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Implementation and evaluation of Heskes self organizing map counter propagation network for face recognition

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ABSTRACT

Face recognition has attracted a lot of interest in the fields of computer vision and pattern recognition given its extensive applications in security, surveillance, and human-computer interaction. Many linear and non-linear classifiers have been introduced to bring about effectiveness in face recognition, however, the problem of occlusion, light conditions and changes in face persist. The Heskes-self-organizing map (SOM) counter propagation network (CPN) model leverages the competitive learning and self-organizing features of SOM CPN with Heskes layer to improve the effectiveness and accuracy of face recognition systems. Heskes-SOM CPN was implemented and evaluated on MATLAB R2016a using 600 images captured with the aim of digital camera. The implemented model was trained with 360 face images and tested with 240 face images using accuracy, sensitivity, specificity, and false positive rate as performance metrics at four distinct threshold values of 0.23, 0.35, 0.50, and 0.75. The major objective of the research was achieved by investigating with 50×50 and 200×200 face dimensions. Empirical results and statistical evidence established that Heskes-SOM CPN has high accuracy of approximately 97.92%, high specificity of 98.33%, high sensitivity of 99.44%, and a very low filter performance rating (FPR) of 1.67%. Therefore, Heskes-SOM CPN is presented as a novel CPN model for face recognition.

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1. INTRODUCTION

Face recognition is an inherent ability in humans, however, machines are now equipped with the same ability to recognize human faces through pattern recognition [1], [2]. Face recognition is essential in several fields, such as security, surveillance, education, and human-computer interaction and its application is fast increasing [3]–[9]. The three basic stages involved in face recognition are shown in Figure 1 as situated in studies [10]–[12], while it may be four or five stages in some cases [13], [14]. Several linear models have been successfully implemented for face recognition, however, the advent of artificial neural network (ANN) has led to the implementation of some non-linear models which are more accurate in handling face recognition [14]–[16]. Nevertheless, there is still need for improved models that can better handle differences in facial expressions, varying illumination conditions, occlusion, and changes in face, as these challenges still limit face recognition systems in real life application [17]–[19]. Study has established that improving the classification stage will lead to improvement in the face recognition ability of models [20]. Therefore, this study presents the implementation and evaluation of an improved classifier for face recognition.

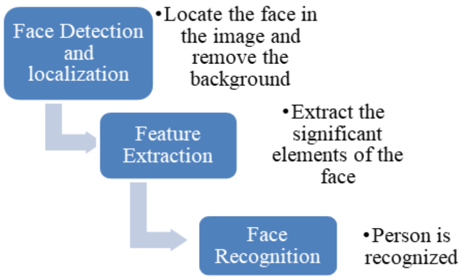

Figure 1. Basic components of face recognition system [12]

Classification is a crucial stage in face recognition and classifiers with high accuracy can help in overcoming the identified face recognition poblems [21], [22]. Various classifiers have been developed to handle classification in face recognition domain [20]. Additionally, ANN has spurred great improvement in classifiers used in face recognition leading to the introduction of convolution neural network (CNN) [8], [15], recurrent neural network (RNN) [23], and counter propagation network (CPN) [10]. CPN is of interest in this study due to its self-hybrid learning procedure. Nielsen [10] postulated CPN in 1987 by combining supervised and unsupervised learning, hence, it primarily consists of two layers, which are a vector quantization layer (VQL) called Kohonen self organizing map (SOM) layer introduced by Teuvo Kohonen in 1984, followed by a classification layer known as Grossberg layer [10]. Today, CPNs are multilayer networks that operate by combining the input, clustering and the output layers for face recognition [24]. The basic structure of CPN is shown in Figure 2. Modification of either Kohonen (middle) layer and Grossberg (classification) layer or both layers of CPN has led to various variants of CPN, which includes fuzzy CPN [25], adaptive CPN [24], revised CPN [26], improved SOM, modified CPN [13], and parallel CPN [27]. However, none of these CPN variants has been able to fully overcome the problems of face recognition.

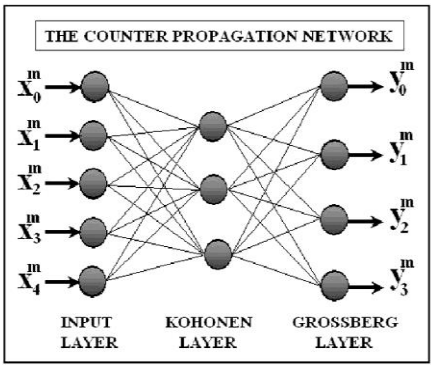

Figure 2. Basic structure of CPN [27]

Recently, Villman *et al.* [28] described new CPN variants including Heskes-SOM CPN, neural gas (NG) CPN, and a few others. These newly described CPN variants are resulting from the modification of either the middle layer or classification layer of the original Kohonen CPN [10]. However, these new variants were only described, but were neither implemented nor evaluated. Only NG CPN has been recently implemented [14]. There is need to not only implement these newly described CPN variants, but to equally evaluate their performance for face recognition. Therefore, this paper presents the implementation and evaluation of Heskes-SOM CPN for face recognition.

This study is significant and relevant as it implements Heskes-SOM CPN to improve the competitive learning process of CPN [10] by merging the inherent topological mapping capabilities of SOM [29] with the energized continuous learning process introduced by Heskes [30] for better classification. This is made possible by replacing the Kohonen SOM layer with Heskes-SOM layer. Therefore, the implemented Heskes-SOM CPN model replaces the middle Kohonen-SOM layer with Heskes-SOM layer because it has similar learning procedure according to Villman *et al.* [28] and the scheme of Heskes-SOM CPN is expressed in (1). The input is X, the middle layer, which is the Heskes-SOM layer is expressed in (2), and the classification layer (C-layer) remains the same as that of the original Kohonen CPN as expressed in (3). This study presents the implementation and evaluation of Heskes-SOM CPN for face recognition because Heskes-SOM CPN yields high accuracy, sensitivity and specificity, and would be able to tackle face recognition issues. Heskes-SOM CPN is presented as a novel CPN variant through empirical performance evaluation and statistical validation using scattered line graphs.

$$\mathrm{X} \xrightarrow[\text{Heskes-SOM}]{} \mathrm{W} \xrightarrow[\text{Crisp}]{\Sigma(\mathrm{x,W})} \Xi \xrightarrow[\text{Perceptron}]{\mathrm{y(x)}} \mathscr{L} \tag{1}$$

$$\xrightarrow[\text{Crisp}]{\Sigma(\mathrm{x,W})} \Xi \; \mathscr{L} \tag{2}$$

$$\Xi \xrightarrow[\text{Perceptron}]{\mathrm{y(x)}} \mathscr{L} \tag{3}$$

The remaining sections of this paper are arranged as follows: the connected works are reviewed in section 2. Section 3 describes the methodology employed, including the training and testing phases of the algorithm. Section 4 compiles an analysis of the empirical result and discussion, while section 5 presents the conclusion of the study and recommendation.

2. RELATED STUDIES

Adeyanju *et al.* [13] conducted a performance evaluation of an improved self-organizing feature map (SOFM) and modified CPN techniques in face recognition using 6 face images from 40 individuals taken with a digital camera to construct an Africa database with 240 face images. MATLAB was used for the pre-processing of the images, and local histogram equalization was used to normalize them in order to improve their contrast. Each image was reduced in size from 600×800 pixels to four alternative dimensions: 50×50, 100×100, 150×150, and 200×200 pixels using principal component analysis (PCA). SOFM and modified CPN techniques were used as classifiers for face recognition and evaluated with best selected similarity threshold value, while 140 images were used for training and 100 images for testing. According to the results of this study, modified CPN performed better at face recognition than SOFM in terms of computation time and recognition accuracy as performance metrics [13].

Gosavi *et al.* [31] performed a comprehensive analysis of various feature extraction methods, including active shape model (ASM), active appearance model (AAM), Gabor features, template-based, and others, coupled with various neural classification networks for face recognition, including CNN, backpropagation neural network (BPNN), radial basis function (RBF), and probabilistic neural network (PNN). The strategies used in the literature's methodologies and algorithms were examined, and it becomes clear that each one is distinct and performs at its best. These strategies were further compared in the study based on their benefits and drawbacks. Therefore, probabilistic bayesian neural networks (PBNN) and CNN are shown to be more accurate than the others, however these two have some minor drawbacks, most notably image scaling [31].

Kortli *et al.* [12] carried out a thorough comparison on several well-known strategies for local, holistic, and hybrid approaches, and a taxonomy of the categories they fall under was presented by outlining the benefits and drawbacks of the schemes of each technique in terms of robustness, accuracy, complexity, and discrimination. The database utilized for facial recognition was one intriguing aspect highlighted, while the most popular databases, including those for supervised and unsupervised learning were described in general. The most intriguing techniques' numerical findings were presented along with information about the experiments and problems they were used to solve. Finally, a thorough assessment of future approaches for facial recognition systems was included in the study.

Villman *et al.* [28] presented a description of new CPN variants in a recent work based on the modification of different layers of the conventional CPN that was first proposed by Nielsen in 1987 [10]. Various VQL were explored in details, as well as how to send the data to the classification layer. The information bottleneck paradigm was examined in relation to this, and thoughts on network training were given. As a result, unlike in the original approach, both layers were not handled individually during training. To put it more specifically, detailed description of the vector quantization of the model was described.

Olagunju *et al.* [14] introduced NG convolutional polynomial neural network (CPNN) as a novel model for face recognition. The study was based on replacing the middle Kohonen layer with a NG layer because both layers have similar functionality as VQL. The study was implemeneted using MATLAB2016a, while the model showed a high sensitivity, high specificity and low computational time. However, despite the contributions of various studies reveiewed, it is clear that the challenges of face recognition still persist and there is need for a non-linear model that can better recognize human face. This identified gap informed this study.

3. METHOD

The methodology used in this research includes data collection, pre-processing, feature extraction, face classification and results evaluation. A dataset of 600 digital camera-captured facial images was used to implement the Heskes-SOM CPN model. Captured face images were pre-processed by improving image quality through histogram equalization [32], while image resolution were reduced in sequence to 50 by 50 and 200 by 200 pixels by PCA. Figure 3 shows the grayscale face images. The model was implemented using MATLAB2016a, while dimentionally reduced 360 images and 240 images were used during the training and the testing phases respectively. Sensitivity, specificity, accuracy and false positive rate (FPR) were the performance metrics used to evaluate the model's adaptability to changes in facial features as used by Adeyanju *et al.* [13], while threshold values were established at 0.23, 0.35, 0.50, and 0.75. Figure 4 shows the flowchart of the training and testing phases of the Heskes-SOM CPN.

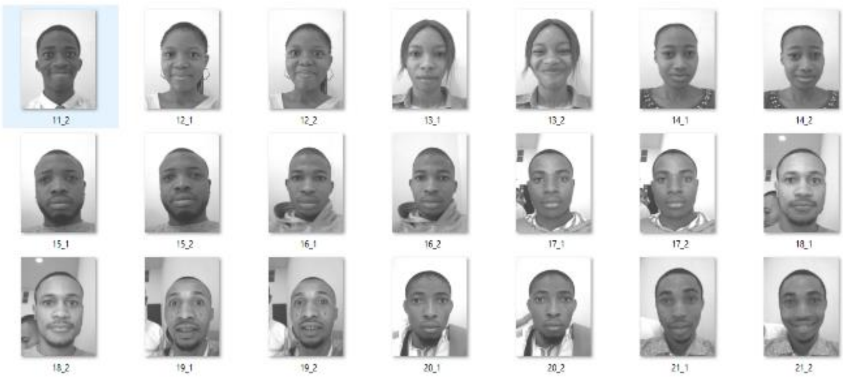

Figure 3. Grayscale face images

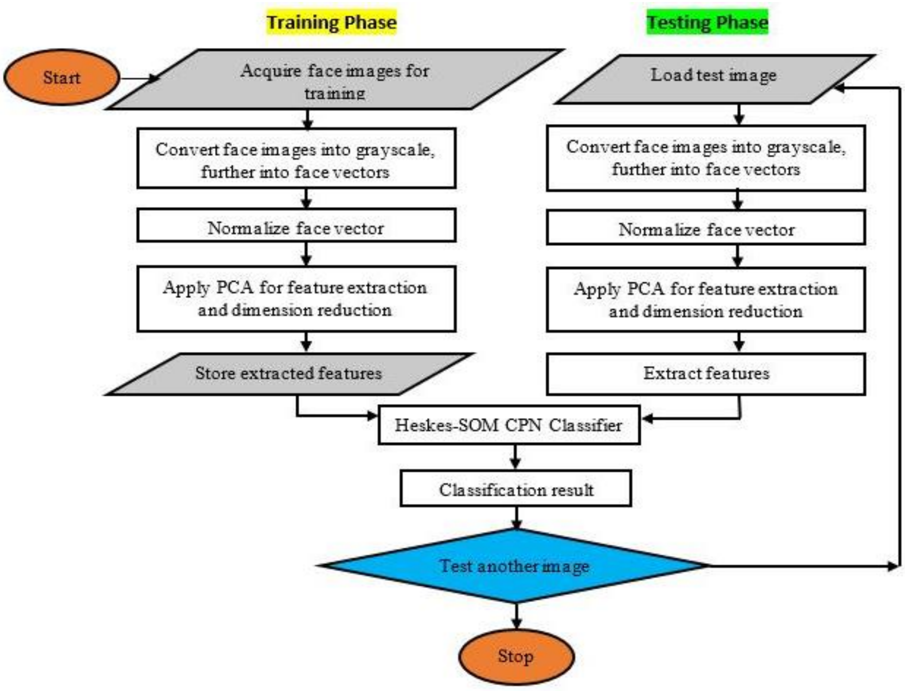

Figure 4. Flowchart of face training and testing phases using heskes-SOM CPN algorithm

4. RESULTS AND DISCUSSION

The results and discussion of the performamce of Heskes-SOM CPN using specificity, sensitivity, accuracy, and FPR as evaluation metrics is presented in this section. The image resolution has no effect on the performance of Heskes-SOM CPN, but the threshold value has significant effect as different results were gotten at different threshold values. Heskes-SOM CPN model performed admirably with a high sensitivity of 99.44%, high specificity of 98.33%, high accuracy of roughly 97.92% and an extremely low FPR of 1.67% as shown in Table 1. It has 179 true positive (TP) out of 180 at threshold from 0 to 0.23 with only 1 false negative (FN), while it has 51 true negative (TN), and 9 false positive (FP); which implies that it correctly classified 179 face images out of 180 trained face images, and correctly recognized 51 untrained face images out of 60. That is, it precisely recognized 230 face images out of 240 testing images. These findings show that Heskes-SOM CPN is robust and reliable across a range of face dimensions. Therefore, statistical and empirical findings support the usefulness of Heskes-SOM CPN in face recognition.

Table 1. Evaluation results of Heskes-SOM CPN

Threshold	TP	FN	FP	TN	Sensitivity (%)	Specificity (%)	Accuracy (%)	FPR (%)
0.23	179	1	9	51	99.44444	85	95.83333	15
0.35	178	2	6	54	98.88889	90	96.66667	10
0.5	177	3	3	57	98.33333	95	97.5	5
0.75	176	4	1	59	97.77778	98.33333	97.91667	1.66667

4.1. Sensitivity evaluation

Figure 5 presents the sensitivity results of Heskes-SOM CPN, showing 99.44%, 98.89%, 98.33%, and 97.78% at 0.23, 0.35, 0.5, and 0.75 threshold values respectively. Heskes-SOM CPN has its highest sensitivity of 99.44% at the lowest threshold range of 0 to 0.23, and its lowest sensitivity of 97.78% at the highest threshod range of 0.51 to 1.0; this implies that sensitivity of Heskes-SOM CPN is inversely propotional to threshold values as shown in Figure 5. However, face dimension does not affect sensitivity of Heskes-SOM CPN because the model yieded the same result at 50×50 and 200×200 face resolutions. It should be noted that in real life application, threshold range for the implementation should be set from 0 to 0.23 to get a high sensitivity. Generally, using sensitivity as a parameter to test the performance of Heskes-SOM CPN at 50×50 and 200×200 pixel gives a high sensitivity across the threshold values.

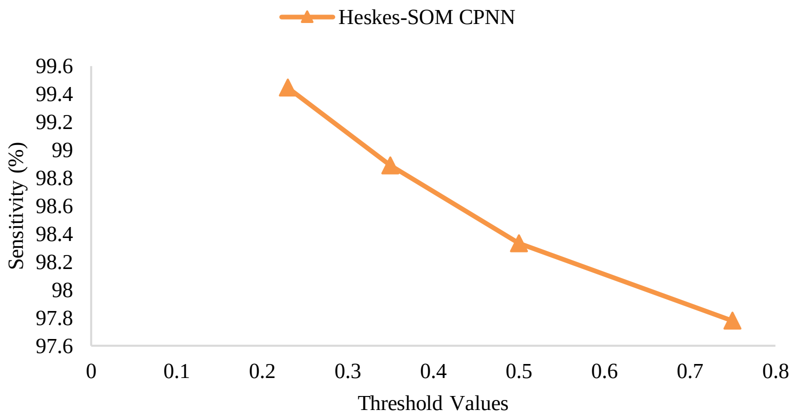

Figure 5. Sensitivity evaluation of Heskes-SOM CPN

4.2. Specificiy evaluation

Figure 6 presents the results of performance of Heskes-SOM CPN offering 85%, 90%, 95%, and 98.33% at 0.23, 0.35, 0.5, and 0.75 threshold values respectievly. This indicates that the model has high specificity across the threshold values, which implies that its specificity is directly proportional to the threshold values. It also implies that the specificity of Heskes-SOM CPN is highest at the highest threshold. Its highest specificity is 98.33%, while its lowest specificity is 85%. However, image dimension does not affect the specificity of Heskes-SOM CPN.

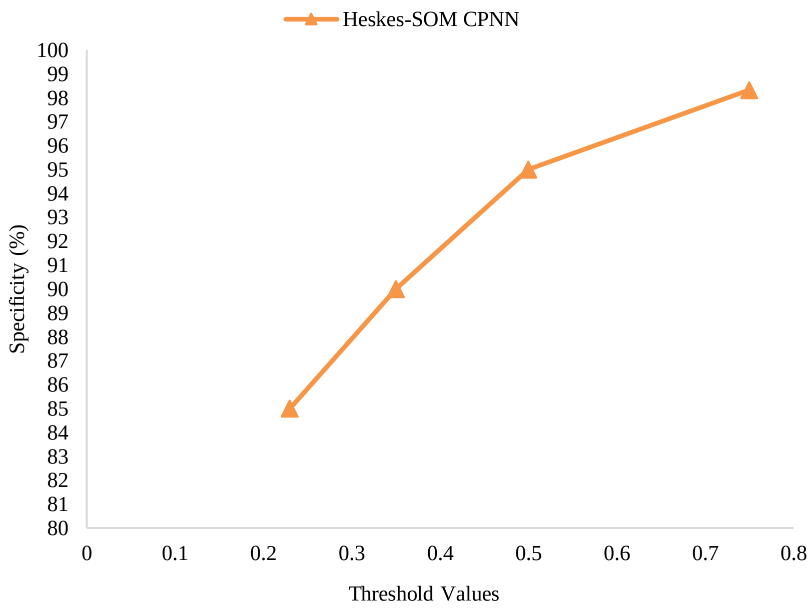

Figure 6. Specificity evaluation fo Heskes-SOM CPN

4.3. Accuracy evaluation of Heskes-self-organizing map counter propagation network

Figure 7 shows the accuracy results of Heskes-SOM CPN as 95.83%, 96.67%, 97.5%, and 97.92% at 0.23, 0.35, 0.5, and 0.75 threshold values respectievly. It is obvious that accuracy increases as threshold values increases, that is, accuracy is also directly proportional to threshold value. Therefore, threshold values from 0.51 to 1.0 should be chosen to achieve high accuracy for real life application because Heskes-SOM CPN has its highest accuracy at the highest threshold range of 0.51 to 1.0.

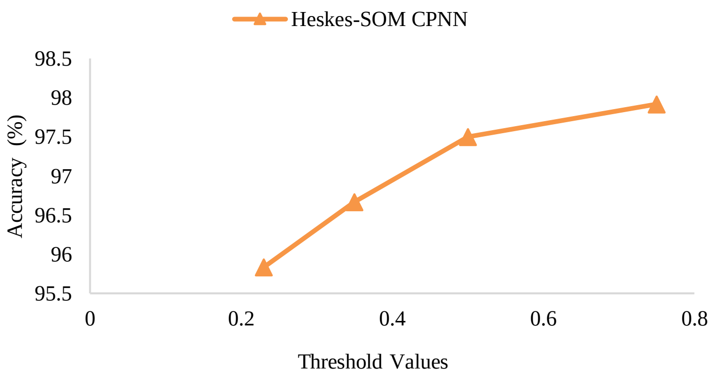

Figure 7. Plot of accuracy evaluation of Heskes-SOM CPN

4.4. False positive rate evaluation

The proportion of positive cases that were incorrectly classified as negative by Heskes-SOM CPN is low. Figure 8 shows the result of FPR of Heskes-SOM CPN as 15%, 10%, 5% and 1.67% at 0.23, 0.35, 0.5 and 0.75 threshold values respectively. Highest FPR of Heskes-SOM CPN at threshold range of 0 to 0.23 is 15%, while its lowest FPR is 1.67% at the highest threshold range of 0.51 to 1.0. FPR is inversely proportional to threshold values, with its lowest FPR of 1.67% at 0.75 threshold value. Generally, FPR has inverse relationship with the performance of the models. Therefore, low FPR indicate high performance of Heskes-SOM CPN model, which makes it reliable for face recognition.

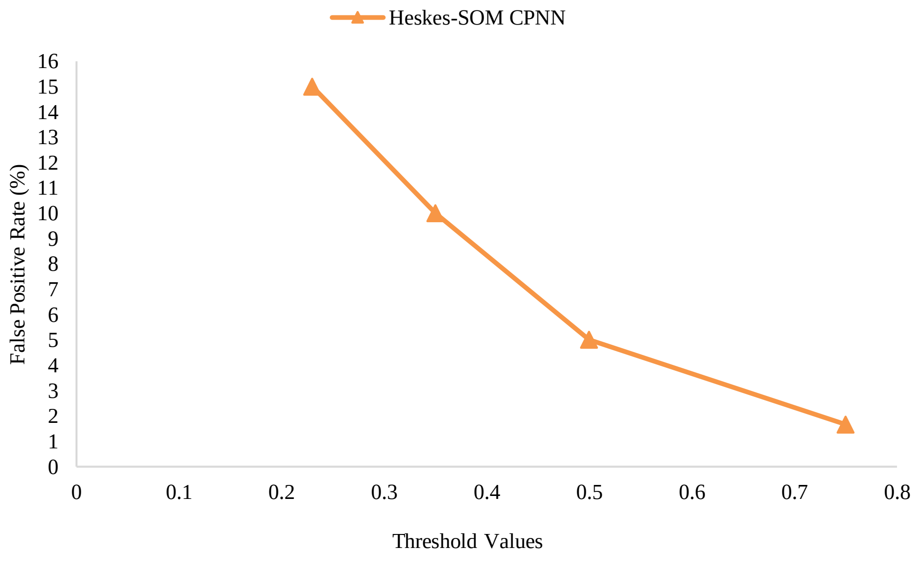

Figure 8. FPR evaluation of Heskes-SOM CPN

4.5. Result validation

The validation of the result is established using sensitivity and accuracy as shown in Table 2. Heskes-SOM CPN performs better than the original CPN implemented by Adeyanju *et al.* [13] at 50×50 image resolution. However, the number of testing and training images used in the two studies varied, which may be responsible for the difference in the performance of the system.

Table 2. Validation of results

Evaluation metrics	Sensitivity (%)	Accuracy (%)
CPN	83	81
Heskes-SOM CPN	99.44	97.92

5. CONCLUSION

The implementation and performance evaluation of Heskes-SOM CPN has been successfully carried out in this research. By utilizing sensitivity, specificity, accuracy and FPR as performance evaluation metrics, it has been empirically established that Heskes-SOM CPN has great prospect in face recognition due to its outstanding performance across various thresholds. The evaluation results of Heskes-SOM CPN implemented as a new CPN variant revealed extremely high sensitivity of 99.44%, high specificity of 98.33%, excellent accuracy of 97.92%, and significantly low FPR of 1.67%, which makes it an excellent choice for face recognition application. This non-linear model will contribute significantly in solving the identified problems in face recognition domain. This research has not only implemented Heskes-SOM CPN, but it empirically established that Heskes-SOM CPN is a novel model with high sensitivity, specificity, accuracy and low FPR. This implies that the performance of Heskes-SOM CPN is significantly high in face recognition. The validation conducted equally revealed that Heskes-SOM CPN outperformed the original CPN, and it has the chance of outperforming other existing linear and non-linear algorithms in real life application. Therefore, Heskes-SOM CPN should be embraced in real life scenario. A wider scope performance evaluation can be carried out between Heskes-SOM CPN and the existing face recognition algorithms to determine which one performs best in future studies. Additionally, in future research, others variants of CPN described by previous researchers can be implemented using the same number of training and testing images to further check if there could be any variant which could have better performance than Heskes-SOM CPN.

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REFERENCE

[1] A. J. O'Toole and C. D. Castillo, "Face recognition by humans and machines: three fundamental advances from deep learning," *Annual Review of Vision Science*, vol. 7, pp. 543–570, 2021, doi: 10.1146/annurev-vision-093019-111701.

[2] B. Mandal, R. Y. Lim, P. Dai, M. R. Sayed, L. Li, and J. H. Lim, "Trends in machine and human face recognition," *Advances in Face Detection and Facial Image Analysis*, pp. 145–188, 2016, doi: 10.1007/978-3-319-25958-1_7.

[3] J. García-Rodríguez and J. M. García-Chamizo, "Surveillance and human-computer interaction applications of self-growing models," *Applied Soft Computing Journal*, vol. 11, no. 7, pp. 4413–4431, 2011, doi: 10.1016/j.asoc.2011.02.007.

[4] I. Adjabi, A. Ouahabi, A. Benzaoui, and A. Taleb-Ahmed, "Past, present, and future of face recognition: A review," *Electronics*, vol. 9, no. 8, pp. 1–53, 2020, doi: 10.3390/electronics9081188.

[5] C. Mingtsung, Q. Wei, H. Jiaqi, and Z. Zhuomin, "Research on the application of face recognition system," *Journal of Physics: Conference Series*, vol. 1684, no. 1, 2020, doi: 10.1088/1742-6596/1684/1/012126.

[6] S. Wang, "The application of face recognition system," in *Advances in Social Science, Education and Humanities Research*, 2022, vol. 631, pp. 242–247, doi: 10.2991/assehr.k.220105.046.

[7] I. O. Joshua, M. O. Arowolo, M. O. Adebiyi, O. R. Oluwaseun, and K. A. Gbolagade, "Development of an image processing techniques for vehicle classification using OCR and SVM," *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals, SEB-SDG 2023*, 2023, doi: 10.1109/SEB-SDG57117.2023.10124622.

[8] R. S. Babatunde, A. N. Babatunde, R. O. Ogundokun, A. R. T. Abdulahi, and A. González-Briones, "An evaluation of the performance of convolution neural network and transfer learning on face gender recognition," *Ambient Intelligence – Software and Applications – 14th International Symposium on Ambient Intelligence (ISAmI 2023)*, Springer, Cham, pp. 63–73, Sep. 2023, doi: 10.1007/978-3-031-43461-7_7.

[9] H. Benradi, A. Chater, and A. Lasfar, "A hybrid approach for face recognition using a convolutional neural network combined with feature extraction techniques," *IAES International Journal of Artificial Intelligence*, vol. 12, no. 2, pp. 627–640, 2023, doi: 10.11591/ijai.v12.i2.pp627-640.

[10] R. Hecht-Nielsen, "Counter-propagation networks," *Applied Optics*, vol. 26, no. 12, pp. 4979–4984, 1987.

[11] R. Jafri and H. R. Arabnia, "A survey of face recognition techniques," *Journal of Information Processing Systems*, vol. 5, no. 2, pp. 41–68, 2009, doi: 10.3745/jips.2009.5.2.041.

[12] Y. Kortli, M. Jridi, A. Al Falou, and M. Atri, "Face recognition systems: A survey," *Sensors*, vol. 20, no. 2, 2020, doi: 10.3390/s20020342.

[13] I. Adeyanju, O. Awodoye, and E. Omidiora, "Performance evaluation of an improved self-organizing feature map and modified counter propagation network in face recognition," *British Journal of Mathematics & Computer Science*, vol. 14, no. 3, pp. 1–12, 2016, doi: 10.9734/bjmcs/2016/22588.

[14] K. Olagunju, A. Oke, A. Falohun, and M. Adebiyi, "Neural gas counter propagation neural network (NG CPNN): a novel model for face recognition," *2024 IEEE International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG2024)*, no. 112, 2024.

[15] S. Guo, S. Chen, and Y. Li, "Face recognition based on convolutional neural network & support vector machine," *2016 IEEE International Conference on Information and Automation, IEEE ICIA 2016*, pp. 1787–1792, 2017, doi: 10.1109/ICInfA.2016.7832107.

[16] B. O. Makinde, O. D. Fenwa, A. S. Falohun, and O. A. Odeniyi, "Performance evaluation of kernel-based feature extraction techniques for face recognition system," *FUOYE Journal of Engineering and Technology*, vol. 4, no. 1, 2019, doi: 10.46792/fuoyejet.v4i1.285.

[17] M. Hassaballah and S. Aly, "Face recognition: challenges, achievements and future directions," *IET Computer Vision*, vol. 9, no. 4, pp. 614–626, 2015, doi: 10.1049/iet-cvi.2014.0084.

[18] A. A. Azeta, D. O. A. Iboroma, V. I. Azeta, E. O. Igbekele, D. O. Fatinikun, and E. Ekpunobi, "Implementing a medical record system with biometrics authentication in E-health," *2017 IEEE AFRICON: Science, Technology and Innovation for Africa, AFRICON 2017*, pp. 979–983, 2017, doi: 10.1109/AFRCON.2017.8095615.

[19] Y. El Madmoune, I. El Ouariachi, K. Zenkouar, and A. Zahi, "Robust face recognition using convolutional neural networks combined with Krawtchouk moments," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 4, pp. 4052–4067, 2023, doi: 10.11591/ijece.v13i4.pp4052-4067.

[20] H. Yang and X. A. Wang, "Cascade classifier for face detection," *Journal of Algorithms and Computational Technology*, vol. 10, no. 3, pp. 187–197, 2016, doi: 10.1177/1748301816649073.

[21] R. S. Kute, V. Vyas, and A. Anuse, "Component-based face recognition under transfer learning for forensic applications," *Information Sciences*, vol. 476, pp. 176–191, 2019, doi: 10.1016/j.ins.2018.10.014.

[22] O. Fowora, O. Okesola, A. Adebiyi, and M. Adebiyi, "Towards the integration of iris biometrics in automated teller machines (ATM)," *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals, SEB-SDG 2023*, 2023, doi: 10.1109/SEB-SDG57117.2023.10124646.

[23] Q. Yang and C. Guo, "Face recognition based on sparse representation and RNN optimization," *International Journal of Digital Content Technology and its Applications*, vol. 5, no. 9, pp. 314–322, 2011, doi: 10.4156/jdcta.vol5.issue9.35.

[24] Y. Dong, C. Sun, and X. Tai, "An adaptive counter propagation network," in *Eighth ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing (SNPD 2007)*, Jul. 2007, vol. 3, pp. 695–700, doi: 10.1109/SNPD.2007.372.

[25] V. Sakhre, S. Jain, V. S. Sapkal, and D. P. Agarwal, "Fuzzy counter propagation neural network control for a class of nonlinear dynamical systems," *Computational Intelligence and Neuroscience*, vol. 2015, 2015, doi: 10.1155/2015/719620.

[26] S. F. Jiang, C. Fu, C. M. Zhang, and Z. Q. Wu, "A revised counter-propagation network model integrating rough set for structural damage detection," *International Journal of Distributed Sensor Networks*, vol. 9, no. 11, pp. 1-10, 2013, doi: 10.1155/2013/850712.

[27] A. I. Margaris and E. Kotsialos, "Parallel counter-propagation neural networks," *Proceedings of the International Conference on Theory and Applications of Mathematics and Informatics - ICTAMI 2004*, 2004.

[28] T. Vilman, R. Schubert, and M. Kaden, "New variants of counter propagation neural network for classification learning- a formal description of strategies and respective approaches," *Machine Learning Reports*, University of Applied Sciences Mittweida Technikumplatz, pp. 3-19, 2021.

[29] M. Cottrell, M. Olteanu, F. Rossi, and N. Villa-Vialaneix, "Theoretical and applied aspects of the self-organizing maps," *Advances in Intelligent Systems and Computing*, vol. 428, pp. 3–26, 2016, doi: 10.1007/978-3-319-28518-4_1.

[30] T. M. Heskes and B. Kappen, "Learning processes in neural networks," *Physical Review A*, vol. 44, no. 4, pp. 2718–2726, 1991, doi: 10.1103/PhysRevA.44.2718.

[31] V. R. Gosavi, G. S. Sable, and A. K. Deshmane, "Evaluation of feature extraction techniques using neural network as a classifier:

a comparative review for face recognition,” *International Journal of Scientific Research in Science and Technology*, vol. 4, no. 2, pp. 1082–1091, 2018.
[32] M. Sunaryo and M. Hariadi, “Preprocessing on digital image using histogram equalization: an experiment study on MRI brain image,” *International Journal of Computer Science and Information Technologies*, vol. 7, no. 4, pp. 1723–1727, 2016.

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