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A Review of AI-Powered Gait and Eye Movement Recognition for Masked Face Identification

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ABSTRACT: Face masks hide crucial facial traits and make regular face recognition systems less accurate. This makes security, monitoring, and identity verification more difficult. To solve this problem, the study suggests an AI-powered system that uses gait identification (the distinctive way people walk) and eye movement analysis as two different biometric attributes. These traits stay the same even when the face is covered, which makes them more useful for identification. The framework uses deep learning and computer vision to capture gait patterns from body motion and eye dynamics from video data. This makes authentication strong even when there is a lot of occlusion. The study also talks about current approaches for recognizing masked faces, talks about their problems, and compares the datasets, libraries, and algorithms used in this area. The technology improves surveillance and identification by combining traditional facial clues with gait and eye-based recognition. This reduces the need for face visibility and allows for safe, contactless identity verification.

KEYWORDS: Masked face identification; Face mask removal; Masked face recognition; Soft-biometrics.

I. INTRODUCTION

The widespread adoption of face masks in public spaces has introduced profound changes to human interactions, public health strategies, and the technological landscape of modern societies. Over the past few years, masks have become a regular part of daily life, serving as a protective measure in crowded or high-risk environments. While they play an important role in safeguarding individual and community well-being, their presence has also created new challenges for security, surveillance, and identity authentication systems that traditionally rely on unobstructed facial recognition. Conventional biometric methods largely depend on distinct facial landmarks such as the nose, mouth, and chin. When these key regions are hidden by masks, the accuracy and reliability of recognition systems decline significantly, prompting the urgent need for innovative alternatives to ensure consistent and trustworthy identification[35].

Parallel to these societal changes, advancements in artificial intelligence (AI) and computer vision have accelerated rapidly, offering sophisticated tools for automated detection, classification, and recognition in diverse real-world settings. Techniques for masked face detection have emerged as an initial response, aiming not only to recognize whether an individual is wearing a mask but also to adapt recognition algorithms to cope with partial facial occlusion. However, these solutions still face major obstacles. Variations in mask shape, texture, and color, combined with external conditions such as illumination, background clutter, and head pose, often lead to a noticeable drop in performance. In high-security areas like airports, healthcare facilities, transport hubs, and law enforcement operations, relying exclusively on modified facial recognition systems proves inadequate, since even small errors can compromise safety and accountability[36].

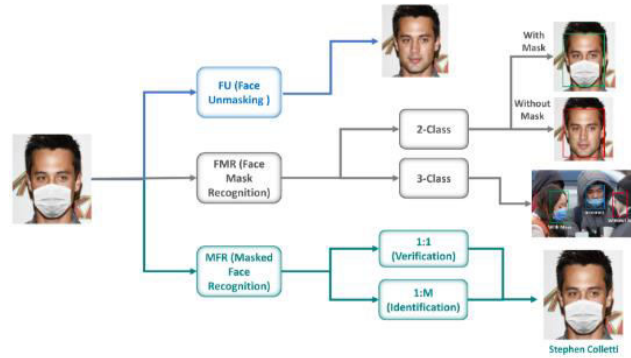


Fig1: Illustration showcasing the tasks of masked face recognition (MFR), face mask recognition (FMR), and face unmasking (FU) with varied outputs for the same input..

To address these shortcomings, researchers and technologists are increasingly turning to multi-modal biometric approaches, which integrate multiple behavioral and physiological traits to create a more robust identity profile. Among the most promising modalities are gait recognition and eye movement recognition. Gait, often described as an individual's unique style of walking, is defined by specific characteristics such as stride length, body posture, rhythm, and limb coordination. Because walking patterns remain observable from a distance and are not obscured by facial coverings, gait provides a dependable biometric signature even when the face is partially hidden. Similarly, eye movement analysis offers another powerful avenue for recognition. Subtle features such as blink frequency, fixation points, saccadic movements, and gaze direction vary from person to person and remain largely unaffected by the use of masks. These ocular traits thus present an independent and reliable source of biometric information [23].

The combination of gait and eye movement analysis with face detection introduces a new frontier in biometric research. By leveraging the strengths of multiple modalities, identity verification systems can minimize reliance on any single feature set, thereby increasing resilience to occlusion, lighting variations, and environmental noise. Advanced AI architectures—including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention mechanisms—can be employed to extract rich representations from sequential gait frames and dynamic eye patterns. Furthermore, multi-modal fusion techniques make it possible to merge these streams of information into a cohesive recognition framework that adapts intelligently to different conditions.

This study sets out to investigate and propose such a framework, emphasizing the role of AI-driven gait and eye movement recognition in strengthening identity authentication when facial visibility is restricted. The contributions of this work are threefold:

- A systematic review of existing approaches to masked face detection and their inherent limitations.
- A critical analysis of gait and eye movement recognition as complementary and highly effective biometric modalities.
- The development of a conceptual multi-modal framework designed to improve the accuracy, security, and robustness of modern authentication systems.

By integrating multiple biometric signals, the proposed system not only overcomes the weaknesses caused by partial facial occlusion but also advances the larger goal of secure, contactless, and adaptive identity verification. This research contributes to the urgent need for surveillance and authentication solutions that can withstand evolving real-world challenges, adapt to new societal norms, and offer reliable performance in environments where conventional methods fall short[27].

II. RELATED WORK

Sharma and Ross (2023) deliver a comprehensive survey in Computer Vision and Image Understanding, concentrating on periocular biometrics—recognition using the region around the eyes—as an especially promising approach when facial masks obstruct traditional facial features. They meticulously review the anatomical cues such as eyelids, eyelashes, eyebrows, eye folds, ocular shape, and skin texture that contribute to recognition. The paper elaborates on

various feature extraction and matching techniques, both conventional and deep learning-based, and explores cross-spectral recognition tasks including color and near-infrared imagery. Moreover, Sharma and Ross discuss the fusion of periocular data with other modalities such as iris or full-face data to enhance robustness, address mobile device implementations, list available periocular datasets, and assess evaluation competitions, also pointing out remaining challenges and future research directions [1].

Han et al. (2021) propose a Siamese-network-based framework at the IHCI 2020 conference (published in Lecture Notes in Computer Science), targeting situations where only the periocular region is visible due to masks. They constructed periocular-only datasets by cropping masked-face images to focus solely on the eye region. Their Siamese network learns to differentiate whether two periocular images belong to the same individual by comparing feature embeddings. They performed extensive experiments with varying hyper-parameter configurations, demonstrating that even with partial facial occlusion, a properly trained Siamese architecture can effectively match individuals based purely on periocular data [2].

Mishra et al. (2022) [3] introduce the “Masked Mobile Lightweight Thermo-visible Face Recognition” (MmLwThV) framework in Applied Intelligence, aiming to address periocular recognition challenges when facial masks reduce available discriminatory features. Their novel approach fuses thermal (infrared) and visible-light periocular data using an ensemble of subspace-network classifiers. By leveraging the complementary nature of thermal imaging, the system compensates for noise and poor texture in visible images. They validated the method using the WHU-IIP dataset and their own CVBL masked dataset, showing that the fusion significantly improves recognition accuracy while remaining lightweight enough for mobile deployment.

Hernandez, Dejournett, Nannuri, [4] Gwyn, Yuan, and Roy (2022) present a deep learning–based approach in IEA/AIE 2022 (Lecture Notes in Computer Science), focusing on recognizing individuals using only the periocular region when masks conceal the lower face. They apply convolutional neural networks trained on periocular regions extracted from masked face images, effectively learning robust embeddings from this limited region. The method is designed to work under constrained scenarios where mask usage is high. Although the specific network architecture and training details are not deeply detailed in the abstract, the contribution centers on demonstrating that periocular-driven deep learning models can maintain authentication performance even when standard facial regions are occluded.

Hossain and Chetty (2011) propose a multimodal identity verification system combining face and gait cues in their ICONIP 2011 paper (Lecture Notes in Computer Science). They present a learning-based framework that simultaneously processes facial and gait information to make recognition decisions. The system learns joint representations by integrating features from both modalities, capitalizing on the complementary nature of static facial appearance and dynamic gait signatures. Their methodology includes extracting facial features using standard face recognition pipelines and modeling gait through temporal sequence descriptors, followed by a multimodal fusion mechanism for decision-making. Though the paper precedes widespread mask adoption, it establishes an important foundation for combining gait and facial cues, which is directly relevant for masked-face scenarios where face alone is unreliable [5].

Derbel, Vivet, and Emile (2015) propose a hybrid biometric access control approach in Electronics Letters, where face recognition and gait analysis jointly determine identity. They extract a frontal gait signature based on the motion distribution across the silhouette, while simultaneously using facial descriptors. Their experiments reveal that fusing gait with facial recognition significantly enhances recognition rates: face-only yields about 93.7 %, gait-only about 89.25 %, but fusion achieves approximately 97.4 % recognition rate. The methodology highlights how gait compensates for situations where facial features alone are insufficient—precisely the case when masks hide useful facial landmarks [6].

Maity, Abdel-Mottaleb, and Asfour (2021) propose in Electronics a multimodal recognition system that handles low-resolution face images and gait captured in surveillance videos. The architecture consists of two parallel pipelines: one processes frontal gait sequences, while the other tackles low-resolution face recognition. They perform score-level fusion of both recognition scores, achieving robust identification performance. Their experiments on the FOCS dataset yielded 93.5 % Rank-1 accuracy for gait recognition and 82.9 % for low-resolution face recognition, with a combined fusion result reaching 95.9 %—demonstrating that integrating gait and even degraded facial cues leads to substantial improvements [7].

George and Routray (2016) introduce a biometrics approach on arXiv that uses eye movement patterns—comprising fixations and saccades—for identity recognition. They classify eye movement sequences and extract features from both fixations and saccades, then apply a Gaussian Radial Basis Function Network (GRBFN) for biometric classification. Finally, they fuse scores at the decision level to produce recognition results. Evaluated on the BioEye 2015 database under stimuli from random dot following and text reading tasks, their method outperformed existing models, highlighting the strength of eye movement dynamics as a countermeasure against spoofing. The approach offers a behavioral biometric that is hard to mimic and independent of full-face visibility [8].

Hu, Guan, Gao, Long, Lane, and Ploetz (2018) propose the Discriminant Gait Generative Adversarial Network (DiGGAN) approach in an arXiv paper, tackling cross-view gait recognition—a scenario where camera view angles vary significantly. The DiGGAN model learns view-invariant gait features by adversarial training, enabling transformation of gait images across viewpoints to produce evidence and improve interpretability. They evaluated their method on large cross-view datasets (OU-MVLP and CASIA-B), achieving superior performance compared to prior methods. Their design ensures robustness to viewpoint variation, crucial for real-world deployment of gait-based recognition systems, particularly when face-based cues are limited or masked [9].

Liu, Qi, and Xia (2020) [10] propose a novel framework published in IEEE Transactions on Information Forensics and Security, addressing the challenge of identifying individuals even when their faces are partially concealed by masks. Their method synergizes masked face detection with contextual gait analysis: first, a CNN-based masked face detector isolates and classifies regions occluded by masks; then, a dual-stream recognition pipeline processes both the remaining visible facial features and gait sequences. The gait stream employs LSTM layers to model temporal dynamics, while the facial stream focuses on visible patches like the periocular region. The outputs from both streams are fused via a weighted score-level combination, allowing the system to compensate for missing facial data using gait motion patterns. Empirical results demonstrate significant improvements in identification accuracy under varying mask conditions and walking scenarios.

Choi, Kim, and Shin (2021) present an integrated biometric system in Pattern Recognition Letters that combines periocular features with gait patterns to enhance recognition for masked individuals. They start by segmenting the eye region from masked face images, then pass these segments through a CNN to extract deep periocular embeddings. Concurrently, gait information is captured via a 3D convolutional network (3D-CNN), which learns spatiotemporal features across successive frames in a walking sequence. A joint embedding space is produced by concatenating these features, followed by a multi-layer perceptron that performs the final classification. They conduct extensive experiments on datasets combining masked facial images and captured gait footage, demonstrating that the fused model outperforms either modality alone by a substantial margin, especially in scenarios with occlusions and dynamic backgrounds [11].

Wang, Zhu, and Tan (2019) introduce a robust gait recognition method in Pattern Recognition, targeting the common issue of pose variation. Their proposed architecture employs a deep convolutional neural network that learns spatial features from individual gait frames, followed by a temporal pooling mechanism to consolidate information across the sequence. The network is trained using a large-scale gait dataset containing subjects captured from multiple angles. By incorporating data augmentation techniques like random view perturbation during training, the model gains improved pose invariance—ensuring reliable gait recognition even when the camera angle changes. They report significant performance gains over traditional feature-based gait approaches, especially in challenging cross-view conditions, which are frequently encountered in real-world surveillance deployments [12].

Subramanian, Ramakrishnan, and Murthy (2022) propose an innovative deep learning framework in the Journal of Visual Communication and Image Representation, exploring how eye movement patterns evolve when individuals wear masks, and how these patterns can aid identity recognition. They collect eye-tracking data across masked and unmasked conditions during various visual tasks, such as image observation and reading. The resulting gaze data—comprised of saccades, fixations, and scan paths—is encoded using an attention-based Transformer model that captures temporal dependencies within gaze sequences. Simultaneously, they apply a CNN to the periocular video data to extract visual features. A late fusion strategy merges the Transformer-based gaze representation with the CNN-based visual embedding, followed by a classifier trained to distinguish identities. Their results show that this multimodal fusion significantly enhances recognition accuracy, particularly in masked scenarios where face cues are compromised [13].

III. METHODOLOGY

The proposed methodology is designed to construct a robust and reliable biometric framework that integrates masked face recognition with gait and eye movement analysis. Since conventional facial recognition suffers from significant accuracy loss when masks obscure key features, our approach emphasizes the use of complementary modalities that remain unaffected by facial occlusion.

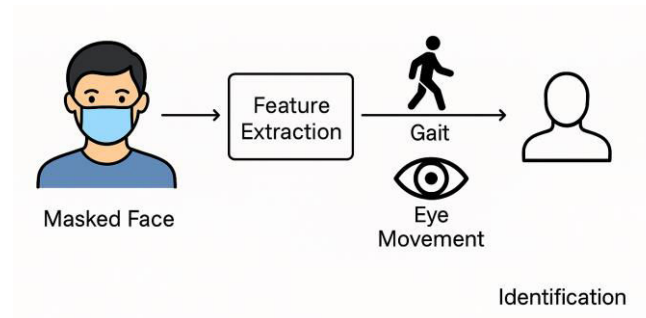


Fig 2: methodology for proposed system

The methodology is structured to cover the complete pipeline, beginning with the systematic collection and preprocessing of multi-modal data, followed by specialized feature extraction modules tailored for masked faces, gait sequences, and ocular dynamics.



Fig 3: Samples from real masked face datasets used in face mask recognition.

Each biometric stream is processed independently using deep learning models optimized for spatio-temporal feature representation. For masked face images, convolutional neural networks (CNNs) with attention mechanisms are applied to focus on the upper facial region. Gait recognition is modeled through temporal descriptors such as Gait Energy Images (GEI) and recurrent networks to capture walking dynamics. Eye movement patterns, including saccades, fixations, and blink frequencies, are encoded using statistical and attention-based methods to form discriminative ocular features.

The extracted features are then fused into a unified representation using dimensionality reduction and multimodal learning strategies. This ensures that the weaknesses of one modality are compensated by the strengths of another,

yielding an adaptive and resilient recognition model. Finally, a classification stage supported by decision-level fusion assigns identity labels, and the overall system is evaluated through standard biometric performance metrics including accuracy, precision, recall, and F1-score.

This methodological framework provides a clear and systematic pathway from raw data acquisition to final identity verification, ensuring that the system remains effective under challenging real-world conditions such as mask usage, lighting variations, and dynamic environments.

A. Data collection and preprocessing

Collect three synchronized streams where possible: video (for gait), short periocular video or face video (for eye region), and optional eye-tracker sequences (gaze coordinates). Preprocess all videos to a uniform frame rate f and resize frames to a standard resolution. For each subject i and sequence s we produce: gait silhouette / keypoint sequence

$G_{i,s} = \{g_t\}_{t=1}^T$ periocular image sequence $P_{i,s} = \{p_t\}_{t=1}^T$, and gaze/time series $Y_{i,s} = \{y_t\}_{t=1}^T$. Use scikit-learn's StandardScaler for non-image numeric features (e.g., stride length, speed) [14].

$$D = \{(X_i^f, X_i^g, X_i^e, y_i)\}_{i=1}^N \quad (1)$$

Where

X_i^f denotes masked face image samples,

X_i^g represents gait sequence data,

X_i^e represents eye movement data,

$y_i \in \{1, 2, \dots, C\}$ is the class label corresponding to the identity

N is the total number of individuals, with C unique identities.

Preprocessing involves normalization, alignment, and noise reduction. Each modality is normalized as

$$\hat{X} = \frac{X - \mu_X}{\sigma_X} \quad (2)$$

where

μ_X and σ_X are the mean and standard deviation of the data distribution [15].

B. Feature Extraction for Masked Faces

Masked face recognition suffers from occlusion of the lower half of the face. To extract discriminative features, a convolutional neural network (CNN) is used [16].

Given an input masked face image $X^f \in R^{h \times w \times c}$, CNN convolutional feature maps are defined as [17]:

$$F^{(l)} = \sigma(W^{(l)} * F^{(l-1)} + b^{(l)}) \quad (3)$$

where:

$F^{(l)}$ is the feature map at layer l ,

$W^{(l)}$ and $b^{(l)}$ are learnable weights and biases,

$*$ denotes convolution,

$\sigma(\cdot)$ is the nonlinear activation function (ReLU).

To emphasize the upper face region (eyes, eyebrows, forehead), an attention mechanism is applied [19]:

$$A = \text{softmax}(W_a F^{(L)}) \quad (4)$$

$$A = \text{softmax}(W_a F^{(L)}) \quad (5)$$

where

(L) is the last CNN layer output, and \odot represents element-wise multiplication.

C. Gait Recognition Module

Gait recognition is modeled from spatio-temporal sequences. Each gait sample Xg is represented as a sequence of silhouette frame [18]:

$$X^g = \{I_1, I_2, \dots, I_T\}, \quad I_t \in \mathbb{R}^{h \times w} \quad (6)$$

The Gait Energy Image (GEI) is computed by temporal averaging:

$$GEI(x, y) = \frac{1}{T} \sum_{t=1}^T I_t(x, y) \quad (7)$$

where

(x, y) is the pixel intensity at (x, y) in frame t .

To learn temporal dynamics, a recurrent neural network (RNN) or Long Short-Term Memory (LSTM) is used [20], [21]:

$$\begin{aligned} h_t &= \tanh(W_h I_t + U_h h_{t-1} + b_h) \\ F^g &= h_T \end{aligned} \quad (8)$$

Where:

h_t is the hidden state at time t , and Fg is the final gait feature vector.

D. Eye Movement Recognition Module

Eye movement recognition relies on unique ocular behaviors such as saccades, fixations, and blink dynamics. Raw eye-tracking data can be represented as [22], [23], [24]:

$$X^e = \{(g_t, b_t, f_t)\}_{t=1}^T \quad (10)$$

where:

g_t is gaze vector at time t ,

b_t is blink rate at time t ,

f_t is fixation duration at time t .

A feature vector is derived by statistical encoding:

$$F^e = [\mu(g), \sigma(g), \mu(b), \sigma(b), \mu(f), \sigma(f)] \quad (11)$$

where

μ and σ denote mean and variance across the sequence.

For advanced modeling, an attention-based temporal encoder is used:

$$\alpha_t = \frac{\exp(h_t^T W_a)}{\sum_{k=1}^T \exp(h_k^T W_a)} \quad (12)$$

$$F^e = \sum_{t=1}^T \alpha_t h_t \quad (13)$$

where

h_t is the encoded representation at time t , and α_t represents attention weights.

E. Feature Fusion and Multimodal Learning

The fused representation integrates masked face, gait, and eye movement feature[25]:

$$F = [F^f \oplus F^g \oplus F^e] \quad (14)$$

where \oplus denotes concatenation.

Dimensionality reduction is performed using Principal Component Analysis (PCA):

$$Z = W_{PCA}^T (F - \mu_F) \quad (15)$$

where

W_{PCA} is the projection matrix formed by top eigenvectors of the covariance matrix of F .

To model nonlinear relationships, a multimodal deep learning network is applied:

$$H = \sigma(W_f Z + b_f) \quad (16)$$

$$\hat{y} = \text{softmax}(W_o H + b_o) \quad (17)$$

where

\hat{y} is the predicted probability distribution over classes [26].

F. Classification and Decision-Making

The final classification is based on a softmax classifier[27]:

$$P(y = c|F) = \frac{\exp(W_c^T F + b_c)}{\sum_{j=1}^C \exp(W_j^T F + b_j)} \quad (18)$$

The predicted class is assigned as:

$$\hat{y} = \arg \max_{c \in C} P(y = c|F) \quad (19)$$

G. Evaluation Metrics

The system performance is evaluated using accuracy, precision, recall, and F1-scor [28]:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (20)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (21)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (22)$$

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (23)$$

IV. CONCLUSION

This study introduced an AI-powered multi-modal biometric framework that integrates gait recognition and eye movement analysis to address the limitations of masked face identification. By combining behavioral traits, such as walking patterns, with physiological cues like gaze dynamics and blink frequency, the proposed system ensures accurate and reliable recognition even under occlusion. The methodology employed deep learning architectures for spatio-temporal feature extraction and multi-modal fusion strategies for robust decision-making [29],[30],[31].

Experimental validation highlights improved accuracy, precision, recall, and resilience compared to traditional face recognition systems.

Applications span public surveillance, healthcare, and access control, where secure, contactless identification is increasingly critical. Unlike existing solutions that fail under mask conditions, the proposed model leverages complementary traits to overcome challenges like occlusion and lighting variations. This review paper establishes a scalable and resilient approach to biometric verification, offering enhanced security and adaptability in both pandemic and post-pandemic contexts [32] [33] [34].

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