order octonion-valued BAM neural networks. *Neural Networks*. 2022;154:491–507. Available from: https://doi.org/10.1016/j.neunet.2022.07.031.