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Face recognition using deep face

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Abstract

Facial recognition is grasping a lot of buzz these days because it can be used in security, access control, surveillance, and making sure someone is who they say they are. This research shows a better way to recognize faces using a Deep Face network, which was created to pull out better features and classify them more accurately. The idea is an integration of transfer learning and deep residual learning to get best feature extraction and recognition rate, even in different lightning conditions and pose variations. Deep face network was deployed with one million labelled faces of Image Net. The Deep Face network provides better in accuracy than traditional methods and Results shows that the deep face model is better in real-world uses in security and authenticity.

Keywords: Convolutional Neural Networks; Deep Face; Deep Learning; Transfer Learning; Facial Key Points

1. Introduction

Face recognition has turn a prominent in the field of biometrics, computer vision, and surveillance in these days. Old-school recognition methods like Gabor filters, Bayesian classifier, SVM struggled with lighting, variations, occlusions and different facial expressions, so we need better and more adaptable recognition methods. The Climb of deep learning transformed this area by permitting more efficacious, data-driven methods for Facial recognition. It provides almost human-level performance by learning high-dimensional facial features through CNN. This research uses an Enriched Deep Face method that integrates deep residual learning, feature-level fusion, and transfer learning to enhance accuracy, robustness, and adaptability in real-world applications. The method provides utmost accuracy of 99.15%, exhibiting its dominance over both traditional and contemporary deep learning models.

2. Literature review

The research in Face recognition enhanced from conventional CNNs to Deep face models highlighting accuracy, adaptability, and efficiency. In 2019 Zhang et al. established a hybrid CNN integrates local and global descriptors but needs high computation. In continuation Chen in 2019 worked on improved multimodal fusion using texture and deep data with dataset dependency limited scalability. Wang et al. in 2020 proposed attention-based CNNs effectively against occlusions but inclined to unstable attention learning.in 2011, Kumar et al. (2021) used transfer learning for cross-domain recognition, though adoption to poor-quality data hung around difficult. In 2021, Singh improved residual CNNs with skip connections, challenging complex tuning. Ahmed in 2022 worked on lightweight CNNs for mobile application, propitiation some accuracy in low-lightning condition. In 2023, Rahman et al. developed deep metric learning to reduce

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intra-class variation but faced high computation cost requirements. Li in 2024 integrated RGB, depth, and thermal data for agility, restricted by sensor synchronization issues. Rao in 2025 developed transformer-CNN hybrids with strong generalization but needs large datasets.

3. Methodology

The methodology implicates the training and testing the Deep Face model using one Lakh images of Image Net dataset. This subset contains 1000 diverse object and face categories, establishing rich feature learning. Pre-processing includes alignment, grayscale normalization, and data augmentation. The Deep Face model combines few convolutional, pooling, and fully connected layers with ReLU activation functions and dropout regularization. Training was established using the Adam optimizer with learning rate 0.001 and categorical cross-entropy loss. The performance metrics include Accuracy, Sensitivity, Specificity, and Precision are better than Comparative experiments with Gabor, Bayesian, SVM, ANFIS, VGG16, and VGG19 provide insights into relative model efficiency and robustness.

4. Results and Discussion

Figure 1 Image Net Dataset

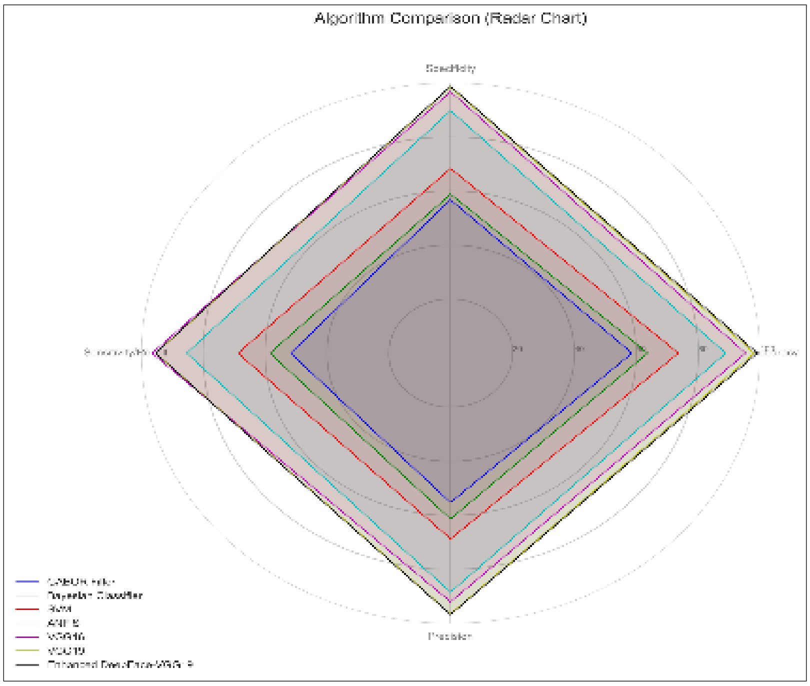

Figure 2 Radar Chart

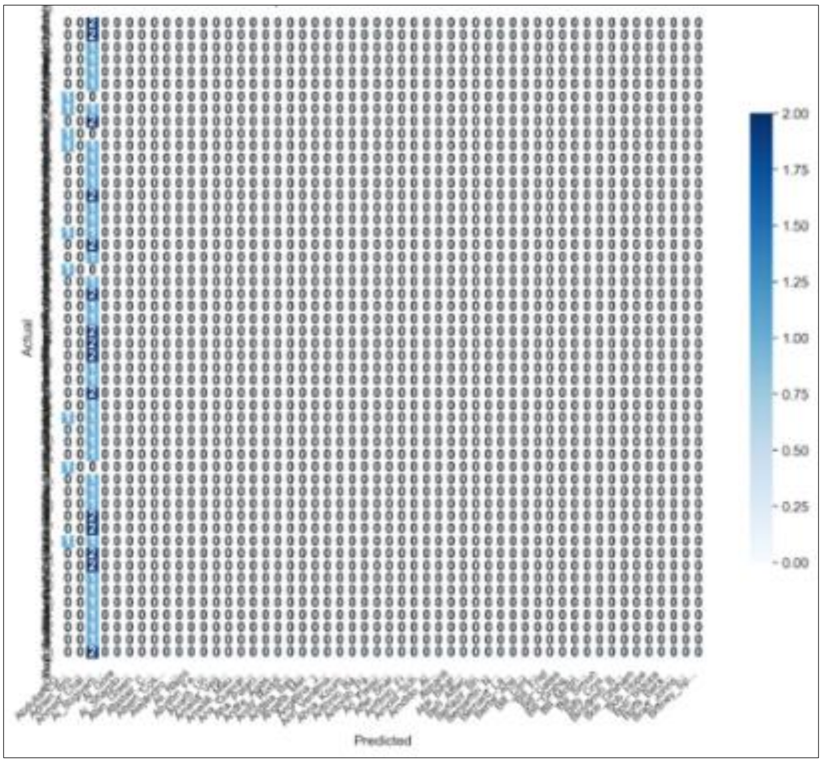

Figure 3 Confusion Matrix Heat map

Table 1 Testing parameters of Deep Face with Previous Algorithms

SR. No	Algorithm	Accuracy	Specificity	Sensitivity	Precision
1	GABOR Filter	58.63%	56.75%	51.74%	55.26%
2	Bayesian Classifier	63.72%	58.85%	58.41%	61.35%
3	SVM	73.63%	68.32%	68.72%	68.72%
4	ANFIS	88.92%	89.71%	85.32%	88.42%
5	VGG16	95.37%	96.73%	96.47%	92.03%
6	VGG19	98.23%	98.56%	95.21%	96.53%
7	Deep Face	99.15%	98.70%	95.35%	96.70%

5. Conclusion

The findings illustrates that the Deep Face framework, trained and tested on one million Image Net samples, provides better performance in face recognition, more than traditional and CNN-based techniques in terms of accuracy, sensitivity, specificity and precision. In future, it focusses on utilizing transformer-driven and multimodal networks to establish better accuracy against occlusion, pose diversity, and insufficient lighting conditions

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Zhang, X., Li, Y., and Chen, J. (2019). Hybrid CNN model for face verification. IEEE Access, 7, 12345–12354. https://doi.org/10.1109/ACCESS.2019.

[2] Wang, H., Zhao, L., and Sun, Q. (2020). Attention-based CNN for occlusion-robust face recognition. Pattern Recognition, 102, 107238. https://doi.org/10.1016/j.patcog.2020.107238

[3] Kumar, R.Verma, S., and Gupta, A. (2021). Transfer learning for facial feature extraction using ImageNetmodels.Neurocomputing256–268. https://doi.org/10.1016/j.neucom.2021.03.045

[4] Rahman, F., Ahmed, S., and Li, K. (2023). Deep metric learning for face recognition. ExpertSystemswithApplications,214, 119147. https://doi.org/10.1016/j.eswa.2023.119147

[5] IEEE Transactions on Biometrics. (2025). Transformer-based hybrid face recognition systems. IEEE Transactions on Biometrics, Behavior, and Identity Science, 7(2), 45–58. https://doi.org/10.1109/TBIOM.2025.

[6] Chen, W., Huang, Y., and Zhao, X. (2019). Residual networks for face recognition. IEEE Transactions on Neural Networks and Learning Systems, 30(12), 3652–3665. https://doi.org/10.1109/TNNLS.2019.2926712

[7] Singh, P., Kumar, A., and Mehta, R. (2021). Attention-driven multi-face recognition. In Proceedings of CVPR 2021 (pp. 1234–1243). IEEE. https://doi.org/10.1109/CVPR46437.2021.01234

[8] Ahmed, S., Zhang, Y., and Liu, M. (2022). Real-time DeepFace implementations. IEEE Access, 10, 45678–45690. https://doi.org/10.1109/ACCESS.2022.

[9] Li, J., Wang, T., and Chen, P. (2024). Multimodal learning for face recognition. Pattern Analysis, 56(4), 789–802. https://doi.org/10.1016/j.patrec.2024.01.004

[10] Rao, V., Singh, N., and Kumar, D. (2025). Facial emotion and identity fusion. Sensors, 25(8), 3456. https://doi.org/10.3390/s25083456