Facial recognition based on enhanced neural network

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ABSTRACT

Accurate automatic face recognition (FR) has only become a practical goal of biometrics research in recent years. Detection and recognition are the primary steps for identifying faces in this research, and The Viola-Jones algorithm implements to discover faces in images. This paper presents a neural network solution called modify bidirectional associative memory (MBAM). The basic idea is to recognize the image of a human's face, extract the face image, enter it into the MBAM, and identify it. The output ID for the face image from the network should be similar to the ID for the image entered previously in the training phase. The tests have conducted using the suggested model using 100 images. Results show that FR accuracy is 100% for all images used, and the accuracy after adding noise is the proportions that differ between the images used according to the noise ratio. Recognition results for the mobile camera images were more satisfactory than those for the Face94 dataset.

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1. INTRODUCTION

The ability to recognize an individual based on their face has become an increasingly important and widely discussed topic in recent years. Face detection (FD) is the essential step of it [1], [2]. Face recognition (FR) system performance has improved dramatically, mainly when used in different applications in many areas where it can be employed for criminal identification or as an alternative to a password [3], [4].

FR is the system by which an individual is recognized by comparing live capture or digital image data with that individual's stored record [5], [6]. Images with faces in them are crucial for intelligent vision-based human-computer interaction (HCI), prompting researchers to focus on tasks including face tracking, emotion identification, facial posture estimation, and facial recognition [7], [8]. Progress achieved in detecting and recognizing still images and videos using frontal view, lateral face view, or facial emotions, including dissatisfaction, happiness, and gloominess [9], [10]. Recently, the FR system has drawn more research aimed at improving the recognition process and has two primary tasks: identification and verification [11], [12]. In biometrics for human authentication, FR plays a crucial role as it is one of the biometric techniques used in banks, laptops, and industries for security purposes [13], [14].

The quick progress of machine learning-based systems has made HCI applicable to many new domains, including unmanned aerial vehicles (UAV) detection [15], Lung segmentation [16], speaker identification [17], video summarization [18], handwriting recognition [19], contextual anomaly detection [20], temperature prediction [21], food recognition [22], face retrieval system [23], wildfire detection [24], and many more. Therefore, an unsupervised neural network that contrasts favorably with other techniques has been used. The framework joins in local image sampling with neural network of self-organizing maps. Images of the various individuals will be scanned and used as a database [25]. The suggested approach of FR uses the modify bidirectional associative memory (MBAM) neural network discussed in this research. The following outline depicts the portions of the paper: the relevant research is reported in section 2. The core algorithm of the suggested scheme is shown in section 3. Section 4 provides a comprehensive breakdown of the suggested system. The MBAM evaluates and contrasts the proposed plan and similar ones in section 5. The summary of the findings is offered in section 6.

2. LITERATURE REVIEW

Zangeneh *et al.* [26] propose a new hybrid mapping approach employing deep convolution neural networks (DCNNs) for low-resolution face identification. The proposed architectural design uses two DCNN sub-parts to converge low- and high-density facial images via nonlinear diversion. Their comprehensive experimental assessments demonstrate that the suggested technique to enhances detection capability greatly, particularly for very low-resolution face images of the probe (5 percent enhancement in recognition accuracy).

The approach proposed by Kumar *et al.* [27] may be used indoors and outdoors . It allows the visually impaired to access the world with minimal difficulty by navigating around obstacles and identifying the person's location in front of them. The analysis of the scheme's implementation shows that 75% of the blind find it provides and supports a 90% correct outcome for FR and a 95% accurate outcome for difficulty detection.

Li *et al.* [28] have examined FR systems by images taken in the wild in low-quality circumstances. They offer experimental results and complete analysis for 2 of the most excellent and significant systems in existing observation systems; the following three assistance are prepared: i) super-resolution methods for low-quality FR tested through attitude experiments; ii) With actual research and low-quality subsets of large scale datasets, the research faces re-identification on a variety of public face datasets, A current baseline performance for different deep learning depends on methods and enhances them by adding a pre-training process and completely coevolutionary design of the generative adversarial network (GAN); and iii) by using a recent supervised system of discriminatory learning, they find low-quality face recognition. Evaluations based on complex components of the UnConstrained College Students (UCCS) and surveillance cameras (SC) faces datasets.

Deng *et al.* [29], to get highly biased attributes for face identification, an additive angular margin loss (ArcFace) has been devised. Since it corresponds precisely to the euclidean radius on the curved spacetime, the suggested ArcFace has a simple geometric meaning. They offered arguably the best detailed investigational evaluation on 10 FR standards against all recent FR approaches. This comprises a sophisticated huge image archive encompassing trillions of couples as well as a large-scale video data set. They show that ArcFace can be easily adopted with little operational strain and routinely outperforms the recent techniques.

Chen *et al.* [30] used a mighty CNN technic. MobileFaceNets is explicitly designed for high-precision real-time face verification on mobile and authentication devices and utilized less than a million factors. Due to ArcFace on the pure MS- Celeb-1's failing, M was drilled, and now the 4.0 MB. For modern, huge CNN models, this equates to hundreds of megabytes.

Zhi and Liu [31] have built an efficient model of FR that is based on primary component analysis, support vector machine (SVM), and genetic algorithm (GA). Within this model, primary component analysis is used to reduce the number of components, while SVM and GA are used to optimize the results. In 2003, running a series of simulations using their face database to assess the model's ability to create a high-efficiency biometric system with a maximum overall accuracy of 99%.

3. MODIFIED BIDIRECTIONAL ASSOCIATIVE MEMORY (MBAM)

MBAM is an updated neural network of bidirectional associative memory by adapting the net construction, convergence, and learning process. For construction modification, the net size becomes static (2 neurons) for any any pattern length. This net size caused the learning weight matrix to become small (4 matrices). This net has reached infinite stored patterns for learning process adjustment; that is to say, it retains its efficacy even if the number of patterns stored is grown. Finally, the issue of convergence procedure correlation is solved, so MBAM net can effectively retrieve and store the correlation patterns, and the net in real-time is speedy and feasible. The use of MBAM eliminates most of BAM's drawbacks, except for the issue of scaling and shifting. Furthermore, its ability to recognize patterns with substantial noise increases. Figure 1 at Appendix shows the net's architecture [32], [33].

4. PROPOSED METHODOLOGY

Among the many intricate and well-researched fields of computer vision, FR stands out. The research will suggest an improved method for FR using neural network called modify bidirectional associative memory

(MBAM) to describe a neural network MBAM-based facial recognition technique. This system is divided into four phases, as shown in Figure 2.

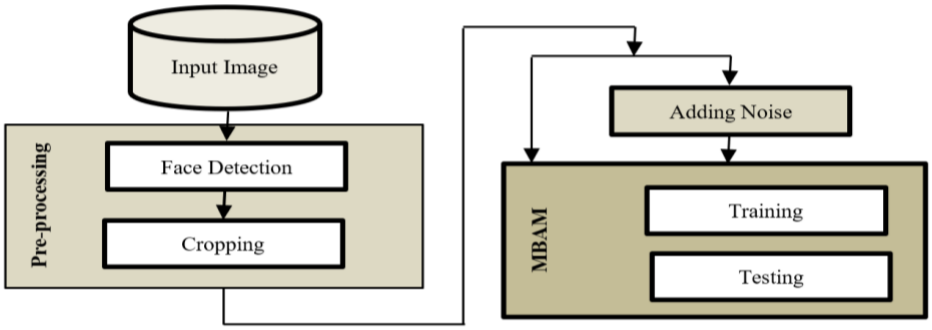


Figure 2. The schema represents how all the phases work

In the first phase, the input images used in the research are of two types, the first is images taken from the phone's camera, and its size is (130×130), and its type is jpg, as shown in Figure 3, and the second type of dataset is Face94 [34] (Facial images) standard consisting of 153 persons (female and male). Most of the people depicted are first-year college students, making them around 18 to 20 years old, while there are also some more senior people in the collection. Some of the people have beards or eyeglasses. Figure 4 depicts the image format, which is 24-bit color JPEG shot with an S-VHS camcorder using a simulated lighting setup consisting of fluorescent overhead lights and tungsten bulbs.

Preprocessing, which occurs during phase 2, consists of two steps. The first step, depicted in Figure 5, is face detection, which uses the Viola-Jones (V-J) algorithm [35]–[38] to identify humans. Following the FD procedure, the second step will define the face depending on the cropping of the face, as presented in Figure 6.

Figure 3. phone's camera

Figure 4. Face94 standard dataset

The third phase is phase training and testing the MBAM network. Firstly, the network is learning using cropping faces images with their ID (a random code generated by a network with each input image in the training phase). Also, converting images with their code to binary images is done. Secondly, after training the network on face images with their code and testing the network is doing, the ID matching with ID for cropping face images is called the recognition phase, and the ending result shows in Figure 7. Finally, each cropping image may be added to some noise in the fourth phase and entered into MBAM to ensure network efficiency.

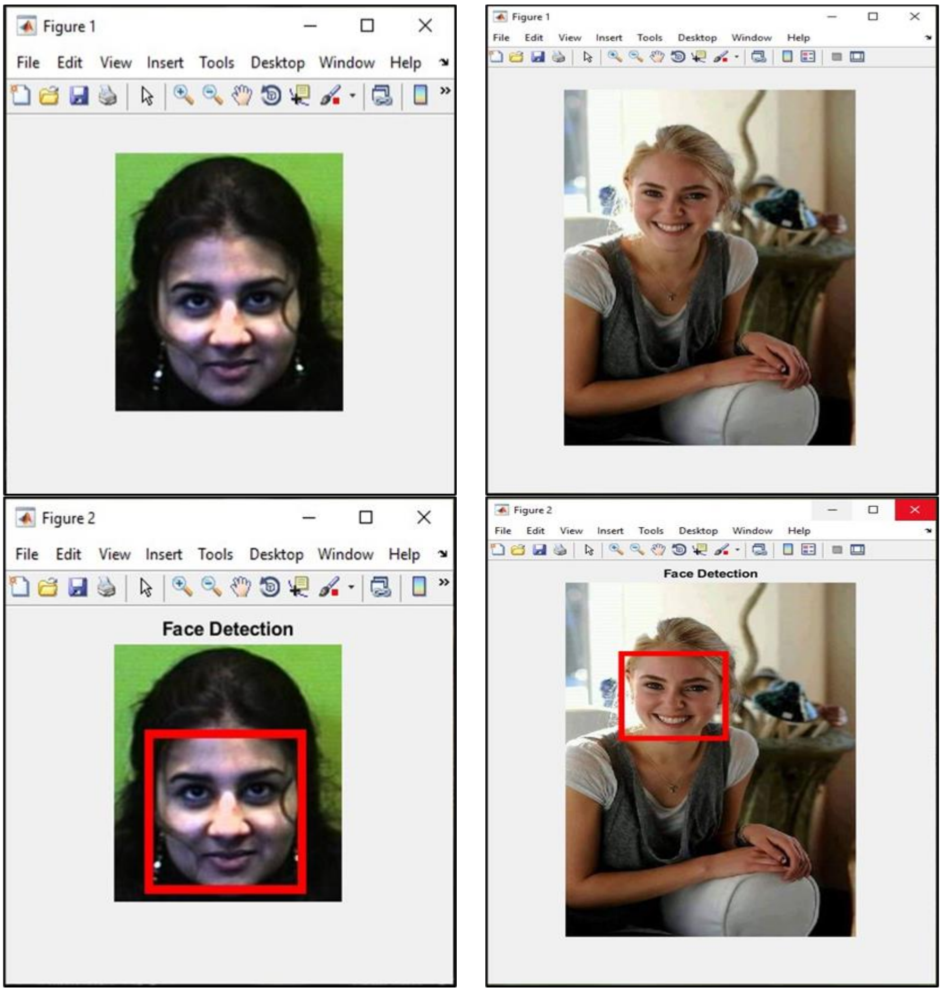


Figure 5. FD by V-J algorithm

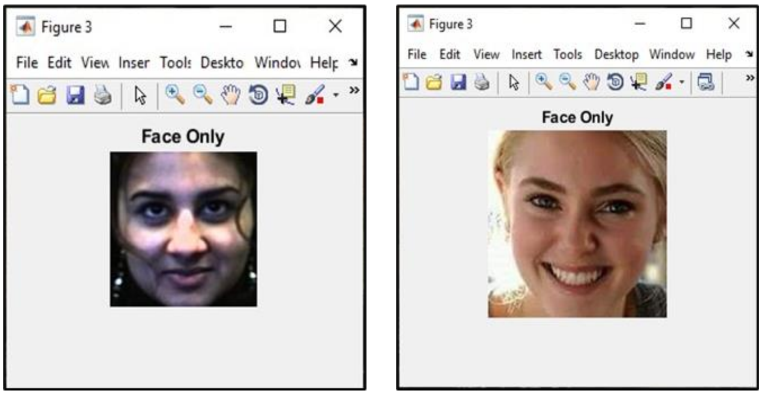


Figure 6. Cropping the face image

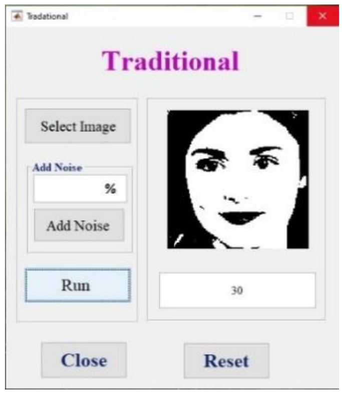


Figure 7. Recognition phase

5. RESULTS AND DISCUSSION

This part presents an experiment to estimate the MBAM net in FR. The proposed system has experimented on two types of images (camera and Face94 standard) and tested on the same two groups previously mentioned after adding some noise to it. These experiments proved the efficiency of the net in recognizing faces by examining the noise rate (mistakes and missing bits).

5.1. Different number of stored images vs. retrieval rate

In this experiment, for MBAM, the task was to find out the maximum image retrieval with image codes. The process stopped when it succeeded in fully recognizing the stored images. Table 1 shows the MBAM network retrieval ratio.

Table 1. The MBAM network retrieval ratio for two groups of images

No. stored images	MBAM net retrieval	
	Images of camera	Face94 standard images
1	100%	100%
2	100%	100%
3	100%	100%
4	100%	100%
5	100%	100%
100	100%	100%

5.2. Performance analysis

In the previous experiment, it was noticed that all the images used in the research were recognized. That is, all the images were retrieved as a result of the work of the MBAM network, whose structure is designed to accommodate large numbers of images at the same time, despite the small size of the network structure. Figure 8 illustrates the image retrieval process.

5.3. Different noise rates vs. retrieval rates

This experiment implements the retrieval process for images with different noise ratios. Table 2 shows the MBAM network retrieval rate for the previously trained images after adding varying noise ratios ranging from 10% to 90%. Tables 3 and 4 illustrate the recognition result after adding the noise to the collected mobile camera and Face94 images, respectively.

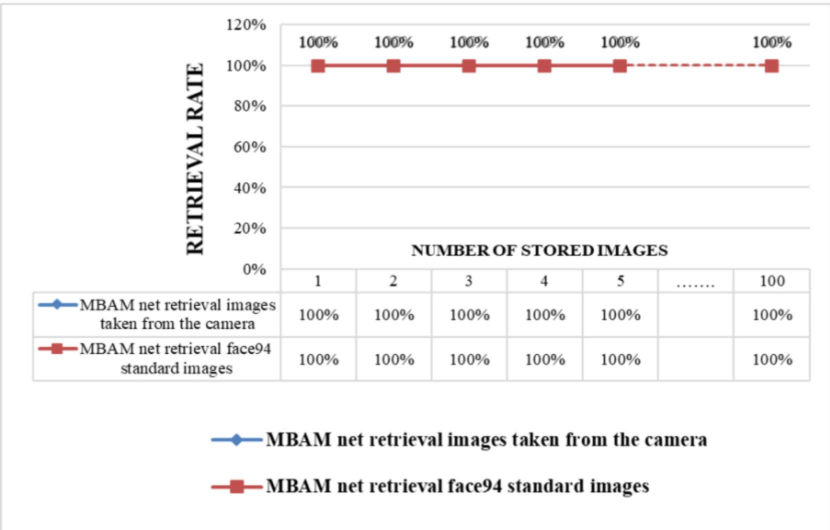
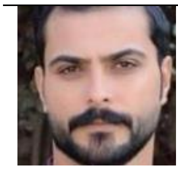
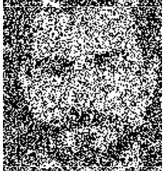
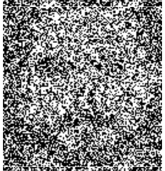
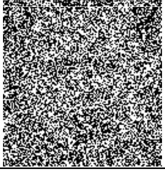


Figure 8. Diagram illustrating the process of retrieving images by MBAM net

Table 2. The MBAM network retrieval ratio for images after adding noise in different ratio

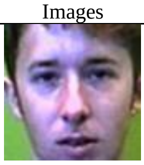
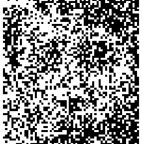
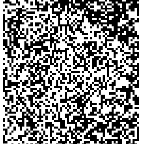
Noise Ratio	MBAM net retrieval	
	Images of camera	Face94 standard images
10%	100%	100%
20%	100%	97%
30%	100%	94%
40%	100%	88%
50%	100%	66%
60%	100%	63%
70%	100%	51%
80%	77%	44%
90%	48%	36%

Table 3. Illustrating the recognition result after adding the different noise ratios to mobile camera images

Images of camera	Code recognition	Noise Ratio	Image after adding noise	Code recognition in a test phase	Correct/incorrect recognition
	4	10%		4	Correct
		20%		4	Correct
		30%		4	Correct
		40%		4	Correct
		50%		4	Correct
		60%		4	Correct
		70%		4	Correct
		80%		31	incorrect
		90%		22	incorrect

Retrieval efficacy for MBAM is satisfied. For standard images, when the noise rate is 10%, the MBAM retrieval is 100%. But also, when the noise rate is 20%, the network retrieval is 97%. It became clear that network retrieval became inaccurate in the Face94 standard images stored whenever the noise ratio became high. While the camera takes the images, the retrieval efficiency for the MBAM network is very accurate. But when the noise ratio is 80% or 90%, the network retrieval is reduced, as shown in Figure 9, which compares results with all images used in the research with different noise rates.

Table 4. Illustrating the recognition result after adding the different noise ratios to Face94 images

Face94 Standard Images	Code recognition	Noise Ratio	Image after adding noise	Code recognition in a test phase	Correct/incorrect recognition
	3	10%		3	Correct
		20%		3	Correct
		30%		3	Correct
		40%		3	Correct
		50%		7	Incorrect
		60%		5	Incorrect
		70%		8	Incorrect
		80%		6	Incorrect
		90%		15	Incorrect

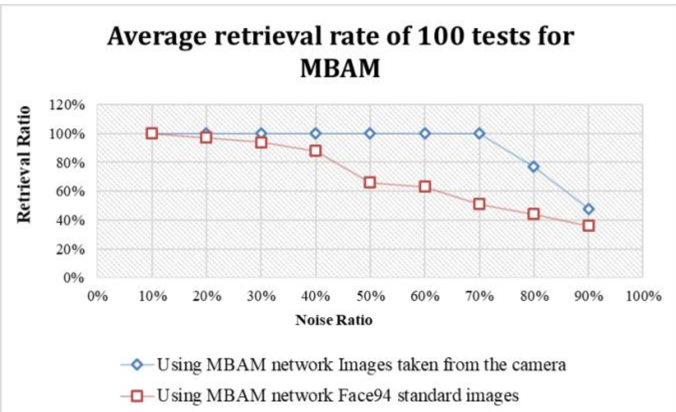


Figure 9. Comparison of results with different noise rates

5.4. Comparative analysis of the methods

An analytical comparison was made between the current research and the suggested method. Table 5 shows this comparison. It is noted that the planned way accomplished the highest percentage of discrimination compared to recent studies.

Table 5. Comparison between preceding systems and the proposed approach

Reference No.	Year	Dataset	Preprocessing and Features Method	Classification Method	Recognition accuracy
Zangeneh *et al.* [26]	2020	FERET, LFW, and MBGC	Feature extraction convolutional neural network (FECNN) and super resolution and FECNN (SRFECNN)	VGGnet	81.4% for FERET 6×6
Kumar *et al.* [27]	2017	Camera	measuring the facial component values (Euclidean distance equation)	Neural Network	90%
Li *et al.* [28]	2019	SCface and UCCS	Match-net, 6-channel-net, Siamese-net	DCGAN	73.6% vs. UCCS result
Deng *et al.* [29]	2019	LFW, YTF, CALFW, and CPLFW. IJB-B, IJB-C, and MegaFace	MxNet	Softmax loss	CPLFW= 92.08, YTF= 98.02, CALFW= 95.45, LFW= 99.83,
Chen *et al.* [30]	2018	CASIA-Web	MobileFaceNet	PReLU	92.59% TAR@FAR1e-6 on MegaFace and 99.55% on LFW
Zhi and Liu [31]	2019	CAS-PEAL	GA, geometric relationship for face template, and principal component analysis (PCA)	SVM	99%
Proposed System	2022	Phone's Camera and Face94 Standard Images	FD (Viola-Jones algorithm) and Cropping the Face	MBAM	100%

6. CONCLUSION

The using an MBAM to build an FR system in this paper is suggested. The second phase is preprocessing the input image based on the V-J algorithm for FD. Finally, the MBAM neural network is applied to face classification. The retrieval ratio of the network for two groups of images is 100 %, and after adding noise is a different ratio. Moreover, the literature review was presented, and a comparison between the preceding systems and the proposed approach is made in this paper.

APPENDIX

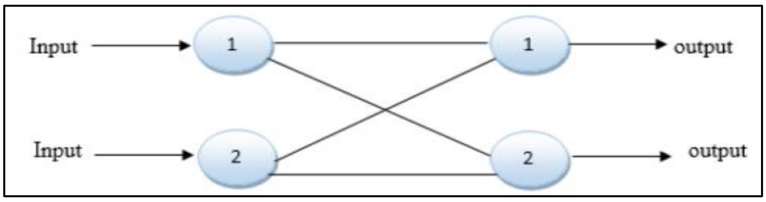


Figure 1. The MBAM net

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REFERENCES

[1] R. Qarooni, J. Prunty, M. Bindemann, and R. Jenkins, "Capacity limits in face detection," *Cognition*, vol. 228, p. 105227, Nov. 2022, doi: 10.1016/j.cognition.2022.105227.
[2] W. Wang *et al.*, "TNNL: A novel image dimensionality reduction method for face image recognition," *Digital Signal Processing: A Review Journal*, vol. 115, p. 103082, Aug. 2021, doi: 10.1016/j.dsp.2021.103082.
[3] C. Yu and H. Pei, "Face recognition framework based on effective computing and adversarial neural network and its implementation in machine vision for social robots," *Computers and Electrical Engineering*, vol. 92, p. 107128, Jun. 2021, doi: 10.1016/j.compeleceng.2021.107128.

[4] F. V. Massoli, F. Carrara, G. Amato, and F. Falchi, "Detection of face recognition adversarial attacks," *Computer Vision and Image Understanding*, vol. 202, p. 103103, Jan. 2021, doi: 10.1016/j.cviu.2020.103103.
[5] K. G. Shanthi, S. Sesha Vidhya, K. Vishakha, S. Subiksha, K. K. Srija, and R. Srinee Mamtha, "Algorithms for face recognition drones," *Materials Today: Proceedings*, vol. 80, pp. 2224–2227, 2021, doi: 10.1016/j.matpr.2021.06.186.
[6] D. T. T. Vijaya Kumar and R. Mahammad Shafi, "Analysis and fast feature selection technique for real-time face detection materials using modified region optimized convolutional neural network," *Materials Today: Proceedings*, vol. 81, pp. 563–569, 2022, doi: 10.1016/j.matpr.2021.04.011.
[7] M. Ahmady, S. S. Mirkamali, B. Pahlevanzadeh, E. Pashaei, A. A. R. Hosseinabadi, and A. Slowik, "Facial expression recognition using fuzzified Pseudo Zernike Moments and structural features," *Fuzzy Sets and Systems*, vol. 443, pp. 155–172, Aug. 2022, doi: 10.1016/j.fss.2022.03.013.
[8] K. Hümmer, J. Coenen, I. Konstantinidis, H. Lausberg, and I. Helmich, "Impaired recognition of nonverbal expressions of emotions in depressed individuals," *Psychiatry Research*, vol. 302, p. 114031, Aug. 2021, doi: 10.1016/j.psychres.2021.114031.
[9] H. Rodger *et al.*, "The recognition of facial expressions of emotion in deaf and hearing individuals," *Heliyon*, vol. 7, no. 5, p. e07018, May 2021, doi: 10.1016/j.heliyon.2021.e07018.
[10] C. Gan, J. Yao, S. Ma, Z. Zhang, and L. Zhu, "The deep spatiotemporal network with dual-flow fusion for video-oriented facial expression recognition," *Digital Communications and Networks*, Jul. 2022, doi: 10.1016/j.dcan.2022.07.009.
[11] R. Biswas, V. González-Castro, E. Fidalgo, and E. Alegre, "A new perceptual hashing method for verification and identity classification of occluded faces," *Image and Vision Computing*, vol. 113, p. 104245, Sep. 2021, doi: 10.1016/j.imavis.2021.104245.
[12] K. H. Rahouma and A. Z. Mahfouz, "Design and implementation of a face recognition system based on API mobile vision and normalized features of still images," *Procedia Computer Science*, vol. 194, pp. 32–44, 2021, doi: 10.1016/j.procs.2021.10.057.
[13] K. G. Shanthi, P. Sivalakshmi, S. V. S., and S. L. K., "Smart drone with real time face recognition," *Materials Today: Proceedings*, vol. 80, pp. 3212–3215, 2021, doi: 10.1016/j.matpr.2021.07.214.
[14] K. Alhanaee, M. Alhammadi, N. Almenhali, and M. Shatnawi, "Face recognition smart attendance system using deep transfer learning," *Procedia Computer Science*, vol. 192, pp. 4093–4102, 2021, doi: 10.1016/j.procs.2021.09.184.
[15] F. A. Abdulmunem and S. A. Mahmood, "UAV detection method using convolution neural networks optimized by hyper parameters tuning," in *IICETA 2022 - 5th International Conference on Engineering Technology and its Applications*, May 2022, pp. 140–146, doi: 10.1109/IICETA54559.2022.9888450.
[16] H. Ayad, I. W. Ghindawi, and M. S. Kadhm, "Lung segmentation using proposed deep learning architecture," *International journal of online and biomedical engineering*, vol. 16, no. 15, pp. 141–147, Dec. 2020, doi: 10.3991/ijoe.v16i15.17115.
[17] A. M. Jalil, F. S. Hasan, and H. A. Alabbasi, "Speaker identification using convolutional neural network for clean and noisy speech samples," in *1st International Scientific Conference of Computer and Applied Sciences, CAS 2019*, Dec. 2019, pp. 57–62, doi: 10.1109/CAS47993.2019.9075461.
[18] S. K. Jarallah and S. A. Mahmood, "Query-based video summarization system based on light weight deep learning model," *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 6, pp. 247–262, Dec. 2022, doi: 10.22266/ijies2022.1231.24.
[19] A. K. Hussein, "Fast learning neural network based on texture for Arabic calligraphy identification," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 3, pp. 1794–1799, Mar. 2021, doi: 10.11591/ijeecs.v21.i3.pp1794-1799.
[20] S. A. Mahmood, A. M. Abid, and W. A. K. Naser, "Contextual anomaly detection based video surveillance system," in *Proceedings - 2021 11th IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2021*, Aug. 2021, pp. 120–125, doi: 10.1109/ICCSCE52189.2021.9530859.
[21] H. K. Hoomod and Z. S. Amory, "Temperature prediction using recurrent neural network for internet of things room controlling application," in *2020 5th International Conference on Communication and Electronics Systems ({ICCES})*, Jun. 2020, pp. 973–978, doi: 10.1109/icces48766.2020.9137885.
[22] A. K. Hussein, "Feature weighting based food recognition system," *Journal of Logistics, Informatics and Service Science*, vol. 9, no. 3, pp. 191–207, 2022, doi: 10.33168/LISS.2022.0314.
[23] S. A. Alazawi, N. M. Shati, and A. H. Abbas, "Texture features extraction based on GLCM for face retrieval system," *Periodicals of Engineering and Natural Sciences*, vol. 7, no. 3, pp. 1459–1467, Oct. 2019, doi: 10.21533/pen.v7i3.787.
[24] A. S. Mahdi and S. A. Mahmood, "An edge computing environment for early wildfire detection," *Annals of Emerging Technologies in Computing*, vol. 6, no. 3, pp. 56–68, Jul. 2022, doi: 10.33166/AETiC.2022.03.005.
[25] N. Deotale, S. L. Vaikole, and S. D. Sawarkar, "Face recognition using artificial neural networks," in *2010 The 2nd International Conference on Computer and Automation Engineering, ICCAE 2010*, Feb. 2010, vol. 2, pp. 446–450, doi: 10.1109/ICCAE.2010.5451595.
[26] E. Zangeneh, M. Rahmati, and Y. Mohsenzadeh, "Low resolution face recognition using a two-branch deep convolutional neural network architecture," *Expert Systems with Applications*, vol. 139, p. 112854, Jan. 2020, doi: 10.1016/j.eswa.2019.112854.
[27] P. M. Kumar, U. Gandhi, R. Varatharajan, G. Manogaran, J. R, and T. Vadivel, "Intelligent face recognition and navigation system using neural learning for smart security in internet of things," *Cluster Computing*, vol. 22, no. S4, pp. 7733–7744, Nov. 2019, doi: 10.1007/s10586-017-1323-4.
[28] P. Li, L. Prieto, D. Mery, and P. J. Flynn, "on low-resolution face recognition in the wild: Comparisons and new techniques," *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 8, pp. 2000–2012, Aug. 2019, doi: 10.1109/TIFS.2018.2890812.
[29] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "ArcFace: Additive angular margin loss for deep face recognition," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2019, vol. 2019-June, pp. 4685–4694, doi: 10.1109/CVPR.2019.00482.
[30] S. Chen, Y. Liu, X. Gao, and Z. Han, "MobileFaceNets: Efficient CNNs for accurate real-time face verification on mobile devices," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10996 LNCS, Springer International Publishing, 2018, pp. 428–438.
[31] H. Zhi and S. Liu, "Face recognition based on genetic algorithm," *Journal of Visual Communication and Image Representation*, vol. 58, pp. 495–502, Jan. 2019, doi: 10.1016/j.jvcir.2018.12.012.
[32] N. A. A. Jabr and E. I. A. Kareem, "Modify bidirectional associative memory (MBAM)," *International Journal of Modern Trends in Engineering and Research (IJMTER)*, vol. 2, no. 08, pp. 136–151, 2015, [Online]. Available: https://www.ijmter.com/issue-papers/?select_Volume=2&select_issue=8.
[33] R. H. Hasan, N. A. Alhadi, and E. A. Kareem, "Password authentication based on modify bidirectional associative memory (MBAM)," *International Journal of Recent Trends in Engineering & Research (IJRTER)*, vol. 2, no. June 2017, pp. 261–267, 2016, [Online]. Available: https://www.ijrter.com/issue-papers/?select_Volume=2&select_issue=2.
[34] D. L. Spacek, "Facial images: Faces94," 2022, [Online]. Available: https://cmp.felk.cvut.cz/~spacelib/faces/faces94.html.
[35] C. A. Ruiz-Beltrán, A. Romero-Garcés, M. González, A. S. Pedraza, J. A. Rodríguez-Fernández, and A. Bandera, "Real-time

embedded eye detection system," *Expert Systems with Applications*, vol. 194, p. 116505, May 2022, doi: 10.1016/j.eswa.2022.116505.

[36] G. V. Sai Prasanna, K. Pavani, and M. K. Singh, "Spliced images detection by using Viola-Jones algorithms method," *Materials Today: Proceedings*, vol. 51, pp. 924–927, 2021, doi: 10.1016/j.matpr.2021.06.300.

[37] T. Paul, U. A. Shammi, M. U. Ahmed, R. Rahman, S. Kobashi, and M. A. R. Ahad, "A study on face detection using viola-jones algorithm for various backgrounds, angles and distances," *Biomedical Soft Computing and Human Sciences*, vol. 23, no. 1, pp. 27–36, 2018.

[38] M. K. Mathur and P. Bhati, "Face objects detection in still images using viola-jones algorithm through MATLAB Tools," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 5, no. 2, pp. 2468–2476, 2017.

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