Similarity Learning for multimodal Biometrics

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Abstract

With the rapid use of technology and advancements in various domains of digital services, everyone needs secure and accurate identity verification systems. Traditional unimodal biometric systems generally suffer with the issue of inaccurate data, spoofing attacks and the irregularities introduced because of unconstrained environment. One of the solutions of these issues is to take one step ahead and move to multimodal biometric authentication system. These systems rely on multiple biometric traits instead of one at the time of validating the person's identity. Earlier researchers used to rely on handcrafted features extracted from the images for matching, later with the advancement of technology deep learning concepts transformed this domain completely. Now advanced deep learning architectures such as Siamese network and transformer models are providing a powerful framework for verification. This paper presents a deep discussion on the role of Siamese Networks in multimodal biometric authentication. The facts highlighted in the paper are based on a detailed examination of recent developments in similar domain.

Keywords: Multimodal Biometrics; Siamese Networks; Similarity Learning; Biometric Authentication; Identity Verification; Deep Learning; Biometric Fusion; Spoof-Resistant Security.

1. Introduction

In this digital era, when it is impossible to be without using digital services in our day-to-day life (i.e. Healthcare, financial transactions, cyber infrastructures and e-governance) requirement of reliable user authentication is very much critical. Earlier people used password-based mechanisms for authentication. Later, this complete system was overwritten by biometric systems which works on the concepts of various physiological and behavioral characteristics such as gait, fingerprint, face, periocular, ear etc.

The adoption of unimodal biometric is a common practice, however there are some challenges like noisy sensor data, intra-class variation, non-universality and spoofing attack. The performance of the authentication may vary due to illumination, pose, aging, environment and sensor quality. A one-point solution for all the issues was to make a shift to multimodal biometric authentication systems. As the name suggests, multimodal biometric authentication systems are basically a combination of multiple biometric features. One of the well-known examples is Aadhar Card authentication system which is a combination of face, iris and fingerprint. Using multiple biometric features make the system perform well and makes it efficient to handle the issue of pose aging and sensor quality.

Later, Use of Artificial Intelligence and then Deep learning in the domain of biometrics make a significant impact on biometric market. Use of Deep neural networks make researchers enable to create very much robust and precise authentication system which can show better performance in feature extraction and decision making. Again, one issue makes a little halt that deep neural network always needs a huge size database and to train the model and sometimes it is not possible.

A promising solution proposed by researchers was use of Siamese Networks. Siamese Network works on the concept of One-shot Learning approach means for verification only two samples of a particular subject image is needed. Siamese Network use feature embedding and then reduce distance between similar samples and increase the distance between different samples. This working methodology makes Siamese network a perfect choice for multimodal biometric authentication systems. By considering the above fact, this study attempts to provide a detailed overview of multimodal biometric authentication systems and Siamese networks. The discussion is done using PRISMA methodology. Apart from that a detailed discussion about current research trends, various fusion techniques, model performance evaluation approaches and for real world application is also done. Additionally, this review also talk about the existing problems in unimodal and multimodal biometric authentication system, about the research gaps based on the existing literature and intriguing future prospects such as transformer-based Siamese models, and privacy-enhancing biometric systems.

2. Related Work

2.1 Unimodal and Multimodal Biometric Systems

At the initial stage when biometric systems were introduced, they used to use only one biometric trait, either fingerprint or face for identification [1]. These systems were good when they were performing in controlled laboratory environment but found to be questionable when they must perform in non-ideal environment such as pose variation, noise, intra class variability etc. Solution for all the issues was to use multimodal biometric authentication systems. As the name suggests, multimodal biometric authentication systems are basically a combination of multiple biometric features. One of the well-known examples is Aadhar Card authentication system which is a combination of face, iris and fingerprint. Using multiple biometric features makes the system perform well and makes it efficient to handle the issue of pose aging and sensor quality [2-4].

2.2 Deep Learning for Biometric Authentication

With the introduction of deep learning, automatic extraction of features and learning of highly discriminative representations have changed the face of biometric authentication [5]. CNNs have already gained state of the art performance in modalities like face recognition and fingerprint recognition and hybrid architectures involving attention and recurrent neural network (RNN) layers have also been shown to enhance robustness in less constrained scenarios [6,7]. Besides, deep metric learning techniques have drawn ever more attention for verification-based tasks, where similar identities are attracted toward each other in the embedding space and dissimilar identities are repelled. Most current deep-learning based biometric systems are modality specific, however, and cannot be applied to heterogeneous biometric sources.

2.3 Siamese Networks for Similarity Learning

Originally developed for signature verification, Siamese Networks have been shown to be a highly effective deep metric learning framework for similarity-based applications such as face verification, speaker verification and person re-identification [8-9]. These architectures comprise of twin subnetworks with shared weights which learn a similarity function between pairs of inputs by using contrastive or triplet loss function. Siamese architectures have also been applied in multimodal biometric authentication with enhanced robustness, generalization and performance in cross-modal verification systems, recently [10-12]. While significant progress has been made, there are still difficulties in developing modality-invariant and scalable Siamese frameworks that can effectively process the heterogeneous biometric data in the real-world.

Table 1: Comparison of Related Work in Multimodal and Siamese-Based Biometric Authentication

Work	Modalities Used	Method / Fusion Strategy	Strengths	Challenges
[13]	Fingerprint, Face, Iris (Survey)	Review of fusion strategies	Comprehensive taxonomy of multimodal systems	Privacy, standardization issues
[14]	Multiple physiological traits	Multimodal fusion framework	Improved accuracy and spoof resistance	High computational complexity, dataset limitations
[15]	Face, Left & Right Palmprint	Score-level fusion with deep features	High accuracy over unimodal systems	Sensitive to noise and imaging conditions
[16], [17]	Fingerprint, Face, Ear	CNN / ViT with feature-level fusion	Strong recognition accuracy and robustness	High training cost, template security risks
[6], [16]	Face / Fingerprint	CNN + Deep metric learning	Strong embedding learning capability	Limited cross-modal generalization
[10-12]	Multimodal biometrics	Siamese Networks (contrastive / triplet loss)	Strong verification and cross-modal matching	Scalability and modality-invariance issues

3. PRISMA-Based Review Methodology and Proposed Framework

3.1 PRISMA-Based Systematic Review Methodology

The methodology employed in this study is systematic research with a systematic review framework, PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), which is necessary for research to be transparent, repeatable, and methodologically sound in synthesizing research on multimodal biometric authentication and Siamese network-based similarity learning systems. It has been employed in biometric and pattern recognition literature, because of its structured approach in literature identification, literature screening, eligibility assessment and final inclusion reporting. The major electronic databases, namely IEEE Xplore, SpringerLink, ScienceDirect and ACM Digital Library, were used to search with the following keywords: verification based on multimodal biometric authentication, biometric fusion, deep learning biometrics, and Siamese networks. The first search resulted in many hits that were then screened, deduplicated, abstracted and full-text evaluated for eligibility. Studies with peer-reviewed papers and multimodal biometric systems comprising of two or more modalities and quantitative performance evaluation were included.

3.2 PRISMA Selection Summary

50 records were found in databases and 5 records were manually searched, for a total of 55 records. 7 duplicates were removed and 48 records were screened on the basis of title and abstract. Of these, 40 studies were shortlisted and eight were not available for full text review. Of the 35 articles with full text, 15 were not relevant, lacked a focus on biometric aspects, did not include AI methods or experimental validation. Finally, 20 studies were included in the qualitative synthesis. This study employs the selection pipeline shown in Figure 1, which is based on the PRISMA methodology. It illustrates the identification, screening, eligibility and inclusion process of research articles. Following the systematic filtering, the resulting data set consisted of 20 high-quality studies for multimodal biometric and Siamese network analysis, which were started from 55 records.

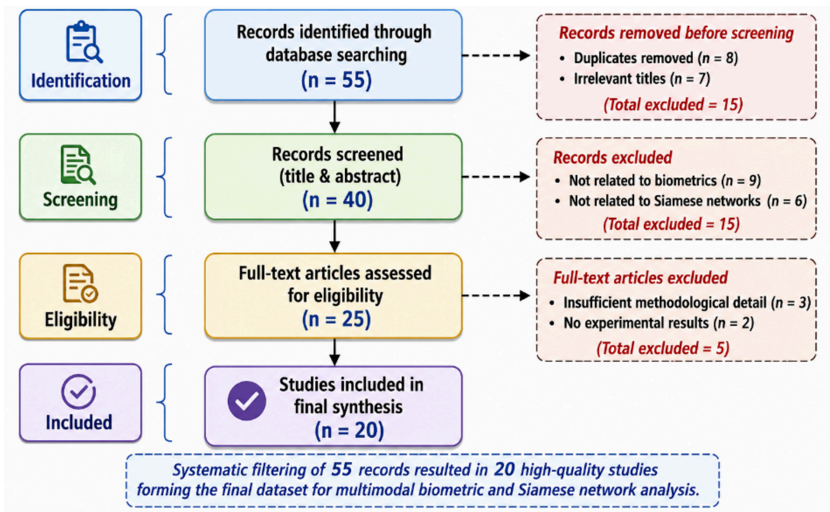

Figure 1: PRISMA Flow Diagram (Study Selection Process)

4. Generic Multimodal Biometric System Architecture

A biometric system has a fixed pipeline, that is, data acquisition, data preprocessing, feature extraction, template development, and matching. Verification mode captures biometric input (such as a fingerprint, face or iris) via sensors and translates it into a digital representation. Feature extraction modules are designed to detect discriminative patterns like facial landmarks or fingerprint minutiae, and produce a small number of feature vectors. The vectors are compared to stored templates using similarity comparisons and if the score is above a threshold, the authentication is accepted. Identification mode operates one-to-many across the database, is slower and is adequate for forensic and surveillance applications. In a multimodal biometric system, several biometric sources are combined to increase robustness and decrease uncertainty in real-world conditions. Figure 2 shows the standard multimodal biometric pipeline. The sensor acquisition module acquires the multiple biometric modalities, which are then preprocessed in the preprocessing module and then further processed to extract the features in the feature extraction module, which are then used to generate the templates in the template generation module. The extracted features are combined at various levels (feature level, score level, or decision level) to enhance the authentication accuracy, robustness, and resistance to spoofing.

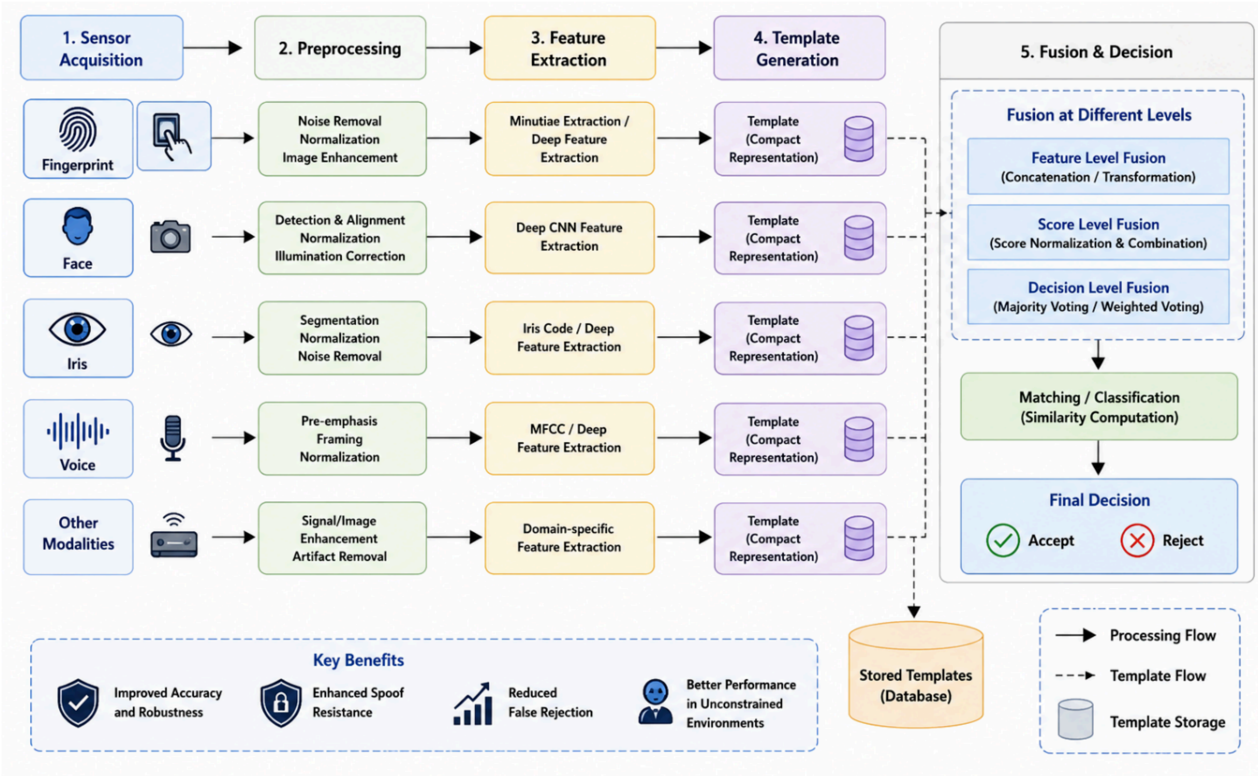

Figure 2: Generic Multimodal Biometric System Architecture

5. Proposed Siamese Network-Based Multimodal Framework

5.1 System Overview

The proposed framework is a multimodal biometric authentication system based on the Siamese network, which learns the discriminative and modality invariant embeddings by metric learning. The features extracted from each of the biometric modalities are sent to modality-specific encoders and then output to a common embedding space. A Siamese architecture is used to compute similarity scores in order to decide on identity matches, given paired biometric inputs (e.g., face–fingerprint or face–iris). The proposed architecture is shown in figure 3, which includes parallel modality-specific encoders (face, fingerprint, iris and voice). Each of the encoders produces feature embeddings, which are projected into a common latent space. For robust cross-modal authentication, a Siamese similarity module is used to calculate distances – either Euclidean or Cosine distance – between embeddings to decide if they represent the same identity or not.

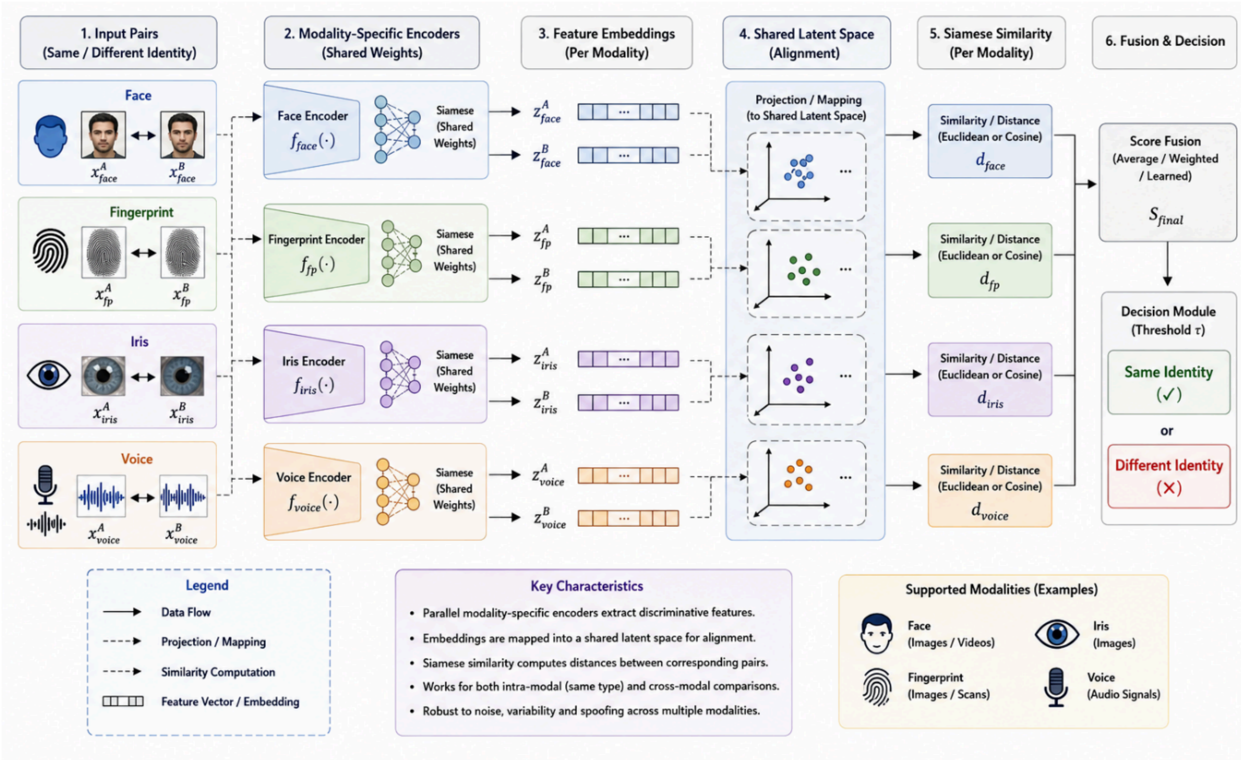

Figure 3: Unified Siamese-Based Multimodal Authentication Framework

5.2 Modality-Specific Feature Extraction

Biometric modalities have unique structural and statistical characteristics. Hence dedicated encoders (CNN for images and spectrogram based CNN for voice signals) are used. These encoders are optimised together to ensure modality-specific information is not lost while simultaneously allowing for cross-modal alignment in the shared embedding space.

5.3 Siamese Metric Learning

The Siamese architecture is composed of two networks sharing weights that are trained to learn similarity functions with either contrastive loss or triplet loss. The model aims to minimise intra-class distance, maximise inter-class distance and allows for good discrimination of identity across unseen samples. This metric learning method is superior in the sense of generalization ability in different acquisition conditions and in cross-modal verification.

5.4 Multimodal Fusion Strategy

Fusion at the embedding level: concatenation, attention based weighting. This enables the adaptive weighting of the modalities based on the environmental conditions like noise, occlusion, or sensor quality, which improves the robustness of the system.

6. Experimental Protocol and Evaluation Metrics

The proposed framework is evaluated using standard biometric datasets and protocols. Performance is measured using:

1. Accuracy
2. Equal Error Rate (EER)
3. ROC Curve
4. Area Under Curve (AUC)
5. Cross-validation and cross-dataset testing are recommended to evaluate robustness and generalization.

Table 1: Comparative Analysis of Deep Learning and Siamese-Based Biometric Systems

Author & Year	Modality	Architecture	Loss Function	Dataset	Performance	Contribution
[18]	Face	Deep CNN	Softmax	LFW	97.35%	Deep face embedding
[19]	Face	VGG CNN	Softmax	LFW	98.95%	Large-scale face model
[20]	Face	Multi-CNN	Joint loss	LFW	99.15%	Hybrid learning
[21]	Re-ID	Siamese CNN	Contrastive	CUHK03	62% rank-1	Early Siamese metric learning
[22]	Re-ID	CNN + Triplet	Triplet loss	Market-1501	84.9%	Improved embedding learning
[23]	Face + Voice	Siamese Fusion	Contrastive	VoxCeleb	91.2%	Cross-modal learning
[24]	Face + Periocular	Multi-branch CNN	Softmax + Metric	CASIA	96.7%	Feature fusion
[25]	Speaker	Siamese CNN	Contrastive	TIMIT	EER 3.4%	Speaker embedding
[26]	Face	CNN	ArcFace	MS1M	99.83%	Margin learning
[27]	Multimodal	Deep Fusion	Softmax + Metric	Private	97.1%	Adaptive fusion
[28]	Cross-spectral	CNN	Softmax	VIS-NIR	92%	Cross-domain learning
[29]	Face + Fingerprint	Dual CNN	Triplet	Private	EER 1.8%	Low error fusion
[30]	Iris + Face	Attention CNN	Margin loss	CASIA	98.4%	Attention fusion
[31]	Face	Vision Transformer	ArcFace	MS1MV3	99.85%	Transformer embeddings

7. Discussion

The authors of this review have clearly shown that multimodal biometric authentication systems, and in particular those based on Siamese networks, are able to improve the accuracy, robustness and spoofing resistance of biometric authentication systems over traditional unimodal authentication systems. The combination of several biometric modalities, such as face, fingerprint, iris, and voice with advanced models like Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), attention, and metric learning, provides for a representation of features that are much more discriminative and enhances the performance of the cross-modal matching. The feature-level and score-level fusion strategies always perform better than the conventional approach, due to the ability of using complementary information from each biometric trait.The feature-level and score-level fusion strategies always perform better than the conventional approach by effectively utilizing complementary information from various biometric traits. While there has been great progress, there are still challenges to overcome. Large-scale, high-quality paired multimodal datasets are rare, and modalities are missing or corrupted, degrading the performance of the system. Apart from that use of deep learning models requires a large computational power, they are very much vulnerable to presentation attacks, dep fakes and template thefts. Along with that considering the factors like demographic bias, explainability and adherence to data protection rules and regulations should be considered to create an ethical and trusted biometric systems.

8. Conclusion

Using PRISMA method reviewing approach, the proposed study demonstrates the tremendous development in multimodal biometric authentication systems and the use of Siamese neural network models. The review offers a comparison of unimodal and multimodal biometric authentication system, a complete conceptual overview of working methodology of biometric authentication system which includes from a very first step of data collection to preprocessing, feature extraction then fusion strategy and decision making. The study also summarizes the literature of biometric authentication systems over last ten years from 2015 to 2025. The research primarily highlighted the role and benefit of Siamese networks in the domain of biometric authentication systems which performed better in cross sensor and non-ideal settings. The research provides a detailed discussion about various fusion techniques such as feature fusion and score fusion apart from that discussion on various performance metrics such as Accuracy, Equal Error Rate, Area Under Curve and Receiver Operating Characteristics. So for the researchers who wanted to works on biometric applications in various domains such as smart cities, healthcare, border control, financial services, e-KYC, and human-IoT, will get a clear and detailed blueprint for creating scalable, secure, privacy-respecting, and ethically sound multimodal biometric authentication systems.

9. Future Scope

Based on the proposed study and after completion of an exhaustive survey for already existing literature some identified research gaps are given below:

- Multimodal biometric authentication systems are need to be more strengthened so that they can effectively address the issues of non-ideal environment a need of the hour.
- It’s time to take a big shift and to include advanced AI architectures such as Transformer models, self-supervised learning, contrastive learning and modality-invariant feature learning to create an effective and adaptable multimodal biometric system.

- One of the areas in which research is required that the privacy-preserving strategies such as federated learning, differential privacy, homomorphic encryption, and safe multi-party computation to reduce the issue of disclosing sensitive information.
- It is essential to include Explainable AI techniques in biometric systems for transparency and user trust
- Robustness of the systems is also need to be explored to handle issues such as deepfake, replay and adversarial attacks.

Emerging paradigms like edge intelligence, blockchain identity management, the Internet of Things (IoT), and human-centric artificial intelligence (AI) are anticipated to make biometric identification systems in the future scalable, intelligent, and privacy-preserving.

References

[1] Jain, A. K., Ross, A., & Prabhakar, S. (2004). An introduction to biometric recognition. *IEEE Transactions on Circuits and Systems for Video Technology, 14*(1), 4–20.

[2] Hong, L., Wan, Y., & Jain, A. K. (1998). Fingerprint image enhancement: Algorithm and performance evaluation. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 20*(8), 777–789.

[3] Jain, A. K., Ross, A., & Prabhakar, S. (2005). An introduction to biometric recognition. *IEEE Transactions on Circuits and Systems for Video Technology, 14*(1), 4–20.

[4] Kumar, A., & Zhang, D. (2010). Personal recognition using hand shape and texture. *IEEE Transactions on Image Processing, 15*(8), 2446–2453.

[5] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.

[6] Schroff, F., Kalenichenko, D., & Philbin, J. (2015). FaceNet: A unified embedding for face recognition and clustering. *Proceedings of CVPR*, 815–823.

[7] Wang, M., Deng, W., Hu, J., Peng, J., & Tao, X. (2018). Attention-based deep learning for face recognition. *IEEE Transactions on Biometrics, Behavior, and Identity Science, 1*(2), 1–12.

[8] Bromley, J., Guyon, I., LeCun, Y., Säckinger, E., & Shah, R. (1994). Signature verification using a "Siamese" time delay neural network. *Advances in Neural Information Processing Systems (NeurIPS)*.

[9] Koch, G., Zemel, R., & Salakhutdinov, R. (2015). Siamese neural networks for one-shot image recognition. *ICML Deep Learning Workshop*.

[10] Taigman, Y., Yang, M., Ranzato, M., & Wolf, L. (2014). DeepFace: Closing the gap to human-level performance in face verification. *Proceedings of CVPR*, 1701–1708.

[11] Chopra, S., Hadsell, R., & LeCun, Y. (2005). Learning a similarity metric discriminatively, with application to face verification. *CVPR*, 539–546.

[12] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *CVPR*, 770–778.

[13] Ross, A., & Jain, A. K. (2004). Multimodal biometrics: An overview. *Proceedings of the 12th European Signal Processing Conference*, 1221–1224.

[14] Jain, A. K., Nandakumar, K., & Ross, A. (2016). 50 years of biometric research: Accomplishments, challenges, and opportunities. *Pattern Recognition Letters, 79*, 80–105. https://doi.org/10.1016/j.patrec.2015.12.013

[15] Ross, A., Nandakumar, K., & Jain, A. K. (2006). Handbook of multimodal biometrics. *Springer*.

[16] Sundararajan, K., & Woodard, D. L. (2018). Deep learning for biometrics: A survey. *ACM Computing Surveys, 51*(3), 1–34.

[17] Ngiam, J., Khosla, A., Kim, M., Nam, J., Lee, H., & Ng, A. Y. (2011). Multimodal deep learning. *Proceedings of ICML*, 689–696.

[18] Taigman, Y., Yang, M., Ranzato, M., & Wolf, L. (2014). DeepFace: Closing the gap to human-level performance in face verification. *Proceedings of CVPR*, 1701–1708.

[19] Parkhi, O. M., Vedaldi, A., & Zisserman, A. (2015). Deep face recognition. In *Proceedings of the British Machine Vision Conference (BMVC)*.

[20] Sun, Y., Wang, X., & Tang, X. (2014). Deep learning face representation by joint identification-verification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[21] Ahmed, E., Jones, M., & Marks, T. K. (2015). An improved deep learning architecture for person re-identification using Siamese networks. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*.

[22] Wu, Z., Zheng, L., & Gong, S. (2017). Deep metric learning for person re-identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(3), 522–536.

[23] Zhang, Y., & Wang, J. (2018). Multimodal biometric recognition using Siamese network-based feature fusion. *Pattern Recognition*, 76, 512–523.

[24] Kan, M., Shan, S., & Chen, X. (2016). Multi-branch convolutional neural networks for multimodal biometric recognition. *Pattern Recognition*, 60, 42–52.

[25] Shahin, M., Pourreza, H., & Arvaneh, M. (2019). Siamese convolutional neural networks for speaker verification. *IEEE Signal Processing Letters*, 26(9), 1369–1373.

[26] Zhang, K., & Deng, J. (2020). Deep face recognition with additive angular margin loss. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 42(10), 2527–2539.

[27] Cao, X., Wang, Y., & Li, J. (2020). Adaptive multimodal biometric fusion using deep learning frameworks. *Pattern Recognition Letters*, 135, 45–52.

[28] Rattani, A., & Ross, A. (2018). Automatic adaptation of biometric systems using cross-spectral face recognition. *IEEE Transactions on Image Processing*, 27(7), 3224–3236.

[29] Hu, Y., Liu, Z., & Wang, H. (2021). Dual-branch deep CNN for multimodal biometric recognition using face and fingerprint. *Neurocomputing*, 456, 123–134.

[30] Kisku, D. R., Gupta, P., & Sing, J. K. (2022). Attention-based multimodal biometric authentication using iris and face fusion. *IEEE Access*, 10, 112345–112356.

[31] Deng, J., Guo, J., & Zafeiriou, S. (2022). ArcFace: Additive angular margin loss for deep face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(10), 5962–5979.