IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15591

Age Detection Using Machine Learning Techniques: A Comprehensive Review

Akshata Pravin Tatar[1], Nikita Balasaheb Korde[2], Kirti Dinkar More[3]

Department of Computer Science,

MVP Samaj's KRT Arts, BH Commerce and AM Science (KTHM) College, Nashik[1-3]

Abstract: Age estimation from facial images has become an important research area in computer vision due to its applications in surveillance, biometric authentication, healthcare monitoring, human-computer interaction, and demographic analysis. However, accurate age prediction remains challenging because the human aging process is nonlinear, highly individualized, and influenced by various biological and environmental factors. Early age estimation approaches relied on handcrafted feature extraction techniques combined with traditional machine learning algorithms, which showed limited robustness in unconstrained environments. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have significantly improved prediction accuracy by enabling automatic feature extraction and hierarchical representation learning from facial images. In addition, techniques such as ordinal regression, label distribution learning, transfer learning, and lightweight deep learning models have further enhanced the performance and efficiency of age estimation systems. This paper presents a comprehensive review of traditional, deep learning, hybrid, and emerging age estimation approaches. The study also analyzes commonly used benchmark datasets, evaluation metrics, major challenges, and recent advancements in the field. Furthermore, issues related to dataset bias, domain adaptation, fairness, and ethical concerns are discussed, along with future research directions toward developing reliable, interpretable, and deployable age estimation systems.

Keywords: Age Estimation, Facial Analysis, Machine Learning, Deep Learning, Convolutional Neural Networks, Facial Aging

INTRODUCTION

Age estimation has gained significant importance due to its applications in surveillance systems, biometric authentication, healthcare monitoring, and adaptive human-computer interaction systems [4]. Accurate prediction of age allows systems to tailor responses based on demographic attributes, improving usability and decision-making processes. However, age estimation remains a complex problem due to the variability in the aging process. Aging is influenced by biological factors such as genetics and hormonal changes, as well as external factors including lifestyle, nutrition, and environmental exposure [1]. These variations result in significant differences in facial appearance among individuals of the same age, creating high intra-class variability [4].

Furthermore, real-world imaging conditions introduce additional challenges. Variations in pose, illumination, occlusion, and image quality significantly affect model performance, particularly when transitioning from controlled datasets to unconstrained environments [2]. Eidinger et al. demonstrated that models trained on real-world images show significant performance variation due to these factors [2]. Traditional machine learning approaches relied heavily on handcrafted features such as Local Binary Patterns and Gabor filters. However, these methods failed to capture complex facial representations [4]. The introduction of deep learning has significantly transformed the field by enabling end-to-end learning from raw images, leading to substantial improvements in performance [3].

FUNDAMENTAL CONCEPTS IN AGE ESTIMATION

Nature of Facial Aging

Facial aging is a gradual and nonlinear process involving both structural and textural changes. Structural changes include craniofacial growth and bone remodeling, while textural changes involve wrinkle formation, skin sagging, and pigmentation variations [1]. These changes occur at different rates across individuals, making age estimation highly complex. Additionally, aging patterns differ across demographic groups such as gender and ethnicity. Guo and Mu demonstrated that race and gender significantly influence aging characteristics, making it difficult to develop universally

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15591

applicable models [4]. This demographic dependency introduces bias if not properly handled during model training. Another important aspect is the uneven progression of aging across life stages. Rapid changes occur during childhood, while aging becomes slower in adulthood and accelerates again in older ages. This non-uniform progression makes linear modeling approaches ineffective [1] [4].

Problem Formulation

Age estimation can be formulated as classification, regression, or ordinal regression. Classification methods divide age into discrete groups, which simplifies prediction but reduces precision. Regression methods predict continuous age values but are sensitive to noise and data imbalance. Ordinal regression has proven to be more effective as it preserves the inherent ordering of age labels. Niu et al. demonstrated that ordinal CNN models consistently outperform traditional regression methods by modeling age as a sequence of ordered outputs [6]. Additionally, label distribution learning captures uncertainty by representing age as a probability distribution rather than a single value [5].

Fig. 1. General workflow of facial age estimation system

Figure 1 illustrates the typical process flow used in facial age estimation systems. The process begins with input image acquisition, followed by face detection and preprocessing to improve image quality. Extracted facial features are then analyzed using machine learning or deep learning algorithms to estimate the age and generate the final prediction results.

EVOLUTION OF AGE ESTIMATION TECHNIQUES

Traditional Machine Learning Approaches

Early approaches relied on handcrafted features such as LBP, Gabor filters, and geometric facial descriptors. These features were combined with classifiers such as SVM and KNN [4]. While these methods provided initial solutions, they were limited by their inability to capture complex facial variations and were highly sensitive to environmental conditions. Moreover, these approaches lacked scalability and failed to generalize effectively across datasets. This limitation motivated the transition toward data-driven deep learning approaches [5].

Deep Learning-Based Approaches

Deep learning has revolutionized age estimation by enabling automatic feature extraction from raw images. CNNs learn hierarchical representations, where lower layers capture edges and textures, while deeper layers capture high-level semantic features related to aging [3]. The DEX model proposed by Rothe et al. demonstrated that deep CNNs trained on large-scale datasets significantly outperform traditional approaches [3]. Similarly, Niu et al. introduced ordinal regression CNN models that improved prediction accuracy by incorporating the ordered nature of age labels [6]. These models also show improved robustness to variations in pose, lighting, and occlusion compared to traditional methods. However, these deep learning models require large annotated datasets and substantial computational resources for training [3] [6] [15]. Advanced discriminative loss functions such as ArcFace have improved facial feature representation learning, indirectly benefiting age estimation performance and robustness [12].

Lightweight and Efficient Models

With the increasing demand for real-time applications, lightweight models have been developed. SSR-Net provides a compact architecture that achieves competitive performance with fewer parameters [7]. EfficientNet further improves efficiency by optimizing model scaling across depth, width, and resolution [13]. These models enable deployment on edge devices, making age estimation feasible for mobile and embedded systems [7] [13].

Advanced Learning Paradigms

Recent research focuses on improving robustness and generalization using advanced techniques. Multi-task learning frameworks simultaneously predict age, gender, and facial attributes, improving feature representation [8]. Transfer learning enables models to leverage pretrained weights, reducing the need for large datasets [13]. Bias mitigation techniques have also been introduced to address fairness issues. Alvi et al. demonstrated methods to remove unwanted bias in deep models, improving fairness across demographic groups [11].

Figure 2 presents the major categories of facial age estimation approaches, including traditional feature-based methods, deep learning architectures, hybrid frameworks, and emerging techniques such as transformers and fairness-aware learning models.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15591

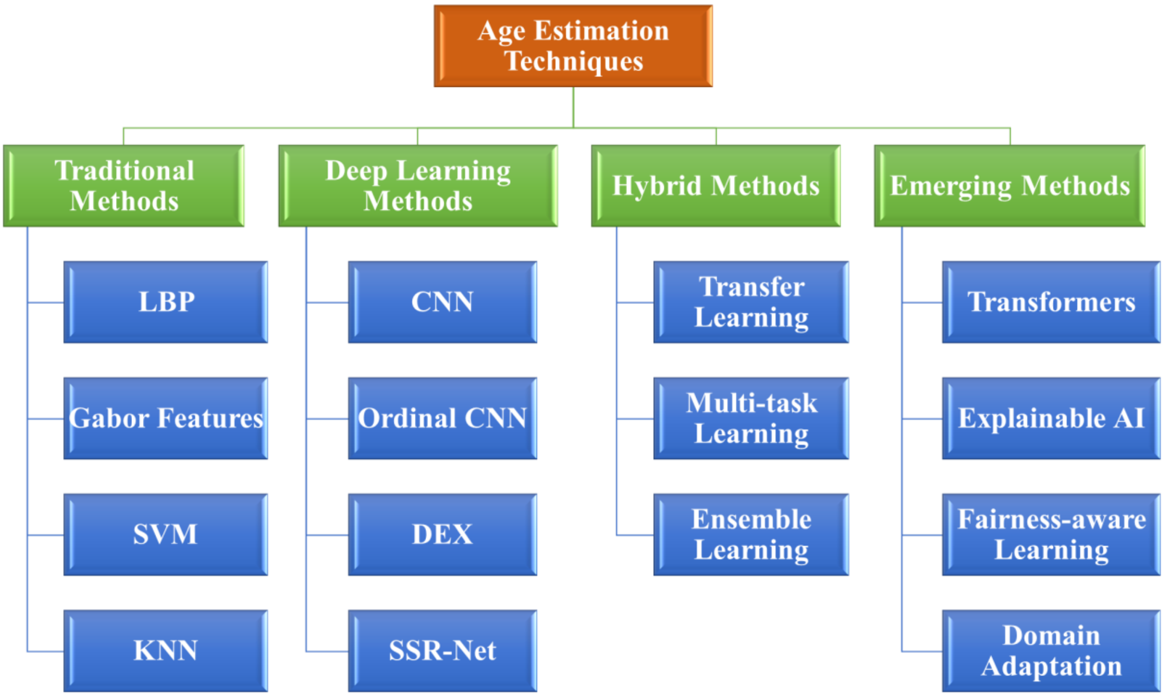

Fig. 2. Taxonomy of machine learning and deep learning techniques used for facial age estimation.

LITERATURE REVIEW AND COMPARATIVE ANALYSIS

Age estimation research has undergone a significant evolution from handcrafted feature-based models to deep learning-based frameworks. Early research primarily relied on manually designed features that attempted to capture texture and shape characteristics associated with aging. Guo and Mu [4] demonstrated that such features are insufficient to model complex aging patterns, especially when demographic variations are considered. Their work highlighted that facial aging is not universal, but varies significantly across race and gender, which limits the effectiveness of generalized models. A major advancement in this domain was the introduction of probabilistic approaches such as label distribution learning (LDL). Gao et al. [5] proposed modeling age as a distribution rather than a single label, which better represents the ambiguity inherent in human age perception. This approach significantly reduced prediction errors in datasets where exact age labels were uncertain or noisy.

The transition to deep learning marked a turning point in age estimation research. Rothe et al. [3] introduced the DEX model, which leveraged large-scale datasets and deep CNN architectures to achieve state-of-the-art performance. Their work demonstrated that deep networks could learn complex aging features automatically, outperforming traditional methods by a significant margin. Similarly, Niu et al. [6] proposed ordinal regression CNNs, which incorporated the natural ordering of age labels into the learning process, resulting in improved prediction accuracy. Recent research has focused on improving efficiency and generalization. Yang et al. [7] introduced SSR-Net, a lightweight architecture designed for real-time applications. Unlike heavy CNN models, SSR-Net reduces computational complexity while maintaining competitive accuracy. This capability is particularly important for deployment in mobile and embedded systems.

Furthermore, studies such as [14] have compared machine-based age estimation with human perception, demonstrating that deep learning models can achieve comparable or even superior performance in certain scenarios. Authors in [15] provided a comprehensive review highlighting that while deep learning models dominate performance metrics, challenges such as dataset bias, domain shift, and fairness remain unresolved.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15591

Table 1: Comparative analysis of age estimation techniques

Ref	Method	Dataset	Approx. MAE (Values vary across datasets)	Contribution	Limitation
[4]	Handcrafted + SVM	MORPH	10-12	Early modeling	Poor generalization
[5]	Label Distribution	MORPH	6-8	Handles ambiguity	High complexity
[3]	CNN (DEX)	IMDB-WIKI	3-5	Deep learning breakthrough	Data dependency
[6]	Ordinal CNN	MORPH	3-4	Order-aware prediction	Complex training
[7]	SSR-Net	UTKFace	4-6	Lightweight model	Slight accuracy drop

Table 1 compares prominent age estimation techniques based on their methodologies, datasets, Mean Absolute Error (MAE), major contributions, and limitations. The analysis shows that deep learning-based approaches achieve significantly better accuracy and robustness compared to traditional handcrafted feature-based methods. From the comparative analysis, it is evident that deep learning approaches consistently outperform traditional models due to their ability to learn hierarchical and nonlinear feature representations [3] [6]. However, this performance gain comes at the cost of increased computational requirements and dependence on large annotated datasets [15]. Another key observation is that no single model performs optimally across all datasets, indicating the presence of domain shift and dataset bias [11] [15]. This highlights the importance of developing domain-adaptive and fairness-aware models.

DATASETS AND EVALUATION

Datasets play a critical role in the performance of age estimation systems. Commonly used datasets include MORPH, IMDB-WIKI, and ChaLearn LAP. The MORPH dataset provides longitudinal facial images, making it suitable for studying aging progression [9]. IMDB-WIKI is one of the largest publicly available datasets, but it contains noisy labels due to automated annotation processes [3]. ChaLearn focuses on apparent age estimation, where labels are derived from human perception rather than actual age [10]. Despite their widespread use, these datasets present several challenges. Dataset imbalance is a major issue, where certain age groups (e.g., young adults) are overrepresented, leading to biased predictions [15]. Annotation noise further complicates training, particularly in large-scale datasets like IMDB-WIKI. Additionally, domain shift occurs when models trained on one dataset fail to generalize to another due to differences in data distribution. Evaluation metrics are essential for assessing model performance [15]. The most commonly used metric is Mean Absolute Error (MAE), which measures the average deviation between predicted and actual age. Other metrics include Root Mean Square Error (RMSE) and Cumulative Score (CS). While MAE provides a simple and interpretable evaluation measure and is widely adopted in age estimation literature, it does not capture distributional errors, which can be important in practical applications [15].

CHALLENGES IN AGE ESTIMATION

Age estimation systems face several fundamental challenges that limit their real-world applicability. One of the primary challenges is intra-class variability, where individuals of the same age exhibit significantly different facial characteristics due to genetic and environmental factors [1]. This variability makes it difficult for models to learn consistent patterns. Another significant challenge is dataset bias, which arises when certain demographic groups are underrepresented. Alvi et al. [11] showed that deep learning models can unintentionally learn biased representations, leading to unfair predictions across gender and ethnicity.

Domain shift is another critical issue. Models trained on controlled datasets often fail to generalize to real-world images due to differences in lighting, pose, and background [15]. This limits the deployment of age estimation systems in practical applications. In addition to technical challenges, ethical concerns play an important role. The use of facial data raises privacy and ethical concerns in surveillance applications [11] [15]. There is also a risk of misuse in sensitive applications such as hiring or law enforcement, making fairness and transparency essential.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁑ Peer-reviewed & Refereed journal ⁑ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15591

CONCLUSION AND FUTURE WORK

Age estimation has evolved significantly over the past decade, transitioning from traditional handcrafted feature-based approaches to advanced deep learning models. The introduction of CNNs and probabilistic learning methods has led to substantial improvements in prediction accuracy and robustness. However, despite these advancements, several challenges remain unresolved. Issues such as dataset bias, domain shift, and ethical concerns continue to limit the deployment of age estimation systems in real-world scenarios. Addressing these challenges requires a combination of technical innovation and responsible AI practices.

Future research should focus on developing models that are not only accurate but also fair, interpretable, and efficient. By addressing these aspects, age estimation systems can become reliable tools for a wide range of applications. Future research in age estimation should focus on addressing both technical and ethical challenges. One promising direction is explainable AI, which aims to improve model transparency by providing insights into decision-making processes. This is particularly important for building trust in real-world applications. Fairness-aware learning is another critical area. Techniques for bias mitigation, such as adversarial training and balanced dataset construction, can help ensure equitable performance across demographic groups [11]. The development of lightweight and efficient models is essential for real-time deployment on edge devices. Models such as SSR-Net demonstrate the feasibility of this approach, but further improvements are needed [7]. Recent healthcare-oriented applications also demonstrate the growing role of AI-based age estimation systems [16]. Additionally, multi-modal learning offers new opportunities by combining facial images with other data sources such as voice or physiological signals. This can improve prediction accuracy and robustness. Finally, cross-domain generalization remains a key research challenge. Developing models that can adapt to different datasets and real-world conditions will significantly enhance practical applicability [15].

REFERENCES

[1]. R. Angulu, J. R. Tapamo, and A. O. Adewumi, “Age estimation via face images: A survey,” EURASIP Journal on Image and Video Processing, vol. 2018, no. 1, Art. no. 42, 2018. doi: 10.1186/s13640-018-0278-6.

[2]. E. Eidinger, R. Enbar, and T. Hassner, “Age and gender estimation of unfiltered faces,” IEEE Transactions on Information Forensics and Security, vol. 9, no. 12, pp. 2170–2179, Dec. 2014, doi: 10.1109/TIFS.2014.2359646.

[3]. R. Rothe, R. Timofte, and L. Van Gool, “DEX: Deep EXpectation of apparent age from a single image,” in Proc. IEEE Int. Conf. Computer Vision Workshops (ICCVW), Santiago, Chile, 2015, pp. 252–257. doi: 10.1109/ICCVW.2015.41.

[4]. G. Guo and G. Mu, “Human age estimation: What is the influence across race and gender?,” in Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition Workshops (CVPRW), San Francisco, CA, USA, 2010, pp. 71–78. doi: 10.1109/CVPRW.2010.5543264.

[5]. B.-B. Gao, C. Xing, C.-W. Xie, J. Wu, and X. Geng, “Deep label distribution learning with label ambiguity,” IEEE Transactions on Image Processing, vol. 26, no. 6, pp. 2825–2838, Jun. 2017. doi: 10.1109/TIP.2017.2689998.

[6]. Z. Niu, M. Zhou, L. Wang, X. Gao, and G. Hua, “Ordinal regression with multiple output CNN for age estimation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 4920–4928. doi: 10.1109/CVPR.2016.532.

[7]. T.-Y. Yang, Y.-H. Huang, Y.-Y. Lin, P.-C. Hsiu, and Y.-Y. Chuang, “SSR-Net: A compact soft stagewise regression network for age estimation,” in Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence (IJCAI-18), Stockholm, Sweden, 2018, pp. 1078–1084. doi: 10.24963/ijcai.2018/150.

[8]. R. Ranjan, V. M. Patel, and R. Chellappa, “HyperFace: A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 41, no. 1, pp. 121–135, Jan. 2019. doi: 10.1109/TPAMI.2017.2781233.

[9]. K. Ricanek Jr. and T. Tesafaye, “MORPH: A longitudinal image database of normal adult age-progression,” in Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition (FGR’06), Southampton, U.K., 2006, pp. 341–345. doi: 10.1109/FGR.2006.78.

[10]. S. Escalera, J. Fabian, P. Pardo, X. Baro, J. Gonzalez, H. J. Escalante, D. Misevic, U. Steiner, and I. Guyon, “ChaLearn Looking at People 2015: Apparent age and cultural event recognition datasets and results,” in Proceedings of the IEEE International Conference on Computer Vision Workshops (ICCVW), Santiago, Chile, 2015, pp. 243–251. doi: 10.1109/ICCVW.2015.40.

[11]. M. Alvi, A. Zisserman, and C. Nellåker, “Turning a blind eye: Explicit removal of biases and variation from deep neural network embeddings,” in Proceedings of the European Conference on Computer Vision Workshops (ECCVW), Munich, Germany, 2018, pp. 556–572. doi: 10.1007/978-3-030-11009-3_34.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15591

[12]. J. Deng, J. Guo, J. Yang, N. Xue, I. Kotsia, and S. Zafeiriou, "ArcFace: Additive angular margin loss for deep face recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 10, pp. 5962–5979, Oct. 2022. doi: 10.1109/TPAMI.2021.3087709.

[13]. M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in Proceedings of the 36th International Conference on Machine Learning (ICML), vol. 97, Long Beach, CA, USA, 2019, pp. 6105–6114.

[14]. H. Han, C. Otto, X. Liu, and A. K. Jain, "Demographic estimation from face images: Human vs. machine performance," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 6, pp. 1148–1161, Jun. 2015. doi: 10.1109/TPAMI.2014.2362759.

[15]. M. M. Badr, A. M. Sarhan, and R. M. Elbasiony, "Facial age estimation using deep neural networks: A survey," in Proceedings of the 15th International Computer Engineering Conference (ICENCO), Cairo, Egypt, 2019, pp. 29–34. doi: 10.1109/ICENCO48310.2019.9027363.

[16]. S. B. Khanagar, F. Albalawi, A. Alshehri, M. Awawdeh, K. Iyer, B. Alsomaie, A. Aldhebaib, O. G. Singh, and A. Alfadley, "Performance of Artificial Intelligence Models Designed for Automated Estimation of Age Using Dento-Maxillofacial Radiographs—A Systematic Review," Diagnostics, vol. 14, no. 11, Art. no. 1079, 2024. doi: 10.3390/diagnostics14111079.

