Beyond Recognition: The Foundation of the Next Generation of AI-driven Facial Technologies and the Marketing Perspective

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Abstract

From a specialised biometric technique, face recognition technology has quickly become a commonplace part of artificial intelligence systems. This article examines the theoretical underpinnings, algorithmic developments, and real-world uses of face recognition. It charts the evolution of robust, scalable models utilising triplet loss, transformer-based architectures, and convolutional neural networks (CNNs). Alongside key assessment metrics and benchmark datasets, core system components such as preprocessing, feature extraction, embedding generation, and classification are investigated. The study illustrates practical applications across industries such as digital identity verification, retail, healthcare, and security, demonstrating the technology's expanding influence and its impact on important issues. A fair perspective on upcoming developments is provided by discussing ethical issues and new regulatory systems. The study also looks at how facial recognition is used in marketing, particularly in payment systems. For academics, practitioners, and politicians seeking to understand and develop face recognition systems across the scientific and societal spheres, this work serves as an extensive reference.

Keywords: face recognition, technology, AI-driven face recognition, marketing, FRP

JEL classification: O31, M31

Paper type: Research article
Received: 2 March 2025
Accepted: 9 June 2025

DOI: 10.54820/entrenova-2025-0055

Citation: Ademi, L., Ramadani, V., & Zeqiri, J. (2025). Beyond Recognition: The Foundation of the Next Generation of AI-driven Facial Technologies and the Marketing Perspective. ENTRENOVA - ENTerprise REsearch InNOVAtion, 11(1), https://doi.org/10.54820/entrenova-2025-0055.

Introduction

One of the most well-known and extensively used technologies in computer vision and artificial intelligence (AI) is face recognition. Fundamentally, face recognition is the process of using a person's visual traits to identify or confirm their identity. Facial recognition, unlike other biometric modalities such as fingerprints or iris scans, provides a contactless, non-invasive means of identity verification, making it appropriate for a variety of applications ranging from social media tagging to surveillance and mobile device authentication (Zhao et al., 2003; Li & Jain, 2011).

Although there has been scientific interest in face recognition since the 1960s, the field really took off in the 1990s, when statistical techniques such as Principal Component Analysis (PCA), also known as the Eigenfaces approach, were introduced (Turk & Pentland, 1991). Later developments, such as Linear Discriminant Analysis (LDA) and Gabor filters, increased the recognition's resilience to changes in facial expressions and illumination. However, the introduction of deep learning brought about the actual change. DeepFace (Taigman et al., 2014), FaceNet (Schroff et al., 2015), and, more recently, ArcFace (Deng et al., 2019) are examples of Convolutional Neural Networks (CNNs) that have significantly increased recognition accuracy and scalability.

Undoubtedly, face recognition has great promise for the future of marketing, as it provides powerful tools for examining consumer behaviour as part of neuromarketing tactics. It also serves as a highly effective, user-friendly way to process payments.

Face recognition is controversial, even though it is widely used. Particularly in law enforcement and surveillance scenarios, ethical concerns have been highlighted by issues such as algorithmic bias, lack of transparency, and data privacy (Buolamwini & Gebru, 2018; Raji et al., 2020). Furthermore, the challenge of implementing these systems ethically is increased by the absence of standardised legislative frameworks for the use of facial data.

The goal of this paper is to provide a basic yet thorough overview of the field of face recognition. The theoretical foundations of face recognition systems, significant algorithmic advancements, well-known applications, current challenges, and potential future research areas will be covered in the following sections. The goal of this study is to create a fundamental resource for scholars, practitioners, and policymakers.

Literature review

This section will provide a literature review of the concept of face recognition, as well as some fundamentals about its techniques and its use. A branch of biometrics and computer vision called face recognition uses facial traits to identify or validate people. Its theoretical underpinnings include knowledge of machine learning, image processing, pattern recognition, and human facial anatomy. This part describes the fundamental ideas of face recognition systems, along with a distinction among key concepts in the field.

Biometrics and the Human Face's Uniqueness

Biometric identification systems use behavioural or physiological traits to identify or authenticate people. The human face is unique among biometric modalities (such as voice, iris, and fingerprint) since it is widely used, non-intrusive, and simple to capture in uncontrolled settings (Jain et al., 2004). However, because of variations in expression, posture, ageing, and ambient lighting, facial features are intrinsically less reliable than other biometrics (Li & Jain, 2011).

The sections below provide literature-based details on the key challenges of facial recognition based on face features.

Aging

Ageing causes facial textures to change naturally over time, which significantly affects the accuracy of face recognition systems. Maintaining age-invariant recognition is essential for both real-time identification and long-term face picture retrieval. Facial datasets, including FG-NET, CACD, and CACD-VS, have been subjected to nonlinear analysis and Coupled Auto-Encoder Networks (CAN) in order to address the impacts of ageing and de-aging (Singh et al., 2019). By analysing the ageing process in face datasets, these models evaluate recognition accuracy across various age groups. Strong similarity metrics that can differentiate aging-affected face characteristics are necessary for efficient age-group classification (Zhang et al., 2020).

Accurate feature extraction, which includes recognising important facial features such as wrinkles, spots, eyebrows, and cosmetics, is crucial to face recognition performance. Reducing image dimensionality with the Active Appearance Model (AAM) has improved recognition effectiveness (Lee & Kim, 2018). Additionally, by mimicking the ageing process over time, sparse-constrained approaches have been proposed to enhance recognition reliability (Wang et al., 2021).

Thermal image

For dependable performance, thermal facial recognition systems, whether for small or large databases, need efficient multi-feature extraction algorithms. Environmental factors, notably illumination, are crucial for thermal image identification in low-resolution circumstances, especially when using Gabor-based algorithms (Sharma et al., 2018). Various facial traits have been extracted using multi-fusion techniques, such as those based on the Gabor Jet Descriptor. Performance rates and recognition accuracy have been shown to increase with fusion algorithms that combine visible and thermal infrared pictures. Furthermore, validation using datasets such as UGC-JU has demonstrated encouraging results in improving recognition outcomes by constructing a universal picture quality score for thermal image assessment (Kumar & Singh, 2019).

Hermosilla et al. (2020) state that robust local matching algorithms are necessary for face identification utilising thermal imaging in uncontrolled situations. To improve accuracy across various conditions, techniques based on binary patterns, Weber Linear Descriptors, and Gabor Jet descriptors have been used. Additionally, it has been suggested that infrared picture feature extraction be improved by using novel entropy-based methods. By facilitating the examination of discriminative facial features across several databases, these methods help thermal face recognition algorithms function more accurately (Almeida et al., 2021).

The iris

An essential part of the human face, the iris is also crucial for biometric facial analysis. In identity verification jobs, iris recognition methods, which often include biometric hashing algorithms, have proven reliable and efficient. Six distinct datasets were used to test iris mapping techniques, which showed improved performance and consistency in recognition accuracy (Patel & Rao, 2017). Systems that combine facial and iris recognition for mobile engagement applications benefit significantly from this resilience. According to Mehta and Kaur (2018), these mobile-based solutions have demonstrated encouraging results in terms of accuracy, consistency, and integration with fusion technology.

Achieving high recognition accuracy is crucial in multi-biometric systems, especially when combining many biometric features. Nevertheless, issues such as iris corner data loss, which frequently occur during filtering and data synthesis in bin-based frameworks, can impair recognition performance. Fusion approaches have been used to improve accuracy and recover lost data in order to address this. Experimental validations confirm the effectiveness and reliability of these fusion-based iris identification techniques, utilising the CASIA-Iris database (Zhou et al., 2019).

Facial expressions

Guo et al. (2013) presented an expression-invariant 3D face recognition technique that blends global face similarity metrics with local geometric characteristics. They evaluated their method on the FRGCv2 dataset using both local descriptors and 3D point cloud registration, successfully identifying neutral and expressive faces with recognition and verification rates of 97.0% and 99.01%, respectively. In a similar vein, Ye et al. (2015) presented a 3D face recognition technique that uses subject-specific curves and combines an expression-irrelevant weighting factor with the iterative closest point (ICP) algorithm to improve matching performance under a range of facial emotions.

Sparse Representation Classification (SRC) and Collaborative Representation Classification (CRC) approaches have been used in subsequent advancements in facial expression analysis (Chen et al., 2014). A neural network (NN) classifier applied to 3D facial models has achieved encouraging results in classifying six basic emotions: pleasure, sorrow, anger, fear, disgust, and surprise (Lee & Park, 2016). Because of their speed and linearity, Modified Local Directional Patterns (MLDP) have also increased the efficiency of expression identification. Furthermore, deep learning methods, including generalised discriminant analysis applied to Deep Belief Networks, have improved video-based facial emotion detection over conventional methods (Wang et al., 2017). Furthermore, Abbad et al. (2018) used geometric shape descriptors and 3D face modelling to address expression variability.

Face Recognition System Components

Several steps make up a typical facial recognition pipeline:

- Face detection: identifying one or more faces in a picture (for example, by employing deep learning detectors like MTCNN or Haar cascades).
- Preprocessing: To enhance image quality and consistency, apply alignment, normalisation, and noise reduction techniques.
- Feature extraction is the process of turning a face image into an embedding, or high-dimensional feature vector, that contains discriminative information.
- Matching and Classification: To ascertain identification, feature vectors are compared using classifiers (such as support vector machines and neural networks) or similarity metrics (such as cosine similarity).

Depending on whether the job is face identification (1: N comparison) or face verification (1:1 comparison), these steps might differ in complexity and provide different computational and performance issues (Zhao et al., 2003).

Representational Learning

Using geometric models, early face recognition systems measured the separations between the lips, nose, and eyes (Brunelli & Poggio, 1993). Global feature extraction techniques based on linear projections were later introduced using statistical methods such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), which produced concise yet significant representations (Turk & Pentland, 1991; Belhumeur et al., 1997).

Convolutional Neural Networks (CNNs), which automatically learn hierarchical feature representations from raw pixels, revolutionised the modern paradigm. To group faces of the same identity closer together in latent space, techniques such as DeepFace (Taigman et al., 2014), FaceNet (Schroff et al., 2015), and ArcFace (Deng et al., 2019) use deep embeddings optimised by contrastive or triplet loss. The recognition accuracy increased significantly with this shift, especially on complex datasets.

Face recognition and marketing

In consumer behaviour analysis and targeted marketing, face recognition payments provide significant advantages. Retailers can offer individualised promotions and loyalty rewards in real time by using the technology to identify repeat customers. By matching marketing messages to individual interests and habits, this kind of personalisation can boost conversion rates and client retention (Zhang et al., 2021). To ensure responsible deployment, precise regulatory requirements and open consumer communication are necessary. However, the use of biometric data in marketing also raises questions about data privacy, permission, and ethical usage.

A revolutionary change in the customer experience, especially in retail marketing, is represented by the incorporation of face recognition technology into payment systems. Face-based payments reduce friction and improve ease of purchase by enabling smooth, contactless transactions, which may boost customer satisfaction and loyalty. According to research, biometric payment systems can improve customer engagement and brand image by expediting checkout processes and creating a sense of innovation and security (Li et al., 2020). Additionally, marketers can use information gathered by facial recognition systems to enhance customer service, optimise store layouts, and personalise offerings, resulting in a more efficient, customised shopping experience.

Face recognition for payments (FRP)

To verify an individual's identity, Face Recognition Payment (FRP) systems use facial recognition algorithms to collect, analyze, and compare biometric facial data (Zhang & Kang, 2019). People must first enrol by connecting their facial data to a bank account or an online payment platform like Alipay, WeChat Pay, Pop Pay, or others in order to access FRP services. Users only need to face the camera on a smartphone or device with FRP enabled in order to complete a transaction. After that, the system records their facial features and compares them with the information stored in the database. The payment is authorised and completed if the facial data matches.

In contrast to other digital payment systems, such as online and mobile payments, FRP offers certain benefits (Moriuchi, 2021; Zhang & Kang, 2019). First of all, it is quicker because the confirmation process takes only a few seconds.

The entire payment procedure only takes 10 to 15 seconds for new users and less than 10 seconds for regular users, according to a Nielsen Norman Group report. This is significantly faster than mobile payments that rely on scanning QR codes (Liu, 2020). Second, users need to stand in front of the camera on an FRP device for it to scan their face; they do not need to touch anything, such as a cell phone.

Thirdly, it is convenient, especially for users who forget to bring their phones or credit cards or who are unable to scan their fingerprints or enter a PIN when making another purchase because their hands are full with other items they have already purchased. Finally, FRP is safer than some conventional payment methods, such as authorising credit card or mobile purchases with a password. FRP, in particular, has advanced rapidly in tandem with the development of 3D cameras and artificial intelligence, and it is currently considered quite secure (Vazquez-Fernandez & Gonzalez-Jimenez, 2016).

However, FRP continues to raise concerns about safety and ambiguity, particularly regarding privacy and security. First, it is possible to hack FRP systems. Standard impersonation hacking techniques include deep morphing, 3D masks, video spoofing, and photograph spoofing (Cho & Jeong, 2017; Edmunds & Caplier, 2018; Li et al., 2018; Ryu et al., 2021; Yeung et al., 2020). Hackers can use non-FRP sources, such as social media, to acquire targets' photos or videos, which they can then show to a FRP system (Cho & Jeong, 2017). 3D masks and deep morphing remain brutal spoofing tactics, despite modern FRP systems implementing privacy-enhancing algorithms to prevent 2D face hacks (Li et al., 2018; Yeung et al., 2020).

The development of 3D printing and scanning, along with artificial intelligence in morphing, has made it easier to create impersonation hacks and provided tools for properly representing a target. To safeguard the privacy of FRP users, additional techniques to thwart these breaches are required. Second, the government or other surveillance firms may use or share the facial data that is gathered by FRP providers (Yeung et al., 2020). Because FRP gathers and preserves high-quality facial data to ensure accuracy, the information it collects can be used to identify individuals outside of FRP, for example, in workplace surveillance or on street cams. To safeguard users' privacy and control the gathering, storing, and use of facial data, rules and regulations are required.

Therefore, although FRP offers certain benefits, users' intentions to continue may be hampered by privacy and security concerns (Zhang & Kang, 2019). To reduce the risks and uncertainties associated with FRP, users must build trust in it. Furthermore, trust can help consumers, FRP technology, and FRP service providers build lasting partnerships, especially when it comes to different FRP services or service providers. Therefore, consumers' intention to continue using FRP should be heavily influenced by their level of trust. To comprehend the fundamental mechanism of trust-building in FRP and its consequences for users who intend to continue using it, the current study proposes and empirically investigates a research model (Li & Li, 2023).

Face Recognition Methods, Algorithms, and Applications

Several paradigm shifts have occurred in face recognition, moving from statistical methods and geometry-based models to deep learning and transformer-based architectures. This section describes the main algorithmic turning points and how they affected the scalability and performance of face recognition systems.

Conventional Methods

Statistical learning techniques and manually created features were the mainstays of early face recognition systems. PCA, one of the first widely used methods, captures the most significant variance across training sets by projecting face images into a lower-dimensional subspace known as the face space (Turk & Pentland, 1991). Although this technique is sensitive to changes in illumination and posture, it performs effectively in controlled environments.

The next one is Fisherfaces' Linear Discriminant Analysis (LDA). By increasing between-class variation and decreasing within-class variance, LDA improves class separability and goes beyond PCA (Belhumeur et al., 1997). Despite addressing some of PCA's drawbacks, LDA requires sufficient samples per class and assumes linear relationships.

The other one is Gabor Filters, which help record spatial frequency, direction, and location information in facial textures by mimicking the response of the human visual system (Liu & Wechsler, 2002). They frequently work in tandem with LDA or PCA.

Face Recognition Applications

Scholarly research indicates that face recognition technology has developed into a widely used tool powering a range of applications in the public and private sectors. Its rapid and precise person identification has made it invaluable in a variety of industries, from marketing to security, and its widespread use presents both potential and moral dilemmas.

Safety and Monitoring

Law enforcement and public security are among the most common uses of facial recognition technology. Governments and organisations use real-time facial recognition in public areas to:

- Identify suspects on watchlists
- Monitor individuals of interest
- Improve border and airport security

Real-time facial surveillance networks connected to national databases are one example of how China's public security systems operate (Qin et al., 2021). Biometric boarding systems, which speed up identity verification and increase security, have been used at airports like Singapore, the United States, and the United Arab Emirates (Jain et al., 2016).

Authentication and Access Control

In access control systems, face recognition is taking the place of more conventional authentication techniques like ID cards and passwords:

- Facial biometrics, such as Apple Face ID, are used by mobile devices for secure payment and unlocking.
- Facial access is integrated into smart homes and workplaces to improve convenience and prevent unwanted entrance.
- Face recognition is used by banking and fintech apps to authenticate customers during KYC (Know Your Customer) and online onboarding procedures (Bhatia, 2021).

Since the COVID-19 pandemic, the benefits of contactless authentication have become even more significant.

Retail and marketing

Face recognition in the business world facilitates data-driven marketing and tailored consumer experiences:

- For individualised ads, retailers utilise it to examine demographic characteristics (age, gender, and emotional expression).
- Depending on who is there, smart shelves and kiosks modify the content.
- By identifying recurring customers, customer loyalty programs allow for customised promotions (Zhang et al., 2021).

These apps are occasionally combined with neuromarketing techniques, such as eye tracking, to improve engagement and product placement.

Assistive Technology and Healthcare

Face recognition in healthcare helps with:

- Patient identification to prevent confusion
- Assistive technologies for those with visual impairments (such as facial recognition glasses);
- Patient emotional state monitoring in mental health applications Additionally, elder care is using emotion-aware AI systems to assess well-being non-invasively (Kumari et al., 2022).

Integrity of Education and Examination

Academic testing and e-learning platforms are increasingly using face recognition to:

- Verify student identity during remote tests
- Use facial analytics to keep an eye on attention and spot questionable activity.
- Automate classroom attendance monitoring (Sultana et al., 2020). Both academic integrity and participation in virtual environments are intended to be improved by these resources.

Integration of IoT and Smart Cities

Face recognition works with Internet of Things (IoT) devices in innovative city projects to control:

- Enforcement of traffic laws (such as locating unregistered drivers)
- Using face-based tickets to access public transport
- Safety of the environment (e.g., identifying individuals in prohibited areas)
- For smooth urban mobility and public service delivery, cities including Tokyo, Singapore, and Dubai are testing face-based systems (Gupta et al., 2020).

Face Recognition Technology: Challenges and Restrictions

Even while face recognition has advanced significantly in terms of accuracy and scalability, several ethical, technological, and sociological issues still prevent it from being widely used and performing reliably. Responsible deployment requires an understanding of and attention to these limits.

Bias and Accuracy Demographic Bias

Face recognition software often exhibits inconsistent performance across demographic groups. For women and people with darker skin tones, Buolamwini and Gebru (2018) showed that commercial facial analysis systems had higher error rates, with accuracy falling below 70% for some subgroups. These differences result from:

- Insufficient representation in training datasets;
- Bad lighting or image quality;
- Oversimplifications of face variety by algorithms.

Privacy and Dataset Limitations

For large-scale face recognition models, millions of labelled photos are needed for incomplete and unbalanced datasets. Nevertheless, datasets such as VGGFace2 or MS-Celeb-1M frequently may include images that were taken from the internet without the user's permission and lack variety in terms of gender, age, and ethnicity Given that biometric data is categorised as "sensitive" under privacy laws such as the GDPR, this raises concerns about data privacy and informed consent (Raji & Fried, 2021).

Uncertainty in Regulation - Croatia and North Macedonia's law on biometric data

Comprehensive frameworks for biometric regulation are lacking in many nations. Implementation differs per nation, even though the EU GDPR mandates consent and purpose limitation for biometric data. On the other hand, some states in the United States have severe regulations, such as Illinois with BIPA, while others do not. Organisations using facial recognition technology face legal exposure and misunderstanding due to the absence of standardised legal standards (Tsamados et al., 2022). Table 1 summarizes key challenges in face recognition.

Table 1
Summary of Key Challenges in Face Recognition

Challenge Area	Description	Key Concerns	Sources
Accuracy & Bias	Systems are often less accurate for women, dark-skinned individuals, and other minorities.	False positives/negatives; demographic unfairness	Buolamwini & Gebru, 2018
Dataset Quality	Training data lacks diversity and consent.	Data privacy; ethical data sourcing	Raji & Fried, 2021
Spoofing & Security	Vulnerable to attacks using masks, photos, or videos.	Security breaches in sensitive applications	Chingovska et al., 2012
Real-world Variability	Performance degrades in uncontrolled environments (e.g., poor lighting, masks, angles).	Lower accuracy in practical deployment	Nguyen et al., 2020
Ethical Concerns	Used without public knowledge or consent; perceived as invasive.	Public distrust; surveillance fears	Kostka et al., 2021
Regulatory Uncertainty	Laws vary widely across regions; there is a lack of transparent governance.	Legal risk; implementation challenges	Tsamados et al., 2022

Source: Authors' work

Unlike many countries, according to the Agency for Personal Data Protection in North Macedonia (Retrieved from Laws - Агенција за заштита на личните податоци), there are no regulations in North Macedonia that specifically regulate facial recognition technology. However, the Law on Personal Data Protection, which aligns with the EU General Data Protection Regulation (GDPR), governs the processing of biometric data. According to this law, biometric data can only be processed in specific ways, such as with express consent or in accordance with legal requirements. Although the Intelligence Agency is permitted to gather and analyse intelligence pertinent to national security, its operations are subject to legislative oversight. According to sources from the Ministry of Digital Transformation in North Macedonia, there are two laws on electronic Communications and the Law on the Security of Network and Information Systems (Cybersecurity) that are being prepared for adoption in May 2025.

On the other hand, according to the Croatian Personal Data Protection Agency (Retrieved from National legislation - Agencija za zaštitu osobnih podataka), more specific laws about facial recognition technology have been enacted in Croatia. To improve the identification of suspects through the analysis of image and video data, the Ministry of the Interior announced in 2019 its intention to purchase a facial recognition system for HRK 2.8 million (€376,000). This method intends to speed the cross-referencing of photos with existing databases, potentially enhancing law enforcement efficiency. Additionally, Croatia enacted the Law on the Implementation of the General Data Protection Regulation (GDPR), which regulates the processing of biometric and other personal data. By mandating legitimate grounds for data processing and protecting people's right to privacy, this regulation ensures that any use of facial recognition technology complies with EU data protection requirements.

Prospects and Developments in Face Recognition

To overcome its limitations and ensure ethical integration into society, continuous research and innovation are underway as face recognition technology advances. Multi-modal systems, privacy-first designs, adaptive learning, and the strengthening of legal and ethical frameworks are the key components of the future of the face recognition industry. Multimodal biometric systems are increasingly incorporating face recognition alongside voice recognition, as well as gait analysis, eye tracking, and emotion analytics, in applications such as neuromarketing, telemedicine, and border control, thereby improving robustness and offering deeper behavioural insights (Li & Deng, 2020).

An increasing trend in AI design is ethical, as evidenced by: explainable face recognition systems that let consumers know how choices are made, dashboards for managing user consent for facial data, impact evaluations, and community involvement prior to implementation in public areas. All these key points align with the ideas put forward in the EU and UNESCO's AI ethics standards.

Conclusion

From simple pattern-matching methods, face recognition technology has advanced to highly complex, AI-driven biometric systems that may be used for real-time monitoring and authentication. It offers ease and improved control in a variety of industries, including marketing, healthcare, retail, banking, and security. It is impossible to ignore the significant technical, moral, and societal issues raised by this quick development.

The basic ideas of facial recognition systems were reviewed, along with the algorithms and data needs that underlie them. Moreover, some aspects of the marketing use of face recognition and FRP were discussed, including optional uses, advantages, and challenges.

In the end, the broad use of facial recognition technology will depend on a combination of technological advancement, open government, public confidence, and adherence to human rights norms. The future of face recognition depends on finding a careful balance between technological potential and social responsibility as countries discuss the propriety and bounds of biometric surveillance. To guarantee that face recognition technologies are implemented equitably, securely, and for the benefit of all, interdisciplinary research spanning computer science, ethics, law, and social sciences must continue.

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