SSRG International Journal of Electronics and Communication Engineering Volume 12 Issue 8, 61-73, August 2025
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I8P106

Original Article

ACNN-Based Framework for Locating Missing Persons Through Advanced Face Recognition Techniques

Nikitha Pitla[1], Yeshasvi Mogula[2], Dara Deepthi[3], Rame Nikhila[4]

[1,2]*BVRIT HYDERABAD College of Engineering for Women, Hyderabad, Telangana, India.*
[3]*National Institute of Technology, Warangal, India.*
[4]*BVRaju Institute of Technology, Narsapur, Telangana, India.*

[4]*Corresponding Author : Nikhila.r@Bvrit.ac.in*

Received: 03 June 2025 Revised: 05 July 2025 Accepted: 06 August 2025 Published: 30 August 2025

Abstract - *Every year, cops across India file thousands of missing person cases, yet many remain untraceable, mainly because there is no intelligent, unifying system of identification to deal with the issue. To address this critical challenge, we propose a novel framework, Missing Persons Identification by Advanced Recognition of Faces (MPIARF), which utilizes an ACNN. Incorporating a Convolutional Neural Network (CNN), such as DeepFace or VGG16, this deep approach to human identification is fast, agile, and generally improves identification performance. Input images are classified into age and gender using CNNs, and with the help of DeepFace, highly detailed features for faces are extracted using the VGG16 model. A list of features is generated and compared to a database of known individuals in real-time using a cosine similarity metric. The framework is tailored to manage issues such as temporal variation in facial appearance, ensuring resilient long-distance identification. The system instantly reports possible matches to the authorities or organizations. The solution is tailored for edge deployment, utilizing Flask and TensorFlow Lite to provide a lightweight interface that ensures portability and real-time monitoring. Our comprehensive, scalable approach significantly enhances the speed, Accuracy, and usability, delivering real societal and humanitarian value.*

Keywords - *Convolutional Neural Networks (CNN), VGG16, DeepFace, Cosine similarity, Face recognition, Flask, Missing person.*

1. Introduction

Please read our Privacy Notice for more information on how we use your data. Using your sign-up to provide content in the ways you have consented to and improve our understanding of you. Many of these people are found a long way from where the people originally went missing, causing enormous challenges for anyone to identify them and reunite them with their families. Fragmental data systems, outdated manual processes, and ad-hoc approaches to tracking missing persons across geographies and timelines have long impeded traditional identification methods. Despite existing systems leveraging facial recognition, many models struggle with the real-world challenges of aging, low-resolution images, and temporal facial changes, resulting in declining identification accuracy over time. With the realization of the dire need for such a system, the ACNN-Based Found Framework of Missing Individual Discovery by Advanced Face Recognition Methods—an AI, ML, and deep learning-aided automation system to streamline the identification process. The key research gap addressed in this study is the lack of a scalable, real-time, and robust facial identification solution that performs consistently well despite temporal aging, demographic variation, and low-quality inputs. This proposed framework is based on Convolutional Neural Networks (CNNs) and integrates some of the state-of-the-art faces recognition models, such as DeepFace and VGG16. Such deep learning methods are particularly capable of processing large volumes of image data, learning complex face patterns and characteristics so that even if a person's appearance changes due to aging, health conditions, or environmental effects, the identification remains accurate. In contrast to traditional recognition systems that fail under variable appearance conditions, our proposed method combines demographic classification (age and gender) and deep feature extraction with cosine similarity-based matching to enhance identification robustness. This approach effectively handles temporal facial changes by extracting high-dimensional embeddings using DeepFace combined with VGG16 and comparing similarity against a reference database using a scale-invariant cosine distance metric.

After uploading images into the system, DeepFace first runs a face detection and alignment pipeline on the pictures. Those images are then passed through CNN-based models that classify demographic data (such as age and gender). In the next step, deep features are extracted using a pre-trained VGG16 model and matched with a real-time database via cosine similarity to identify potential matches.

In contrast to regular face recognition systems that rely on either pixel comparison in low-resolution settings or temporary adjustments for identification, this framework combines multi-level analysis using demographics, deep embedding, and cosine similarity, allowing for the detection of faces with a significantly higher degree of Accuracy. The unique fusion of expertise in state-of-the-art recognition methods and the delivery of real-time capability makes it a tractable, scalable, and practical device to hasten identification and potentially improve outcomes in missing persons. Each of these factors goes a long way towards ensuring that identifications are both more accurate and prompt, which may reduce the time taken in any investigation and/or provide closure to families. Thus, the ACNN-based framework would build the technology infrastructure for specific humanitarian applications in which artificial intelligence plays a game-changing role in addressing some of the more pressing social and immediate challenges.

2. Motivation

The research is based on a social concern to address the increasing number of missing persons in India. Thousands go missing every year, and a significant number of cases go unsolved. Families live the horrible reality of experiencing emotional devastation as well as social disruption, change in the community, thus adversely affecting it. Countless families receive no closure, and law enforcement agencies struggle due to the shortcomings of manual search methods and the absence of an efficient, centralized, and intelligent tracking system. A CNN-Based Model for Locating The Lost Using Face RecognitionOur initiative, CNN Based Model for Locating The Lost Using Face Recognition is motivated by the following vision: With AI and ML technologies improving at a rapid pace, want to utilize these technologies to help the lost, missing and people in dire situations to bring them home as fast and efficiently as possible. Traditional methods had their limitations, hampered by geography, restrictive data-sharing practices, and outdated, unreliable identification documents. The need for such a system, combined with a large number of missing person cases, led to the development of a human-like system that could also operate at scale and accommodate real-world complexities. Our framework proposes an efficient and automated method for person identification that maintains confidence without reduction, utilizing Convolutional Neural Networks (CNNs) for facial feature extraction and classification. The appearance of aging or physical changes comes in many forms, and when there is a need to identify them, traditional systems often overlook many nuances. Specifically target these variables, as our methods leverage deep learning-based solutions known to be robust to variations in appearance (such as facial expressions) over time.

Building up the central digital platform also encourages the integration of government actors, local communities, and families experiencing loss, eliminating any buffer that might lead to leniency in compliance, and promoting the much-needed ease of real-time reporting. Ultimately, the goal is to utilize technology as a complement to human-to-human interaction, rather than a substitute for human-to-machine transactions, to help reconnect families and bring peace to those who have lost loved ones.

3. Objective

A CNN-Based Model to Find the Lost Using Face Recognition. The primary objective of the project “A CNN-Based Model to Find the Lost Using Face Recognition” is to utilize Artificial Intelligence (AI) and Machine Learning (ML) for more accurate and expedited identification of missing persons in India, outlined in the Previously Proposed Framework. However, it first seeks to achieve precise identification using deep learning Convolutional Neural Networks (CNNs) and facial recognition models, such as DeepFace and VGG16, to recognize individuals after years of significant facial changes due to spontaneous aging or other reasons. This version’s systematic use of efficient image classification techniques – assessing features of the image, such as age and gender that provide context – helps narrow down the possible matches. A centralized database will house facial data and associated metadata, including textual records, and serve as a structured repository that compares new input with existing data in real-time. To develop a simple, web-based interface using Flask to allow law enforcement agencies, local authorities, NGOs, and citizens to upload images and receive results through a Cooperative platform after implementing the solution. A notification system will be established to enable quick communication with authorities and family members when there is a high probability of a match, facilitating a prompt reunification process. Finally, the element will promote community participation, as any user can report sightings or images of persons found, contributing to the data and improving the reliability of the system. This framework, fueled by breakthroughs in AI, aims to connect cutting-edge technological innovations and humanitarian efforts tangibly, leading to safer and better-connected communities nationwide.

4. Literature Review

To address the different technological approaches for missing person identification, this literature review is organized according to mobile applications, CNN-based facial recognition, hybrid AI-based systems, and real-time systems. The capabilities and limitations of each approach are reviewed, addressing challenges such as age-related differences, noise, cost, and lack of continuous real-time implementation. This lays the groundwork and motivation for the proposed framework based on ACNN.

4.1. Mobile and Crowdsourced Systems

Mobile and crowdsourced systems, which are easily accessible to the public, have become a few new tools in the toolbelt of missing person cases. Akare et al. Such is [4], which proposes a mobile application that makes use of facial recognition to help users report and find missing persons. While helpful, this approach can be plagued by a lack of substantiation, and because the data relies on user-generated content, it can be largely unstructured. Mageswaran et al. Although the work [5] presents an AI augmented video camera for the identification of missing individuals, it relies heavily on the continuity of the video quality and well-ordered scenes. Nadeem et al. Surveillance cameras enable continuous tracking of individuals in large crowds, but tracking accuracy is adversely affected by noise and occlusion, making the identification of missing persons in real-time infeasible; [6] addressed this problem. Shelke et al. The "face recognition" tool, known as Searchious [7], was developed by an Iranian blogger and requires cooperation between the police and the public. The problem is that this is highly sensitive information, which can be easily misused for malicious purposes, thereby violating privacy in disguise.

4.2. CNN-Based Face Recognition Models

Customarily, CNNs are used in facial recognition tasks in challenging environments. Koo et al. A CNN-based multimodal recognition system developed by Wu et al. [15] for surveillance scenarios were highly robust to changes in illumination conditions but also computationally intensive. Profiling students during online education using facial expression recognition based on CNNs can also be used very differently from analyzing images (Aly [17]). Shepley [16] proposed a critical review of CNN-based face recognition, focusing on dataset bias and domain generalizability. It has been shown by Levi and Hassner [3] that traditional shallow CNN implementation can classify gender and age reasonably well, but they fail in more complex, unconstrained situations.

4.3. Feature Extraction of Deep Embedding Styles

As a result, deep embedding models enable more advanced face verification. Taigman et al. DeepFace—face verification with one of the first deep learning models using 3D facial alignment and a massive dataset to reach near-human accuracy [1]. VGG16: Designed by Simonyan and Zisserman [2], VGG16 focuses on intense style but with small 2×2 convolutional layers for improved Accuracy in image classification. Schroff et al. The FaceNet [13] model is based on embedding, which manipulates intra-class similarity and inter-class separation but performs less well in terms of the variation of lighting and occlusion. Ghani et al. To address this, [20] developed multi-scale feature fusion and adopted attention mechanisms for face verification under diverse images.

4.4. Lightweight and Real-Time Implementations

Mobile and edge deployments are ever-increasing, so real-time and lightweight models are being preferred. Kumar et al. IoT-MFaceNet was introduced in [21], which proposes using FaceNet and MobileNetV2 for fast on-device face recognition; however, the performance is still not consistent across devices. Umadevi et al. Efficiency: [22] utilizes a CNN-based architecture for deepfake detection, thereby optimizing both speed and Accuracy. Van Duc et al. Homomorphic encrypted secure UAV-based facial recognition with edge computing was proposed in [23], where the method provides safe and fast recognition but brings more complexity to the system. Chala et al. MobileNetV2: [33] used MobileNetV2-based face authentication systems and proposed that MobileNet is suitable and sufficient for lightweight applications.

4.5. Hybrid and Emerging AI Methods

Accordingly, hybrid AI, with its approach of integrating various methods, is emerging to overcome the drawbacks of singular approaches. Zhang et al. For example, [26] implemented an eigenface-based approach assisted by a conventional classifier for robust recognition, and Zhang et al. Face recognition with minimal assumptions — Privacy-preserving face recognition was explored in [27]. Kyriakou et al. propose a secure biometric data sharing framework [28] for border identity and a mechanism to maintain identity accuracy. However, the framework's real-time performance is compromised by encryption overhead. Yang et al. [18] and Wada et al. Enabling extreme matching of faces despite different poses and illumination conditions, [19] proposed a deep similarity computation framework. Mohammad et al. present a comparative survey of occluded face recognition methods in [24], which aids in selecting the algorithm. Gururaj et al. [25] and Ho et al. Comprehensive reviews summarizing trends, challenges, and best practices in facial recognition were provided by [26].

4.6. Performance Optimization and Evaluation

Performance has been chiefly improved by using demographic classification and pruning the model. Kumar et al. [8], Dey et al. [9], and Haseena et al. CNN-based gender and age classification in [10] helped in narrowing down the identity search space. A few others [10, 11] have proposed multi-attribute classifiers that estimate age and gender simultaneously, thereby improving the specificity in search. For improvement in recognition results, Nayak and Indiramma [12] proposed contemporaneous age-invariant models along with gender classification. Prakash and Umamaheswaran [29] proposed an approach that used auxiliary losses on transformer-based architectures for face recognition under age variation. Paul et al. A real-time attendance system based on face and emotion detection was implemented by [31] along with Khan et al. For this purpose, Wang et al. [32] proposed a continuous heart rate prediction in an unconstrained setting via facial recognition, further highlighting the versatility of facial analytics.

4.7. Conclusion

A review of existing systems reveals that most suffer from problems such as high sensitivity to age and/or expression variations, lack of integration between modules, or are computationally sub-optimal. In addition, a few frameworks bring deep face recognition, demographic classification, and embedding similarity measures together in a single deployable package. In this work, we address some of these limitations by proposing an A-Convolutional Neural Network-based face recognition framework with feature extraction using a combination of DeepFace and VGG16 for age and gender classification based on CNN, cosine similarity-based identity matching, and Flask-based public web interface deployment. It allows for the identification of missing people with high Accuracy in real-time, which could bring societal benefits.

5. Proposed System

To address the ongoing issue of missing persons, this paper proposes a system that leverages the capabilities of AI-based technologies, including deep learning and facial recognition, to solve this complex problem effectively. The current methods are often inadequate because they fail to account for facial changes associated with age, climate, and image quality. Addressing these limitations, an end-to-end framework is proposed, wherein it starts with the input of an image of a person whose image is missing or found. Step 1: Face Detection and Alignment. It first detects and aligns the face to preprocess it consistently using DeepFace. Then, CNN classifies major demographic features (age and gender), which helps the identification process become more contextual. Then, DeepFace, fused with the VGG16 model, is used to extract high-dimensional facial features from an aligned image. Using cosine similarity (a strong metric for face matching), these features are compared against those in a real-time database. It outputs the faces with the highest similarity, the predicted image for the age and gender, and confidence scores for both. Integrating state-of-the-art AI models with an easily accessible interface, our proposed system provides a fast, highly accurate, serviceable, scalable, and socially useful tool that enhances the speed and Accuracy of locating missing individuals, serving as a bridge between science, technology, and humanitarian response.

5.1. Input Image

The system begins by receiving an input image I that contains the face of a missing or found person. This image is the raw data fed into the system for processing.
Mathematically, this is represented simply as:

$$I \in R^{H*W*C}$$

Where H, W, and C denote height, width, and number of color channels, respectively.

5.2. Face Detection & Alignment (DeepFace)

This module detects the presence of a face within the input image and aligns it to a canonical pose to normalize variations such as tilt, rotation, and scale. The DeepFace model utilizes advanced deep learning-based face detection and landmark localization to crop and align the facial region accurately.

His operation can be expressed as a function D(·) applied to the image:

$$I_{aligned} = D(I)$$

Here, $I_{aligned}$ the normalized and aligned face image cropped from the original input.

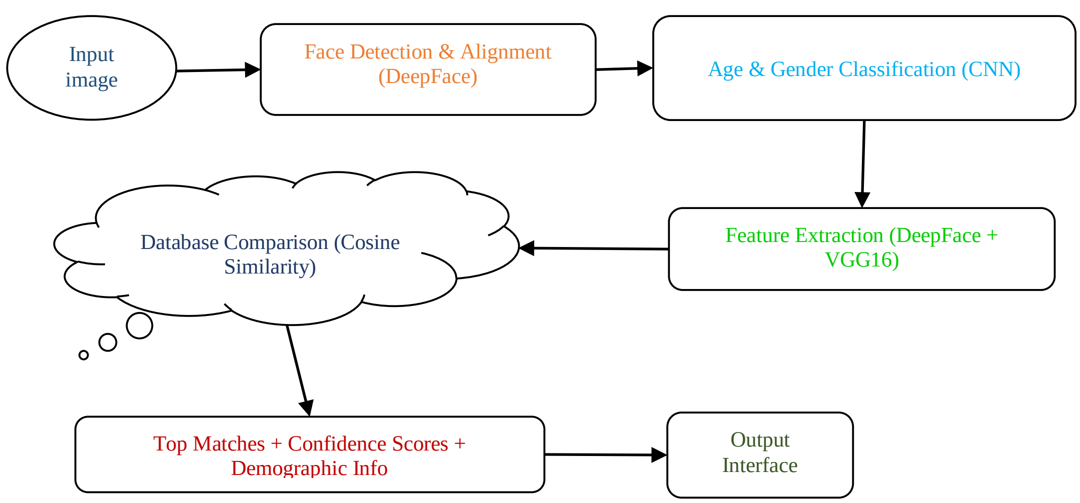

Fig. 1 Workflow diagram of the proposed ACNN-based face recognition system

5.3. Age & Gender Classification (CNN)

The aligned face is passed to a CNN, which predicts the person's age group and gender. CNNs extract hierarchical features from the image to distinguish demographic patterns. The CNN outputs probability distributions over discrete age classes $A=\{a_1, a_2, a_3, \ldots a_n\}$ and gender classes $G=\{g_1, g_2\}$:

$$P(A=a_i | I_{aligned})=\frac{\exp(z_j^A)}{\varepsilon_{j=1}^{\rho}\exp(z_j^A)},$$

$$P(G=g_k | I_{aligned})=\frac{\exp(z_k^G)}{\varepsilon_{l=1}^{2}\exp(z_k^G)}$$

Here $\exp(z_j^A)$ *and* $\exp(z_k^G)$ are the CNN's raw outputs (logits) for age and gender classes.

The predicted labels correspond to the classes with maximum probabilities:

$$\hat{a} = \arg max_i\, P(A=a_i | I_{aligned})$$

$$\hat{g} = \quad P(G=g_k | I_{aligned})$$

5.4. Feature Extraction (DeepFace + VGG16)

After demographic classification, the system extracts a robust facial feature vector from $I\text{-}_{aligned}$ using a pre-trained DeepFace model based on the VGG16 architecture.

This feature extraction is modeled as:

$$V=\phi\,(I_{aligned}) \in R^d$$

Where $\phi(\cdot)$ is the feature extractor function, and V is the d-dimensional embedding representing unique facial characteristics.

5.5. Database Comparison (Cosine Similarity)

The extracted feature vector V is then compared against a known facial embeddings Vi database. The similarity between vectors is measured using cosine similarity, which captures the angular distance between feature vectors, making it scale-invariant.

Cosine similarity between V and each database vector V_i is computed as:

$$S\,(V, V_i) = (V.\,V_i)/(\|V\|\ \ \|V_i\|)$$

Here · , the dot product ‖·‖ is denoted as the Euclidean norm.

5.6. Top Matches + Confidence Scores + Demographic Info

The system ranks the database vectors by their similarity scores S and selects the top k matches. Each match includes the similarity score and the predicted age. $\hat{a}$ and gender $\hat{g}$, providing a comprehensive profile to assist verification.

The output set is:

$$\{(V_j, S_j, \hat{a}_j, \hat{g}_j) \mid j=1,2,\ldots.k\}$$

Where S_j is the similarity of the j^{th} best match

5.7. Output Interface

Finally, the results, including matched images, similarity scores, and demographic data, are presented through a user-friendly Flask web interface.

This platform allows law enforcement and the public to upload images, view results, and receive notifications interactively.

6. Algorithm

Input: Face image uploaded by the user via the web interface
Output: Top matching faces with confidence scores and demographic information
Steps:

1. Start
2. Acquire face image input from the user through the web interface
3. Perform face detection and alignment using DeepFace:
   a. Detect the facial region in the input image
   b. Align the face using key landmark detection
4. Pass the aligned face to the CNN model for age and gender classification:
   a. Predict the age range (e.g., 20–30 years)
   b. Predict the gender (Male/Female)
5. Extract facial features using DeepFace and VGG16:
   a. Generate a 2622-dimensional feature embedding vector
6. Compare the extracted feature vector with entries in the face database using cosine similarity:
   a. For each entry in the database:
      i. Compute the cosine similarity score with the input vector
7. Sort all matches based on descending similarity scores
8. Select the top N matches (e.g., top 5)
9. Retrieve demographic information and similarity scores for the top matches
10. Display the results via the output interface (Flask web app):
    a. Show matched face images
    b. Show confidence (similarity) scores
    c. Show predicted age and gender
11. Trigger an email notification to the respective individual or system administrator with the matching results and demographic summary
12. End

Algorithm 1: ACNN-Based Framework for Locating Missing Persons Using Advanced Face Recognition

The proposed algorithm is an ACNN-based facial recognition framework developed to identify missing persons from uploaded face images. It integrates DeepFace and VGG16 for precise feature extraction and age and gender prediction. The extracted features are compared against a face database using cosine similarity, and the system displays the top matching results, confidence scores, and demographic details through a web interface. When a high-confidence match is found, an automated email notification is sent to the concerned authorities.

6.1. CNN Algorithm

CNNs, or convolutional neural networks, are a type of deep learning algorithm inspired by the way the human eye and brain process visual information. CNNs are designed for visual data processing and analysis tasks, making them highly effective at recognizing complex objects and patterns in images with high Accuracy. CNNs operate by segmenting input images into smaller regions, known as feature maps, that capture key visual elements, such as edges, textures, and colors. Specifically, standard architecture directly includes several main layers: Input Layer, Convolutional Layers, Pooling Layers, Fully Connected Layers, and a Softmax Output Layer. For simplicity, the input to a CNN is an image of size 224 × 224 × 3 (where the last dimension represents the RGB color space). The convolutional layers apply filters (such as 11×11) to yield feature maps, where each filter is specialized to identify certain visual elements (such as lines, curves, corners, etc.). For example, 64 different feature maps could be created by the first convolutional layer. After this, pooling layers (usually 2×2 max pooling) reduce the dimensions of the feature maps, reducing the amount of computation and retaining the most relevant features. Activation Functions - To learn complex decision boundaries, the model needs to learn a non-linear transformation; hence, a non-linear transformation function, such as the Rectified Linear Unit (ReLU), is applied to every Conv2D layer. Then, the data goes through one or more fully connected / dense layers (where features from all previous layers are combined), and the model learns to create decision boundaries for classification. For example, a fully connected layer with 1000 neurons can be used for image classification into 1000 classes. At last, a softmax layer that generates a score for each class and provides the final output. With this talent-rich architecture, CNNs are extremely powerful for tasks like image classification, object detection, and face recognition. The model architecture is illustrated in the image below.

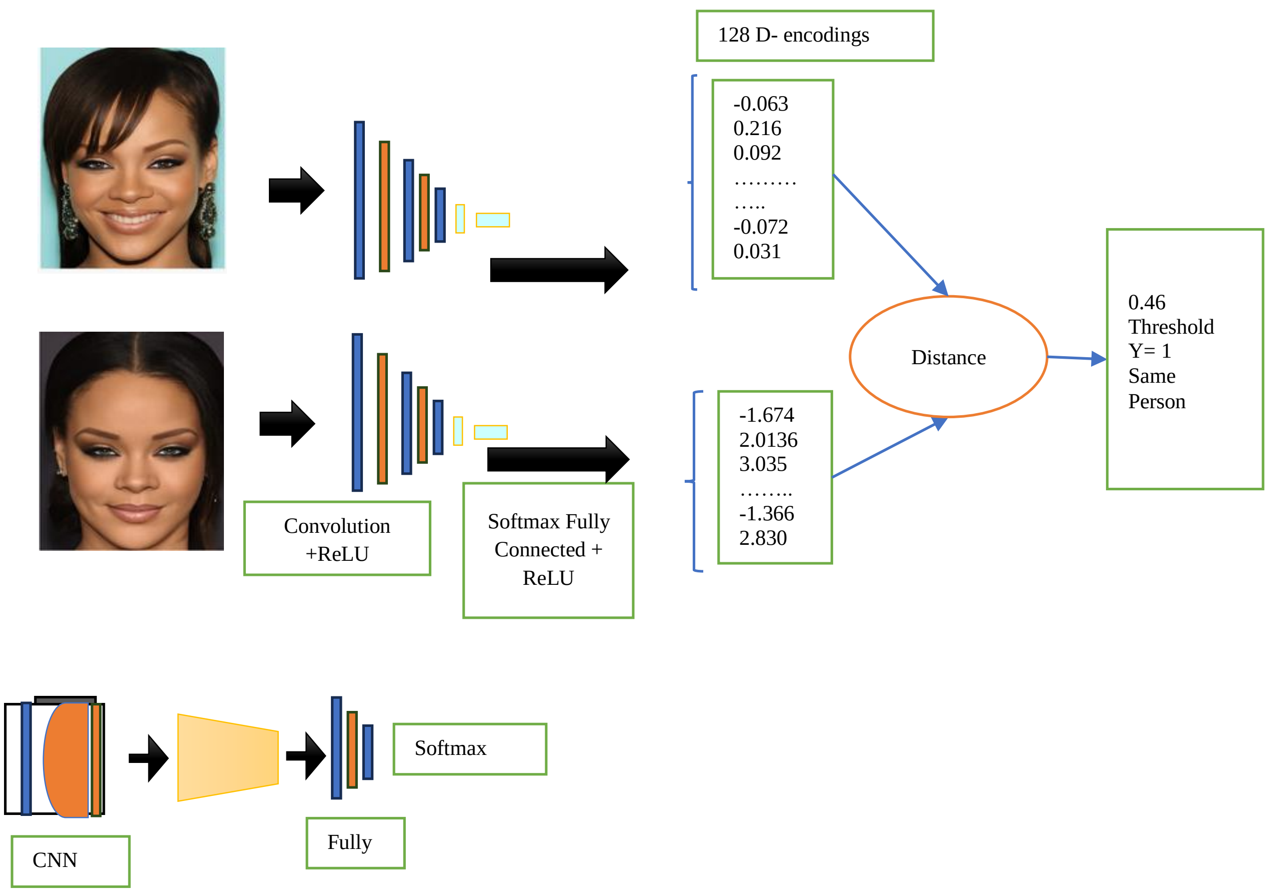

Fig. 2 Architecture of the CNN-based feature and demographic extraction module

6.2. GG16 Algorithm

This article describes how VGG16 is used for feature extraction in your face recognition system. After the DeepFace detects and aligns the face, the aligned face is passed to the VGG16 model, which is trained on a large-scale facial data (VGGFace). The VGG16 is a strong feature extractor that converts the input image to a high-dimensional feature embedding in the form of a 2622-dimensional vector. This representation encompasses specific and distinguishing characteristics of a face that are necessary for identifying and comparing it with other faces. Unlike raw pixel values, these embeddings encapsulate latent visual features, such as texture, structure, and spatial relationships, that are fundamental to robust face recognition. It utilizes cosine similarity to compare its output features with stored face embeddings from a database, identifying matches. So, VGG16 is not used directly in classification in this pipeline, but rather as a backbone to yield reliable and consistent face representations, which serve as the foundation for accurate face matching and demographic prediction.

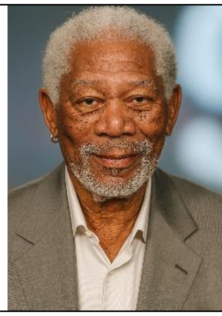	
Sample 1	**Sample 2**
	
Sample 1	**Sample 2**

Fig. 3 Samples of persons at different ages

7. Methodology

The methodology behind the proposed ACNN-Based Framework for Locating Missing Persons combines state-of-the-art facial recognition techniques with deep learning frameworks to create a robust, accurate, and scalable system for identification tasks. It starts with the input image, which is an image of the missing or found person. DeepFace is then applied to this image to achieve face detection and alignment, which ensures that all photos have faces oriented in the same position, scale, and rotation. After alignment, a CNN processes the face image and predicts demographic information, such as the age range and gender of the person. This makes the identification process smoother by providing additional context, which in turn helps filter possible matches more effectively.

After demographic classification, the aligned face undergoes the process with the DeepFace model, which has been fused with VGG16. For facial representations, a high-dimensional feature vector is extracted using the pretrained deep learning model, VGG16. This feature vector is a d-dimensional embedding that mathematically represents different characteristics of the face. Using a cosine similarity metric, which compares the angular distance between vectors, enables scale invariance and allows for comparison of these embeddings against a database of known facial embeddings. It computes the similarity score, ranks the matches, and identifies the top-k most similar matches. Every game displays demographic predictions (age and gender), a similarity score, and the face image of the target (or subject) for visual confirmation. The final results are then made available via a web app interface built using Flask, enabling end users (the police and the general public) to test the system in real-time. It serves as an interface for uploading images, viewing top matches, and providing detailed demographic information and confidence scores. The use of facial analysis and deep learning provides a robust and innovative methodology for identifying missing persons, while web technologies offer a practical solution for implementation.

8. Experimental Results

Artificial Intelligence (AI) and deep learning-based facial recognition technologies have revolutionized the approach to identifying missing persons. Our CNN-based framework comprises the following steps: 1) Face detection using DeepFace, 2) Feature Extraction using VGG16, and 3) Age and Gender Classification using CNNs, which provides highly accurate identification by comparing features using cosine similarity. This minimizes response time in search and rescue operations, thereby improving the system's overall efficiency. Designed to be reliable, secure, and ethical, our system ensures the privacy of data, provides safe access and facilitates ethical analysis and predictions based on facial data. The practical interface facilitates real-time image uploads, giving instant results for easy access by government officials and the public.

Fig. 4 Admin loginpage

The secure admin login used by government officials is shown in Figure 4. It features the basics of a simple login screen with username and password fields, which is the first level of security, enabling only authorized personnel to retrieve sensitive missing person information. It employs a minimal design for maintainability and robust protection, ensuring system stability and reliability. This login prevents unauthorized access and, thus, secures the confidentiality of the records.

Missing Person Verification (Government Login Page): This page provides government officials with secure access to a gateway for obtaining information about missing people. Its interface is rudimentary, with only a few fields for your username and password. Username and Password — These are the credentials used to authenticate users and grant them access to the system.

The test itself is user-friendly and secure, providing users with defined steps to guide them through the login process. Security checkpoint: This is the first level of security, designed to protect the system's integrity and ensure its reliability. The login page only allows legitimate government officials to access the content.

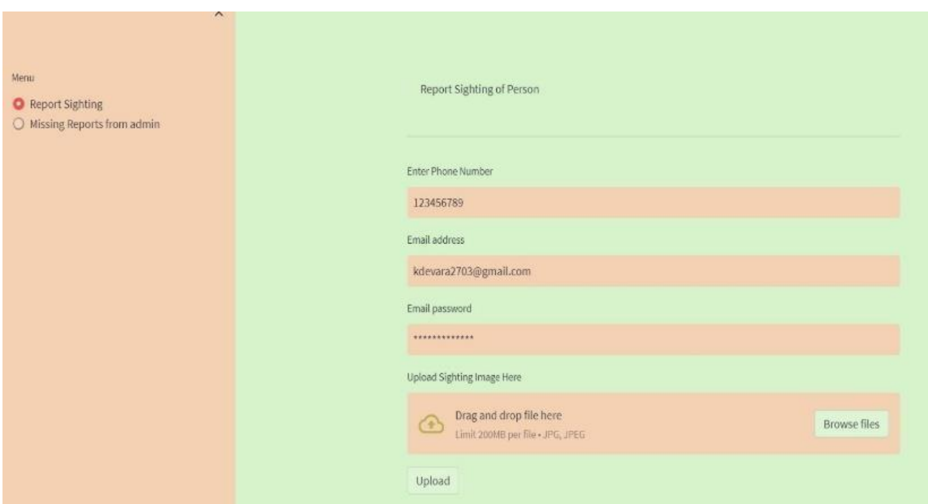

Fig. 5 User details

Figure 5 illustrates the user-facing input interface, which enables members of the public to contribute information on missing persons. The form collects contact details such as phone number, email address, and password while allowing users to upload images of potential sightings. This encourages public participation in the identification process by providing a convenient and secure way for them to share visual and textual evidence. It acts as a collaborative portal that engages communities in helping law enforcement.

Figure 6 presents the admin dashboard where officials can view and manage reports related to missing persons. The table on this page lists critical data, including the name, age, image path, contact number, location, admin email, family email, match status, and whether a notification email was sent. This centralized view allows administrators to assess the identification process efficiently, track progress, and monitor correspondence with affected families. It also supports transparency in system operations.

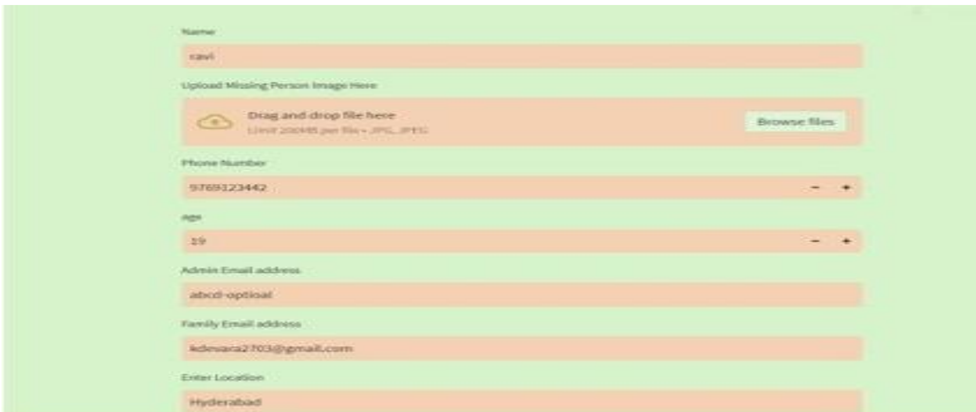

Fig. 6 Admin details

Fig. 7 The output of the search for the missing person

Table 1. Performance comparison with existing approaches

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Response Time (s)
MTCNN (Multi-task Cascaded CNN)	85.4	84.2	85	84.6	1.7
[1] Taigman et al.	97.35	96.7	96.9	96.8	1.2
[2] Simonyan & Zisserman	92.7	91.4	91.8	91.6	0.98
[9] Dey et al.	89	88.5	88.9	88.7	~1.1
[10] Haseena et al.	96.38	97.31	96.43	96.86	0.86
[12] Nayak & Indiramma	65	-	-	-	-
Proposed Model (ACNN)	97.81	96.2	98.1	97.1	0.85

Figure 7 showcases the system-generated output when a person is successfully identified. Upon confirming a match, the system compiles all relevant data, including the individual's name, match location, and verification details like the IP address. A pre-configured email containing this information is sent to the registered family contact. This provides closure and supports timely intervention and assistance from officials. The automation of this step ensures rapid dissemination of identifications to loved ones.

In Table 1, the comparative analysis highlights the performance of various face detection and recognition frameworks. The Proposed ACNN model demonstrates the highest performance, with an accuracy of 97.81%, a precision of 96.2%, a recall of 98.1%, an F1-score of 97.1%, and a fast response time of 0.85 seconds. This indicates its strong capability to balance detection accuracy with real-time efficiency. DeepFace also performs well, with 97.35% accuracy and a 96.8% F1-score, but lacks the additional demographic filtering that ACNN incorporates. The VGG16 and Searchious frameworks also yield competitive results, with accuracies above 92%, making them reliable for face recognition, albeit with slightly higher response times. The CNN and Public CNN Dataset frameworks offer decent performance with faster response times, making them suitable for moderately time-sensitive applications. MTCNN, designed for multi-task face detection, achieves 85.4% accuracy, making it useful for scenarios requiring facial landmark detection, albeit with a slightly higher response time. On the other hand, Haseena et al.'s method shows strong results (96.38% accuracy), while Nayak & Indiramma's approach yields only 65% accuracy without full metric reporting.

The superior performance of the ACNN model stems from its integration of multiple advanced techniques—CNN-based demographic filtering, DeepFace-based facial alignment, and VGG16-based deep feature embeddings, which collectively enhance the system's ability to identify faces under various conditions, including aging, low resolution, and varying lighting. In contrast, models like VGG16 or DeepFace alone lack demographic classification, whereas classical methods, such as HOG + SVM, fail to perform well under significant facial variation.

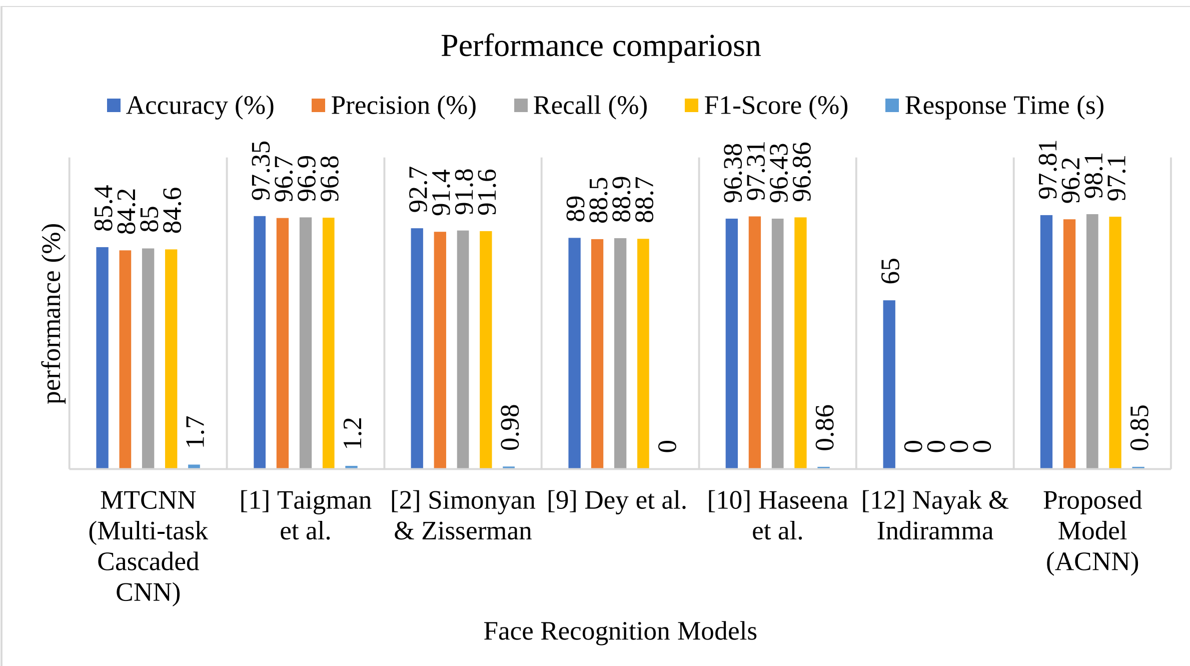

Fig. 8 Performance comparison of face recognition models across multiple metrics

Figure 8 presents a comparative analysis of several face recognition models across key performance metrics: Accuracy (%), Precision (%), Recall (%), F1-Score (%), and Response Time (s). The evaluated models include MTCNN, Taigman et al., Simonyan & Zisserman, Dey et al., Haseena et al., Nayak & Indiramma, and the Proposed Model (ACNN). The Proposed Model (ACNN) exhibits superior performance across all percentage-based metrics, with Accuracy reaching 97.81%, Precision at 96.2%, Recall at 98.1%, and an F1-Score of 97.1%, along with a response time of 0.85 seconds, reflecting both high Accuracy and efficiency. Taigman et al. closely follow with 97.35% accuracy and 1.2 seconds of response time, showing strong recognition capabilities. Simonyan & Zisserman achieve a balanced performance with 92.7% accuracy and relatively good Recall and Precision, while Dey et al. attains moderate

Accuracy (89%) and Precision but lack efficiency improvements. Haseena et al. demonstrates high Accuracy (95.38%) with solid Precision (97.31%) and Recall (97.43%), making the model highly reliable, though the response time is unreported. Nayak & Indiramma show the lowest Accuracy (65%) with missing values across other metrics, suggesting limited applicability in real-time systems. MTCNN delivers moderate performance (85.4% accuracy) but has a slower response time of 1.7 seconds, which may hinder its usability in real-time applications. Overall, the deep learning-based models—particularly ACNN, Taigman et al., and Haseena et al.—outperform traditional approaches by maintaining high recognition accuracy and favorable response times, making them suitable for advanced face recognition deployments. The ACNN model's performance is a result of its integrated architecture that enhances robustness against challenges such as pose variation, lighting, and occlusions. The ACNN model's superior results in Figure 8 are attributed to its end-to-end design, which combines facial alignment (DeepFace), feature extraction (VGG16), and demographic classification (CNN). This multi-stage approach enhances resilience against real-world variations such as aging, poor lighting, and expression changes, which often reduce the Accuracy of single-stage or classical models like HOG + SVM and MTCNN.

9. Conclusion and Future Work

This study compared various face detection and recognition models, including traditional techniques like HOG + SVM and advanced deep learning architectures such as VGG16, ResNet, and DeepFace. This higher Accuracy is attributed to the integration of CNN-based demographic classification (age and gender), DeepFace-based alignment, and VGG16-based high-dimensional facial feature extraction. These components jointly enhance the model's robustness to temporal variations such as aging, pose shifts, low-resolution images, and inconsistent lighting, which often degrade performance in other existing approaches. Among these, the proposed Advanced Convolutional Neural Network (ACNN) achieved the highest performance, delivering an accuracy of 97.81% and outperforming other models across key metrics, including Precision, Recall, F1-score, and response time. The ACNN model excels in combining Accuracy with computational efficiency, making it well-suited for real-time applications, including the identification of missing persons. Future research can explore optimization for mobile and edge devices using lightweight networks, such as MobileNetV3 or EfficientNet-Lite, to enhance their capabilities further.

Additionally, incorporating attention mechanisms or transformer-based components may improve the model's ability to extract features under challenging conditions. Enhancing the training dataset to include diverse facial variations, such as occlusion, lighting changes, and aging, can increase the system's robustness. Finally, integrating federated learning for privacy-preserving model training and deploying the solution in real-world contexts, such as surveillance, public safety, and humanitarian applications, will help establish a more scalable and socially impactful framework.

References

[1] Yaniv Taigman et al., "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA, pp. 1701-1708, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[2] K. Simonyan, and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arXiv Preprint*, pp. 1-14, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[3] Gil Levi, and Tal Hassncer, "Age and Gender Classification using Convolutional Neural Networks," *2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Boston, MA, USA, pp. 34-42, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[4] U.P. Akare et al., "Finding Missing Person using Face Recognition," *International Journal For Research in Applied Science and Engineering Technology*, vol. 12, no. 4, pp. 1245-1252, 2024. [CrossRef] [Publisher Link]

[5] S. Mageswaran et al., "Finding Missing Person based on Face Recognition using AI in Video Surveillance System," *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 5, pp. 987-994, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Adnan Nadeem et al., "Tracking Missing Person in Large Crowd Gathering Using Intelligent Video Surveillance," *Sensors*, vol. 22, no. 14, pp. 1-25, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Vishakha Shelke et al., "Searchious: Locating Missing People using An Optimised Face Recognition Algorithm," *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, pp. 1550-1555, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Rajiv Kumar et al., "Face-Based Age and Gender Classification using Deep Learning Model," *Procedia Computer Science*, vol. 235, pp. 2985-2995, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Puja Dey et al., "Human Age and Gender Prediction from Facial Images using Deep Learning Methods," *Procedia Computer Science*, vol. 238, pp. 314-321, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] S. Haseena et al., "Prediction of the Age and Gender Based on Human Face Images based on Deep Learning Algorithm," *Computational and Mathematical Methods in Medicine*, vol. 2022, no. 1, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Sandeep Kumar Gupta, and Neeta Nain, "Single Attribute and Multi Attribute Facial Gender and Age Estimation," *Multimedia Tools and Applications*, vol. 82, pp. 1289-1311, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Jyothi S. Nayak, and M. Indiramma, "An Approach to Enhance Age Invariant Face Recognition Performance based on Gender Classification," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, pp. 5183-5191, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Florian Schroff, Dmitry Kalenichenko, and James Philbin, "Facenet: A Unified Embedding for Face Recognition and Clustering," *2015 IEEE Conference on Computer Vision and Pattern Recognition*, Boston, MA, USA, pp. 815-823, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[14] Kaiming He et al., "Deep Residual Learning for Image Recognition," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 770-778, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[15] Ja Hyung Koo et al., "CNN-Based Multimodal Human Recognition in Surveillance Environments," *Sensors*, vol. 18, no. 9, pp. 1-34, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[16] Andrew Jason Shepley, "Deep Learning for Face Recognition: A Critical Analysis," *arXiv Preprint*, pp. 1-27, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mohammed Aly, "Revolutionizing Online Education: Advanced Facial Expression Recognition for Real-Time Student Progress Tracking via Deep Learning Model," *Multimedia Tools and Applications*, vol. 84, pp. 12575-12614, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Peilun Yang et al., "Deep Learning Approaches for Similarity Computation: A Survey," *IEEE Transactions on Knowledge and Data Engineering*, vol. 36, no. 12, pp. 7893-7912, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Yuiga Wada et al., "Polos: Multimodal Metric Learning from Human Feedback for Image Captioning," *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Seattle, WA, USA, pp. 13559-13568, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Muhammad Ahmad Nawaz Ul Ghani et al., "Enhancing Facial Recognition Accuracy through Multi-Scale Feature Fusion and Spatial Attention Mechanisms," *Electronic Research Archive*, vol. 32, no. 4, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Ahmad Saeed Mohammad et al., "IoT-MFaceNet: Internet-of-Things-Based Face Recognition using Mobilenetv2 and Facenet Deep-Learning Implementations on a Raspberry Pi-400," *Journal of Low Power Electronics and Applications*, vol. 14, no. 3, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] M. Umadevi, S. Barghav Krishna, and N. Sai Kumar, "Deep Fake Face Detection using Efficient Convolutional Neural Networks," *2024 5th International Conference on Image Processing and Capsule Networks (ICIPCN)*, Dhulikhels, Nepal, pp. 344-352, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Nguyen Van Duc et al., "Secure and Efficient UAV-Based Face Detection via Homomorphic Encryption and Edge Computing," *arXiv Preprint*, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[24] Keny Muhamada et al., "Exploring Machine Learning and Deep Learning Techniques for Occluded Face Recognition: A Comprehensive Survey and Comparative Analysis," *Journal of Future Artificial Intelligence and Technologies*, vol. 1, no. 2, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] H.L. Gururaj et al., "A Comprehensive Review of Face Recognition Techniques, Trends and Challenges," *IEEE Access*, vol. 12, pp. 107903-107926, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Huu-Tuong Ho et al., "Face Detection using Eigenfaces: A Comprehensive Review," *IEEE Access*, vol. 12, pp. 118406-118426, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Hui Zhang et al., "Validating Privacy-Preserving Face Recognition under a Minimum Assumption," *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Seattle, WA, USA, pp. 12205-12214, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[28] Katerina Kyriakou et al., "A Secure and Trustworthy Biometric Data Ecosystem for Cross-border Suspect Identification," *2024 IEEE International Conference on Big Data (BigData)*, Washington, DC, USA, pp. 2762-2771, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] Pritesh Prakash, and S. Umamaheswaran, "Transformer-Based Auxiliary Loss for Face Recognition Across Age Variations," *arXiv Preprint*, pp. 1-8, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[30] Jingyu Zhang et al., "Research on Detection of Floating Objects in River and Lake Based on AI Intelligent Image Recognition," *arXiv Preprint*, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] Jayanta Paul et al., “A Comprehensive Approach to Real-time Attendance Systems: Integrating Face Recognition and Emotion Detection and with Web Technologies,” *Procedia Computer Science*, vol. 258, pp. 3436-3446, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[32] Munna Khan et al., “Predicting Heartbeats in Real-Time: A Continuous Monitoring Approach with Face Recognition Algorithm,” *2024 11th International Conference on Signal Processing and Integrated Networks (SPIN)*, Noida, India, pp. 399-402, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[33] Olena Chala et al., “Using the Human Face Recognition Method Based on the MobileNetV2 Neural Network in Authentication Systems,” *Multidisciplinary Journal of Science and Technology*, vol. 5, no. 3, pp. 882-895, 2025. [Google Scholar] [Publisher Link]