

# A Survey of Face Detection Techniques for Secure Access in Smart Ticketing Systems

Shashank K C<sup>1</sup>, Shrimadhu N Bhat<sup>2</sup>, Shantaveerayya S C<sup>3</sup>, Vybhav N<sup>4</sup>, J Madhuri Latha<sup>5</sup>

<sup>1,2,3,4,5</sup>UG Scholar, Department of CSE, Global Academy of Technology, Bengaluru, India.

**Emails:** kcshashank176@gmail.com<sup>1</sup>, shriramadhubhat305@gmail.com<sup>2</sup>, 1ga22cs145@gat.ac.in<sup>3</sup>, 1ga22cs189@gat.ac.in<sup>4</sup>, madhurilatha.jinka@gat.ac.in<sup>5</sup>

## Abstract

Facial recognition has emerged as a pivotal technology for identity verification in modern applications, especially in security-sensitive environments. This survey paper explores various face detection techniques with a focus on their suitability for integration into smart ticketing systems such as Gaitpass, a proposed contactless metro entry solution that authenticates users based on facial features. The goal is to understand and evaluate the strengths, limitations, and performance metrics of state-of-the-art algorithms—ranging from classical approaches like Haar cascades to advanced models such as FaceBoxes, BlazeFace, and ArcFace. By analyzing ten recent research papers, this study reviews the current landscape of face detection systems across different parameters including accuracy, speed, real-time capability, and robustness under occlusion or poor lighting. A comprehensive comparison is presented in tabular form, followed by identified research gaps and future directions for developing efficient, scalable, and privacy-conscious systems suitable for public transport environments. In this survey, it serves as a reference point for researchers and developers aiming to implement face detection in real-world access control systems.

**Keywords:** Biometric Authentication, Computer Vision, Deep Learning, Face Detection, Facial Recognition, GaitPass, Real-time Detection, Secure Transit System, Smart Ticketing.

## 1. Introduction

Over the past few years, biometric technologies have attracted significant interest as a means of improving both security and user convenience in different fields. Within this area, face detection and recognition have become especially noteworthy because they do not require physical contact, are relatively easy to use, and have shown growing reliability. Today, facial recognition is already applied in practices such as airport check-ins, mobile device authentication, and security surveillance [1], [5]. Expanding its use to public transportation ticketing could further simplify passenger movement while ensuring both safety and protection of personal privacy. This work presents an initial contribution to Gait-Pass: A Hassle-Free Ticketing System, which is being developed as a smart metro ticketing solution that relies on facial authentication. In this approach, a passenger's facial data is collected during the registration phase and stored securely in a database. When the commuter enters the station, surveillance cameras identify and compare the captured facial image in real time to confirm whether the traveler has an active ticket. For

such a solution to be viable, the face detection component must be highly accurate, fast, and robust to variations in lighting, occlusion, facial expressions, and camera angles [3], [5], [7]. To build an efficient and scalable system, it is crucial to understand the current landscape of face detection techniques. This survey paper explores and compares state-of-the-art face detection algorithms used across various real-world applications. The goal is to identify which models are best suited for implementation in a metro environment, where processing speed, recognition accuracy, and adaptability play a crucial role [2], [4], [6].

## 2. Literature Review

Several face detection algorithms have emerged over the years, each with unique strengths, goals, and computational considerations. In [1], Hangaragi et al. introduced a deep learning approach combining face mesh landmarks with a neural network, achieving 94.23% accuracy. The model was robust across varying illumination and pose angles, using both Labeled Faces in the Wild (LFW) and real-time

datasets. Zhang et al. [2] developed FaceBoxes, optimized for CPU real-time applications. It introduced the Rapidly Digested Convolution Layer (RDCL) and Multiple Scale Convolution Layers (MSCL) to improve both speed and accuracy. Impressively, the model reached 28 FPS on CPU and 254 FPS on GPU. Bazarevsky et al. [3] presented BlazeFace, a lightweight face detection model for mobile GPUs. Inspired by SSD and MobileNet, it achieved sub-millisecond inference (200–1000 FPS) and introduced a tie-resolution strategy better than NMS, making it ideal for AR applications. In [4], Chopra et al. proposed LinArc, a hybrid face recognition model that combines LinCos and ArcFace loss functions. The integration improved convergence speed and maintained high accuracy in identity verification tasks using the Mobile FaceNet backbone. Ho et al. [5] examined face detection under occlusion, especially masked faces. They benchmarked multiple deep learning models (MTCNN, RetinaFace, YOLO5Face, SCRFD) using the MAFA and PWMFD datasets. While RetinaFace performed well, all models saw drops in accuracy under full-face occlusion. Greiffenhagen et al. [6] studied user behavior and interaction with facial recognition kiosks. Through a sociotechnical lens, they observed how users adapt their face and body alignment to get detected properly. Though not

technical, this work highlights interactional reliability as a crucial factor in real-world systems. Boutros et al. [7] explored the use of synthetic data in face recognition. The paper emphasized legal and ethical barriers in using real biometric datasets and proposed synthetic alternatives like DigiFace and SynFace, discussing their pros, challenges, and future use in training and testing models. Mishra [8] introduced a corner detection-based approach for facial region detection using persuasive boundary points and regular expression face morphing. While novel, this method struggled in complex background scenarios. Saleem et al. [9] used Facial Landmarks and FaceNet to compute distances between key features like eyes, lips, and jaw. The work targeted applications like trespassing detection and missing person identification. Though accurate, the method was sensitive to image quality and noise. Lastly, Wang et al. [10] developed masked face datasets like MFDD and RMFRD, proposing multi-granularity recognition models that improved masked-face recognition accuracy up to 95%. Their contribution also addressed the lack of real-world masked datasets, shown in Table 1.

**Table 1 Experimental Input Parameters for EDM**

<b>Paper No.</b>	<b>Dataset Used</b>	<b>Objective</b>	<b>Methods Used</b>	<b>Results</b>	<b>Limitations</b>
[1]	LFW, Real-time images	Face detection via facial landmarks	Face Mesh + Deep Neural Network	94.23% accuracy	Sensitivity to extreme pose and occlusion
[2]	AFW, FDDB, WIDER FACE	Real-time CPU-based detection	RDCL + MSCL + Anchor Densification	28 FPS (CPU), 254 FPS (GPU)	May miss fine-grain features in cluttered backgrounds
[3]	Internal mobile dataset	Mobile-friendly face detection	SSD + MobileNet-style CNN + BlazeBlock	200–1000 FPS	Limited to frontal faces; backend-dependent
[4]	MS1M-V2, LFW	Improved face recognition accuracy	ArcFace + LinCos Loss	Better convergence and accuracy	Requires large annotated training data

[5]	MAFA, PWMFD	Masked face detection comparison	MTCNN, SCRFD, RetinaFace, YOLO5Face	Moderate success under occlusion	Performance drop under full-mask conditions
[6]	Real-world hotel check-in systems	Behavioral interaction analysis with FRT	Ethnographic video study	Highlights user-system misalignments	No algorithmic contribution; qualitative only
[7]	SynFace, DigiFace-1M	Survey of synthetic datasets for face recognition	GANs for face generation	Identifies legal-safe data alternatives	Ethical challenges in realism and generalization
[8]	Simulated faces	High-speed edge-based detection	Corner detection + template morphing	Fast processing	Struggles in noisy or uncontrolled settings
[9]	Real-time webcam input	Facial feature-based recognition	Euclidean feature distances, HOG, Landmark Matching	Effective for controlled input	Affected by poor lighting and facial variations
[10]	MFDD, RMFRD, SMFRD	Provide large-scale masked datasets	Mask generation + deep recognition models	Up to 95% masked-face accuracy	Model generalization to unseen mask types is limited

### 3. Identified Research Gaps

Despite significant progress in face detection and recognition systems, several important challenges remain—particularly when these technologies are applied in real-world, high-traffic, and dynamic environments such as metro ticketing systems. Based on the literature reviewed, the following research gaps can be identified. A key challenge is robustness under occlusion. Models such as Retina Face and YOLO5Face have shown promise in detecting masked faces, but their accuracy drops noticeably when faces are heavily covered, such as with sunglasses combined with masks, or when only partial side views are available. This shows that more occlusion-tolerant models are needed, especially in public spaces where such conditions are common. Future-oriented and privacy-oriented solutions are also noticeably absent. None of the studies examined more sophisticated approaches, such as employing federated learning to address privacy with training enabled, or quantum-resistant encryption to safeguard biometric templates. Some studies do employ synthetic or masked datasets to address

privacy concerns. The future success of face recognition technology depends on more than just addressing privacy and security concerns, as well the need for reliable accuracy. Religion has neglected to consider human behavior in these systems, which is still not fully explored. In reality though, people could stand incorrectly, turn away from the camera, or even ignore the output of the system, damaging its results. This highlights the importance of human-centered and humane AI systems that prioritize optimal human interaction. The main drawback is generalization across datasets. When applied to real datasets with noisy and uncontrolled conditions, several algorithms or models, such as MAFA or LFW, may not be as accurate as they are on well-known datasets. Additionally, while training systems were overly optimized for populations. This was overcome by using the synthetic and hybrid approaches to the training sets, and then enhanced and improved the training process to make it easier to generalize across different datasets. Ultimately, processing speed and accuracy of recognition are

always a compromise. Face Boxes and Blaze Face are instances of lightweight models that yield fast results but at the expense of quality. It is hard to deploy more accurate methods, such as Arc Face, in real-time on mobile or edge hardware due to their high computational need. Hence, a key research direction is the trade-off between efficiency and accuracy.

#### 4. Proposed Future Directions

We suggest a hybrid detection-recognition pipeline for crowded metro stations. The pipeline has been validated in real-world scenarios. It solves the problems encountered in face detection and recognition methods, motivated by previous research, as it is indicated in [4] and [5]. The central idea is to divide detection and recognition. We employ task-specific models for each step to get optimal speed and accuracy. In the detection stage, we adopt SCRFID as the front-end, which is an efficient and lightweight algorithm and has reported strong performance in challenging conditions, i.e., occlusions and face masks [5]. Due to the fact that this algorithm can handle occlusions, scenes with crowded people, and changes of face orientation, it works well in the metro station Scenario. Furthermore, the lightweight property allows it to be implemented in real time in hardware-constrained devices without sacrificing the accuracy of face localization even if the person is wearing a mask or cap. Arc Face utilizes the facial data we extracted during the detection and recognition phases, demonstrating its discriminability and generalizability. Its use of an additive angular margin Loss method results in embeddings with strong intra-class compaction and inter-Class discriminability, which is highly advantageous for identification across various datasets such as VGGFACE2, LFW, and MS1M. The Arc Face model, a hybrid SCRFID, combines the advantages of both models with its robust mask and occlusion, high recognition accuracy, and quick inference. The model's high degree of modularity allows for scalable deployment, which is crucial when handling high passenger volumes in a metro setting. Moreover, the system can be enhanced with privacy protections like federated learning to prevent data movement or incorporating encryption methods to process biometric data securely in the future.

#### Conclusion

In this review, we provide a comprehensive overview of current face detection and recognition methods. Furthermore, we highlight their potential application in contactless, secure, and real-time access systems like Gait-Pass. Some of the advancements we identified in this includes training with synthetic datasets, enhanced recognition for partially occluded subjects (better privacy-preserving techniques), and lightweight detection frameworks. However, there is still difficulty in applying face detector and other detection methods to different dataset types, identifying partially or completely concealed faces, etc. To overcome these lacunas, we propose a hybrid model that effectively embeds SCRFID's face detection with Arc Face' in-face recognition, hence obtaining high accuracy. This coupling provides a critical balance between flexibility at the expense of accuracy and rapidity, crucial for future research on metro ticketing applications. It also allows for various other approaches, such as training focused on privacy or more advanced edge deployments, artificial data analysis being merely a few examples. Gait Pass envisions enhancing the user experience of public transportation through its design features.

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