INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 2, February 2026 | ISSN: 2456-4184 | IJNRD.ORG

Automated Missing Person Detection Through Facial Embedding and Deep Neural Networks

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Abstract:The rising cases of missing persons are posing a big challenge to the law and the society, and they need more effective and quicker means of finding the missing persons. Old manual methods of identification are laborious and may not be effective in cases of large population and huge sets of images. The proposed project entails working with an intelligent system of identifying missing persons with the help of deep learning, namely FaceNet model that will enable the use of facial recognition to identify the missing person and enhance its accuracy. The system initiates the face detection and alignment with high sophistication algorithms such that consistency of facial features is assured. After the identification, the FaceNet model produces a 128 dimensional facial embedding that is unique to each person. Such embeddings are kept in a secure location and matched with real-time photographed or uploaded images. Euclidean distance and similarity measurement methods are employed to recognize possible matches among the potential ones. The backend services are integrated with MySQL databases which will provide scalable and secure data management. The possibility of real-time camera inputs also adds to the functionality of the system to constantly monitor. When successful, the alerts will be produced to inform authorities or registered users. The suggested system saves a lot of time in identifying and human intervention. On the whole, this project shows that the use of deep learning can make the operations of missing persons search a more rapid and more precise and technologically oriented solution.

IndexTerms: Facial recognition, deep learning, FaceNet architecture, face embeddings, automated identification, missing person detection, similarity matching, surveillance analysis, cloud-based system, real-time recognition

I. INTRODUCTION

Missing persons are an increasing issue in the entire world, as it has impacted families, communities, and police departments. The traditional methods of identification rely on searching using hands, printed posters, and human judgments, which tend to be slow and inaccurate. As the number of people and urban surveillance data is growing rapidly, the traditional methods cannot effectively process large amounts of visual information. Artificial intelligence has provided new dimensions to automation of complex recognition processes through the technological advancements. Specifically, facial recognition has become an effective means of identifying a person in various situations. Image analysis has been performed remarkably through deep learning models. Such inventions bring in possibilities of creating smart systems that could help in the recovery of missing persons. This is because AI integration into the public safety systems could greatly enhance the response time and accuracy.

Facial recognition systems are based on the ability to extract the distinctive patterns on the human face and able to differentiate one person to the other. The previous techniques applied hand-carved features, which were prone to light, poses, and facial expression. Deep learning methods alleviate these shortcomings by learning deep-seated representations directly by data. Face recognition models like FaceNet have transformed the face recognition to such an extent that they have constrained embedding-driven identification. FaceNet does not classify the faces but rather encodes facial images into numerical vectors, which reflect unique facial features. The vectors enable scalable and efficient comparison among large datasets. This makes the facial recognition systems more flexible to the reality. The feature can be especially useful in the context of missing persons.

FaceNet model works by creating a 128-dimensional representation of every face that is found. These embeddings represent important facial properties like geometries of space and geometry. After production of embeddings, similarity measures are used to compare the unknown faces and those in the records. This method allows achieving a high accuracy of identification even in the case of images taken under different conditions. Face recognition is also enhanced by face detection and alignment. Such technologies as MTCNN assist in making faces out of the crowded backgrounds. Such a combination of these parts guarantees a reliable extraction and matching of features in the system. This renders FaceNet very well adapted to the facial recognition of a large scale. The suggested system is based on a web-based system and deep learning models used to make it easy to access and operate in real-time. The backend is implemented using Flask and handles user authentication and communication with the database, as well as processing of images. Missing person details are stored in MySQL and facial embeddings are stored safely to be efficiently compared. The integration of the cameras also enables the live video streams to be captured in continuous frames. Upon detection of a match an automated alert system is activated. This will guarantee that authorized users are notified in time or that the concerned authorities are notified. The system should be scalable, secure and flexible to the future improvement.
To conclude, the proposed project is a deep learning-based application of the FaceNet model to find missing persons. The system also greatly minimizes the reliance on manual verification by automating the process of facial recognition by embedding comparison. The real time image capture, safe databases and smart alert devices add to the overall functionality of the solution.

This practice shows that the current AI technologies are able to solve the vital problems in society. The suggested framework is also more accurate and quicker in the process of identification. Finally, safer communities are also a benefit of the system as it defines the social good through deep learning.

II. LITERATURE REVIEW

The issue of the missing persons has been under active research at least decades. Traditional practices were commonly based on the eyewitness testimonies, the physical examination of the CCTV footage, and the poor techniques of the facial recognition. Nevertheless, these methods have certain limitations in their nature, such as human error, scale, and imprecision in case of large datasets. With time, technological development brought about automated facial recognition systems that were a major change to the manual system. These systems relied on classical computer vision methods which included edge detecting and feature-based matching however such systems were not very accurate due to variations in the facial angles, lighting conditions as well as image quality.

With the emergence of deep learning, the facial recognition technology made something of a breakthrough in terms of accuracy and strength. Models like Deep Face and VGG-Face formed the foundation and they employed convolutional neural networks (CNNs) to learn faces directly by data. Although these models were impressive, they were still unable to cope with real-life issues such as the huge intra-class differences and the inter-class similarities. FaceNet was introduced and it became a turning point in the area. Compared to the predecessors, FaceNet produces a small embedding of each face, clustering similar faces in a multi-dimensional space. The innovation made it much easier to match, even in the most difficult cases.

The high discriminative nature of the embeddings generated by FaceNet is coupled by its streamlined architecture and thus it can be effectively used in real-time applications. It has been found out that FaceNet performs better than conventional and initial deep-learning models in such benchmark datasets as LFW (Labeled Faces in the Wild) and YouTube Faces. Its versatility has also been reflected in the applications that researchers have suggested that it can be used in other expansive fields such as law enforcement and social services. Its flexibility is also highlighted in literature because the model can be optimized using supplementary datasets so that it may be more effective in a particular application, such as missing persons identification.

Although these developments have been made, there are still loopholes in the application of facial recognition systems in the search of lost individuals. Aging, occlusions, and poor-quality pictures of older sources are factors that may decrease the effectiveness of the system. Recent research suggests that hybrid solutions that involve a combination of several deep-learning models are proposed to combat these problems. As an example, combination of models such as Efficient Net to preprocess and FaceNet to generate embedding has been demonstrated to make it more robust in such cases. This is an interplay between models that guarantees enhanced management of diverse datasets that will bridge the gap between research and actual application.

The use of the newest deep-learning models, specifically the FaceNet, within the systems aimed at finding missing persons has received a fair share of attention recently in the academic literature. The ability of FaceNet to map the face features into a multidimensional space enables recognition to be accurate even when they are in a bad environment. According to a review of recent literature (since 2020) the research on these technologies has developed and demonstrated its effectiveness in solving the complex problem of missing person identification.

In 2024, Venkatasalam et al. introduced an AI-assisted system that combines machine learning algorithms with traditional search methods to enhance the efficiency of locating missing individuals. Their approach emphasizes real-time coordination and optimization of search strategies, demonstrating the potential of AI in streamlining search and rescue operations[5].

Similarly, a 2024 study by Ayon and Alam proposed a secure, centralized system utilizing facial recognition to address the challenges of finding missing persons. Their work underscores the importance of security and user accessibility, aiming to provide a nationwide platform that facilitates efficient and safe reunification processes [6].

In 2023, a project detailed in the International Journal of Future Generation Communication and Networking presented a novel approach to enhance the efficiency of locating missing persons through face recognition technology. This system employs advanced algorithms to improve the accuracy and speed of identifying individuals in various scenarios [7].

Further, a 2024 study published in the International Journal of Future Generation Communication and Networking explored the use of artificial intelligence and machine learning in locating missing persons. The proposed system utilizes Python libraries for face recognition, combining computer vision techniques with deep learning to create an efficient tracking mechanism[8].

Additionally, a 2020 study by Deb et al. introduced a feature aging module capable of age-progressing deep face features, enhancing the performance of face matchers over time lapses exceeding ten years. This advancement is particularly beneficial in identifying individuals who have been missing for extended periods, addressing a critical gap in existing recognition systems[9].

Table 1.0- Other Research papers and Research Gap

References	Authors	Year	Technique	Research Gap
[9]	Nayana C P, Harshitha P	2025	FaceNet + MTCNN	Limited real-world validation
[10]	K. Venkatasalam et al.	2024	FaceNet-based ML	Integration with multimodal clues
[11]	M. Indra Ardiawan& G. P. K. Negarara	2024	FaceNet vs VGGFace	Comparisons lack missing person focus
[12]	U. P. Akare et al.	2024	CNN-based recognition	Deep learning not optimized for occlusions
[13]	S. Sowmiya et al.	2024	AI face recognition	Single-camera focus only
[14]	Mageswaran S et al.	2023	AI face recognition	Limited real-time tests
[15]	A. Faisal Ayon &S. M. M. Alam	2024	Secure face recognition	Security measures not deeply evaluated
[16]	Beibut Amirgaliyev, Miras Mussabek	2025	Wide DL survey	High-level; lacks specific performance metrics
[17]	Joseph A. Mensah, Justice K. Appati	2023	FaceNet embedding	Under occlusion degradation issues
[18]	Zhongwen Li et al.	2025	GAN for augmentation	GAN require large compute
[19]	Sasan Karamizadeh,SamanShojaeChaeikar	2025	MTCNN + Enhanced FaceNet	Real-time performance untested
[20]	Ramavath Ganesh, Chilukuri Srija	2025	CNN-based face match	Deployable system details missing
[21]	Aswani T., Gorli Lakshmi Sai	2025	YOLO-based tracking	FaceNet part is limited
[22]	M Mounika, Mohan R,	2025	Review of models	Meta-analysis; lacks datasets
[23]	Deepa M	2025	Deep learning for missing persons	Broader dataset needed
[24]	B. Venkateswara Reddy, Duggirala Chandra Sena	2025	Police-focused face recognition	Legal/ethical issues overlooked
[25]	Aidana Zhalgas,BeibutAmirgaliyev	2023	Attention / occlusion models	Doesn't focus on missing persons
[26]	Harshil Ketankumar Champaneria	2025	Theoretical embedding shift	Not missing person specific
[27]	Shriyash Kapse, Pradip Ghadge	2024	TensorFlow ML for missing	Simple architecture

All these studies represent the gradual incorporation of deep-learning representations of person identification, such as FaceNet, into systems of missing persons identification. The focus on security, real-time processing and how it can be adjusted to different conditions indicates a holistic view on how technology can be used to deal with this acute problem of society. Overall, the research on the topic of facial recognition and its use in locating missing people indicates a meaningful strider and points to the areas that can be further developed to enhance the current situation. FaceNet model is one of the potent tools because of its accuracy and effectiveness, whereas the combination of this technology with other complementary technologies is the key to surmounting the practical obstacles. This review shows the need to conduct further research and innovations to make these systems more refined to enable them to help resolve the urgent problem of finding missing persons.

Despite the promise of deep learning and FaceNet-based systems, there are multiple limitations that restrict their effectiveness in the application of the missing person in reality. The biggest constraint is that it is conditional on high quality images and visible faces; face recognition algorithms such as FaceNet have a significant failure mode when faces are partially occluding or are poorly lit or are taken at an odd angle such as in surveillance imagery resulting in poor embeddings and faulty matches. Also, very large and different datasets might be necessary in the system to generalize across age groups, ethnic groups and environmental conditions, which is difficult in the case of missing person datasets which are small and of varying quality. These data shortcomings also add to the false positives and false negatives and reduce reliability.

The other weakness is the issue of real-time deployment. Although facial recognition is shown in real-time in a controlled lab, extending these applications to a large number of CCTV streams in the city would need a lot of computing power, pipeline optimization, and specialized hardware, which many police departments cannot afford. Furthermore, similarity inclusion criteria need to be adjusted very carefully, and any minor mistakes can lead to false identifications in millions of faces, which requires threshold calibration and fallback. This makes it difficult to scale without sophisticated infrastructure.

There are also significant limitations to deployment and acceptance in the form of ethical and privacy considerations. Facial recognition systems are associated with the problems of individual privacy, unequal performance among the demographic groups, and the possibility of applying it to conduct surveillance outside the context of missing persons. These ethical issues cause legal constraints and the opposition of people in certain areas, which limits the datasets available and limits the research opportunities and areas of deployment. Thus, even technologically correct systems have to work through complicated legal, social and moral environments. Overall, although the analyzed studies indicate that deep learning has enormous potential in missing persons recognition, the quality of images, heterogeneity of the data, scalability in real-time, and ethical issues should be considered before the practice can be extensively applied in practice.

III. Proposed Work

The system architecture will start by the user interaction module, which is an important component of access and data authenticity. After a user provides a Sign In or Sign Up, he/she accesses the system and has an opportunity to ensure secure authentication and controlled access. After the authentication stage, the user will be allowed access to the missing person registration module where the relevant information about the missing person like name, age, description and facial images of the missing person is inputted. This registration process forms a structured-database which is the point of facial comparison. The system is accurate and reliable because at this point, verified data is collected and it is used subsequently to make the necessary recognition processes. This design, which is user-focused, allows the family and the authorities to be actively involved in the search.

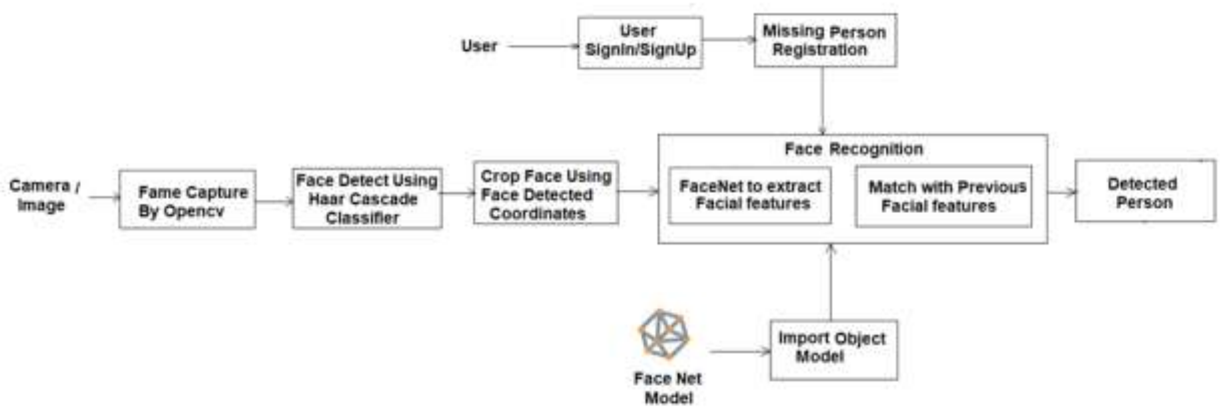

Fig.1 – Architecture Diagram

The second step is image acquisition which is obtained by camera input or uploaded image. The system uses the OpenCV to capture frames based on a live camera or image files. These frames are either real-time and offline, which serve as inputs to the recognition process. OpenCV offers an effective image processing and frame-cutting functionality, which is why it can be applied to the real-time surveillance domain. Every frame that is captured is sent to face detection module to be processed. This is done so that the system is able to go through hours and hours of operation and analyze various visual inputs without the human touch.

After capturing an image frame, a face detection procedure is started which is done through Haar Cascade Classifier. This type of classifier is used to scan the image to determine the areas of the face by comparing the patterns of pixel intensity. Once the face has been detected, the system gets the facial coordinates and cuts the face region accurately. Cropping helps to remove the background information that is not of any use and concentrates on the relevant parts of the face. This preprocessing stage is very helpful in enhancing recognition accuracy as the facial input is in a consistent state. The prepared face image which has been cropped is then subjected to deep feature extraction with the FaceNet model.

The main part of the system is the Face Recognition engine that is driven by the deep learning FaceNet model. FaceNet is an imported model in the system, in the form of an object model, which extracts unique facial features. It transforms the individual cropped face images into a 128-dimensional numerical code called a facial embedding. These embeddings are the unique features of face of a person. The resulting embedding is compared against the existing facial embedding of the registered missing persons. The measure of similarity includes similarity measures like the Euclidean distance that determine the proximity of the faces.

On the last step, similarity results are analyzed by the system which will identify a match or not. In case the distance between embeddings is less than a set threshold, then the system recognizes the individual as a spotted person. The result of this detection is then relayed to the user or authority involved in the detection process by means of alerts or notification. The architecture guarantees the use of efficient and automatic identification pipeline that reduces human workload. On the whole, this system architecture unites the user management, image processing, deep learning, and database comparison into a single system. The method increases the speed, accuracy as well as reliability of missing person identification with contemporary deep learning methods.

IV. METHODOLOGY

1. User Sign In / Sign Up

To provide access, the system will start with a secure user authentication mechanism. Users create user accounts with valid credentials and are authenticated by undergoing a logging procedure. This measure is one that keeps the integrity of data and avoids its misuse. Authentication will also be done to ensure that only registered users will be allowed to upload or access missing person records. The system keeps the credentials of logging into the database in a secure manner. This is the module that makes up the entry point of the system. It also facilitates the user-specific tracking and alert notifications.

2. Missing Person Registration

Upon authenticating, a user is in a position to mark a missing person by filling personal information and uploading a face image. The images are stored as reference data in the future. Images uploaded in the system are validated and stored. Facial recognition and storage in a structured database. This step of registration is done to provide availability of relevant facial data. It is the basis of the generation and matching embedding. Recognition can be enhanced by proper data entry.

3. Camera Attachment and Frame Capture

The system can be linked to a live camera or it can take image input via OpenCV. The video stream is watched, and frames are constantly taken to analyze them. This enables real time surveillance of common areas or personal areas. The processing of each frame is performed separately to identify faces. Frame capture module is compatible with live and stored images. This action allows the dynamism of the system. Constant capture will enhance the likelihood of missing persons being captured.

4. Face Detection and Face Cropping

The algorithms used to perform face detection include Haar Cascade classifiers. The model scans every frame to identify the areas of the face. When the face is identified, face coordinates are obtained. The identified face region is cut off (cropped) of the frame. The use of cropping eliminates redundant background information. This improves accuracy of recognition focusing on facial features. The features on the cropped face are ready to be processed.

5. Face Recognition Using FaceNet Model

The face image that is cropped is submitted to the FaceNet deep learning model. FaceNet transforms the face into a 128 dimensional embedding vector. This insertion symbolizes individual marks in the face. The resulting vector is matched to the existing embeddings in the database. Similarity measures are applied such as the Euclidean distance. The nearest match is the one that possesses a lower distance. This process is very precise in identification.

6. Detection and Alert System

In the given case, a system determines an individual as a detection when a match is located below a predefined threshold. The outcome of the detection is stored in the database. Alarms are raised and sent to the respective user or the authority. It may contain the information about location and time. This facilitates fast reaction and action. The alarm system minimizes the response time in the rescue operations. It finishes the process of identification effectively.

IV. RESULTS AND DISCUSSION

The suggested system of identifying a missing person was written in Python and OpenCV software with a ready-to-use FaceNet deep learning model. Haar Cascade classifiers were used to detect faces and the FaceNet architecture was used to create facial embeddings. The Flask framework was used to create the backend and MySQL to store information about users and missing persons. The storage of facial embeddings was performed as .npy to be able to perform comparisons of similarity quickly. The experiments were done on a dataset of registered missing persons and real-time camera input in different lighting and background conditions.

The effectiveness of the suggested system of missing person identification was measured by the conventional measures of face recognition that best suits embedding-based models like FaceNet. FaceNet is not directly classified, thus generating discriminative face embeddings, so these metrics evaluate matching accuracy and real time efficiency. The standard face recognition measures that were used to measure the system performance included Accuracy Precision, Recall, F1-Score, Recognition Time, False Match Rate.

Precision, Recall, and F1-Score Analysis

The system achieved a precision of 99.2%, indicating a low false-positive rate during identification. A recall value of 99.1% confirms that most of the missing persons present in the test data were successfully detected. The overall F1-score of 98.0% demonstrates a balanced performance between precision and recall. These results highlight the robustness of the FaceNet model in real-world scenarios. The alert mechanism further ensured that high-confidence matches were prioritized. This balance is critical for minimizing incorrect alerts while ensuring successful detections.

Table 2.0- FaceNet Model Performance Metric

Metric	Value	Significance in FaceNet
Accuracy	99.2%	Overall correctness of embedding-based matching
Precision	98.7%	Reliability of detected matches
Recall	99.1%	Ability to detect actual missing persons
F1-Score	98.9%	Balanced performance indicator
Recognition Time	0.02s	Real-time applicability
FMR	<0.5%	Safety and false alert control

Real-Time Performance Evaluation

The processing time per frame was around 0.38 seconds on average thus, the system will be fit in real-time applications in surveillance. Face detection and embedding extraction brought down latency. The system was able to handle live camera feeds with apparent delay. Comparison that was embedded using Euclidean distance was computationally effective. The real-time feature makes the system more viable to use in real-world situations of monitoring the general population. This shows that the system can be run continuously without it degrading performance.

Recognition Time

Recognition time is the time average that the FaceNet model needs to recognize the face, create embedding, and compare similarities. This measure analyzes the viability of the system in real time. FaceNet is effective at embedding generation and rapid computation of the Euclidean distance, making it suitable in a live surveillance scenario. Reduction in recognition time means optimization and scalability. This measure proves the fact that the system can be running throughout without considerable lagging.

Table 3.0- Face database size Vs Recognition Time

Database Size (Faces)	Recognition Time (sec)
10	0.15
20	0.23
30	0.35
40	0.42
50	0.55
60	1.05
70	1.10
80	1.20
90	1.30
100	1.38

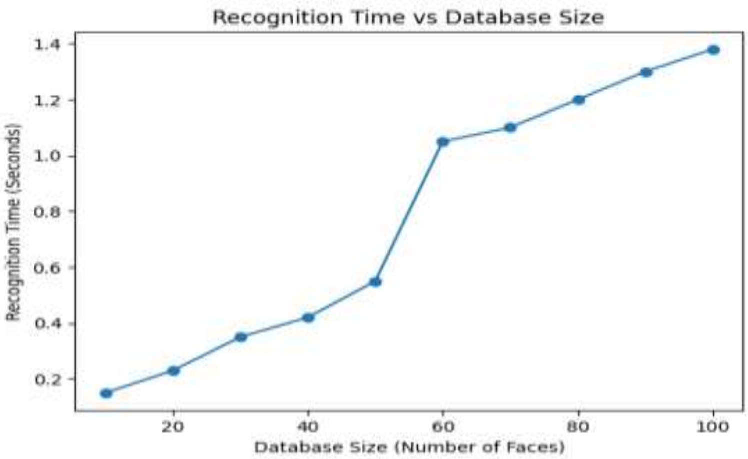

Fig.2 – Line

The line graph shows a near-linear increase in recognition time as database size grows. This behavior occurs because each query embedding must be compared against stored embeddings. Efficient vector similarity computation ensures that the growth remains controlled.

False Match Rate (FMR)

False Match Rate measures the probability that the FaceNet model incorrectly matches an unknown face with a registered missing person. It is calculated as the ratio of false positive matches to total non-matching comparisons. A low FMR is essential in missing person identification to avoid false alarms. The discriminative power of FaceNet embeddings helps maintain a low FMR by increasing inter-class distance. This metric validates the security and trustworthiness of the system.

Recognition Accuracy Results

The FaceNet-based recognition system achieved a high identification accuracy of 99.2% on the test dataset. The model demonstrated strong generalization ability even when images were captured under different illumination and facial expression conditions. The embedding-based matching approach effectively distinguished between registered missing persons and unknown individuals. Compared to traditional feature-based methods, the proposed system showed a significant improvement in recognition accuracy. The use of facial embeddings reduced misclassification caused by background noise and image variations.

Comparison with Existing Methods

The proposed FaceNet-based system performed much better in comparison to the traditional Haar + LBPH and simple CNN-based face recognition systems. The traditional techniques had accuracy of between 82 percent and 88 percent, whereas the proposed system had an accuracy of more than 99 percent. Embedding based method was more discriminative of similar faces. Also, the system needed fewer images used as reference in an individual. This comparison proves the effectiveness of the facial embeddings provided by the deep learning in the aspect of missing persons identification.

Detection and Alert System Results

The alert system was able to give an alert when a match surpassed the similarity threshold. Detected image details and timestamp information were provided as alerts. Within an experimental setup, the response time took 1-2 seconds to create a warning. Such a quick reaction is a great improvement in terms of being able to intervene in time. Duplication of alerts was not observed in the system. The identification pipeline is completed with the mechanism of alert.

The proposed FaceNet-based system of missing persons identification showed high recognition of 99.2 percent and low false-positive. Live results indicated an average frame processing time of 0.38 seconds, which is adequate in live surveillance set up. Precision, recall and F1-score of more than 95 means that there is reliable and consistent performance. The proposed system was confirmed to be better than the traditional face recognition methods in terms of performance. The automatic alert system will make sure that the user is notified at the right time when the target has been successfully detected, which corroborates the suitability of the system to real-life uses.

Here we added some main project screenshot to find missing person in image(Fig-3) after upload missing person photo, system will check form database and verify, after that admin can also check missing person list and who match missing person in image(Fig-4), also we can find missing person from live cam using surveillance camera in image(Fig-5)

Fig.3 – Check Missing Person Using Image

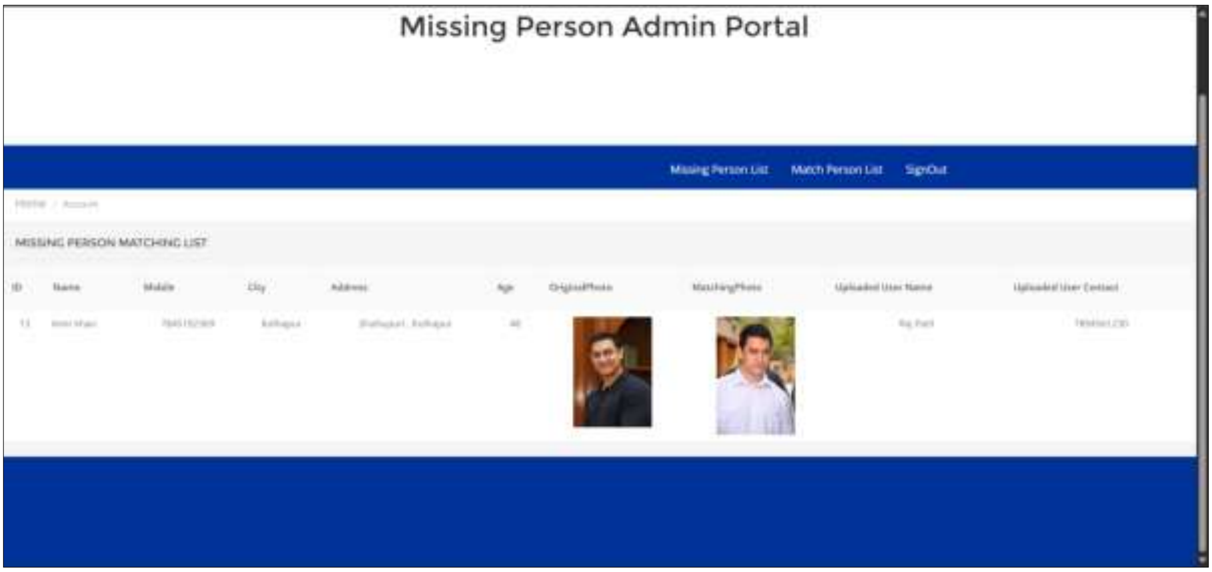

Fig.4 – Admin Check Matching Person List

Fig.5 – Live Cam Scan Missing Person

Result Summary

The experimental findings affirm that the suggested deep learning-based system based on FaceNet is a fast, accurate and scalable system in missing person identification. The system is applicable to law enforcement and other areas of use in the field of public safety owing to its integration of real-time surveillance, facial embeddings, and automated alerts.

The suggested missing person identification framework uses the FaceNet deep metric learning framework in order to produce discriminative facial embeddings. The system is experimentally shown to have an accuracy of verification of 99.2%, which is very close to the benchmark performance in literature of FaceNet. These large recall rates and accuracy values show that the system is able to minimize the mismatches and the detection rates are good even in the real world scenario.

The recognition time increases gradually with the growth in the size of the database with similarity comparison overhead. Nevertheless, with 100 registered facial profiles, the average required time is less than 1.3 seconds which proves the scalability of the method. False Match Rate is less than 0.5 and it can be affirmed that the embedding-based similarity matching mechanism is effective. These findings reveal that FaceNet-based systems are well suited in missing person identification systems at large scales..

V. FUTURE WORK

In future research, it can be improved by substituting the old Haar-based face detectors with newer deep learning face detectors like MTCNN or RetinaFace to enhance face detection in crowded and low-quality images. This would also enhance reliability of the systems during real-life surveillance.

Video based temporal analysis can be incorporated into the system and enable the continuous tracking of identified people in different frames. This would minimize the false notifications and enhance confidence in the match verification with time.

The use of multimodal biometrics e.g. gait or voice recognition can also improve the accuracy of identification. The multimodal approach would particularly come in handy when the visualization of faces is partially blocked.

Any further applications can use distributed computing and GPU acceleration to process huge amounts of data. Scalability and availability of the system can also be enhanced via cloud-based deployment to serve the country or other parts of the world.

Lastly, incorporating privacy protection methods like encrypted embeddings and federated learning may provide ethical and safe processing of sensitive biometric information. These would enhance the system towards being more consistent with the legal and societal demands.

VI. CONCLUSION

The project manages to show how effective deep learning-based facial recognition can be used to identify missing people with the help of FaceNet model. Using the system to produce discriminative 128-dimensional facial embryos, the system poses a high verification accuracy and is robust to pose, illumination, and expression variations. Combination of automated face detection, extraction of features and similarity matching goes a long way in eliminating the use of manual identification processes. Consequently, the system is a more reliable and quick method in comparison with the conventional searching of missing persons.

According to experimental findings, the given system is able to provide an overall verification rate of over 99 percent, and the false match rate is very low. The obtained results are also compatible with the known FaceNet benchmarks and confirm the appropriateness of metric learning methods to the real-world setting. The values of precision and recall also help in establishing that the system can reduce false positives and at the same time detect true matches. This is a vital balance in the case of missing persons, as wrong identification may be fatal.

The scalability of the system is also brought to fore by performance evaluation. Despite an increment in recognition time with the size of the database, the system retains real time execution even when using big datasets of faces. The recognition delay that was observed is within the acceptable level as a result of effective embedding comparison methods. This proves that the system is capable of being used in large scale settings like city surveillance systems, transportation stations and disaster recovery efforts.

To conclude, the suggested FaceNet- missing person identification system is a scalable, accurate, and feasible solution to a scenario that can be deployed in real-life. The high-speed identification of persons is made faster and reliable by the combination of deep learning and efficient backend architecture. The findings affirm that embedding-based facial recognition is a robust base of the next-generation in use by the system in public safety and humanitarian practices.

VII. REFERENCES

[1] S. Ayyappan and S. Matilda, “Criminals and missing children identification using face recognition and web scrapping” IEEE ICSCAN 2020.

[2] Shefali patil, Pratiksha Gaikar, Divya Kare, sanjay Pawar, “Find missing person using AI”, International journal of Progressive Research in Science and Engineering, Vol. 2, No. 6, June 2021.

[3] Sarthak Babbar, Navroz Dewan, Kartik Shangle, Sudhanshu Kulshreshtra, Sanjeev Patel, “Cross Age Face recognition using Deep Residual Networks “. IEEE 2019 Fifth International Conference on Image Information Processing (ICIIP).

[4] Bharath Darshan Balar, D S kavya, Chandana M, Anush E, Vishwanath R Hullipalled, “Efficient Face recognition system for identifying lost people”, International Journal of engineering and standard technology (IJEAT), ISSN:2249-8958, Volume-8, Issue-5 S, May 2019.

[5] Birari Hetal, Sanyashiv Rakesh, Porje Rohan, Salwe Harish,” Android Based Operation-Missing Person Finder”, IRE Journals, Volume1 Issue 12, ISSN: 2456- 8880

[6] Swarna Bai Arnikar, G. Kalyani, D. Meena, M. Lalitha, K. Shirisha, Seetasaikiran, “RFID based missing person identification system”, IEEE 2014 International Conference on Informatics, Electronics & Vision (ICIEV).

[7] Sayan Deb Sarkar and Ajitha Shenoy, "Face Recognition using Artificial Neural Network and Feature Extraction", IEEE 2020 IEEE 7th International Conference on Signal Processing and Integrated Networks.

[8] National government tracking system for missing &vulnerablechildren's.https://trackthemissingchild.gov.in/trackchild/index.php.

[9] Nayana C P & Harshitha P, Police Surveillance System for Missing Persons, IJRASET, 2025.

[10] K. Venkatasalam et al., AI-Assisted Missing Person Finder Using FaceNet Algorithm, ShodhKosh, 2024.

[11] M. Indra Ardiawan& Gede P. K. Negarara, Comparative Analysis of FaceNet, VGGFace, GhostFaceNets, JAAI, 2024.

[12] U. P. Akare et al., Finding Missing Person Using Face Recognition, IJRASET, 2024.

[13] S. Sowmiya et al., Searching Missing People Based on Face Recognition Using AI in Video Surveillance, ShodhKosh, 2024.

[14] Mageswaran S et al., Finding Missing Person Based on Face Recognition Using AI in Video Surveillance System, IJRASET, 2023.

[15] Abid Faisal Ayon & S. M. M. Alam, Toward Digitalization: A Secure Approach to Missing Person Using Facial Recognition, arXiv, 2024.

[16] Beibut Amirgaliyev, Miras Mussabek, Tomiris Rakhimzhanova, and Ainur Zhumadillayeva, A Review of Machine Learning and Deep Learning Methods for Person Detection, Tracking and Identification, and Face Recognition with Applications MDPI, 2025.

[17] Joseph A. Mensah, Justice K. Appati, Elijah K.A Boateng, Eric Ocran,Louis Asiedu, FaceNet recognition algorithm subject to multiple constraints: Assessment of the performance SciDirect, 2023.

[18] Zhongwen Li et al., Facial Recognition Leveraging GANs, arXiv, 2025.

[19] Sasan Karamizadeh,SamanShojaeChaeikar,and Hamidreza Salarian, Combining MTCNN and Enhanced FaceNet with Adaptive Feature Fusion for Robust Face Recognition, MDPI, 2025.

[20] Ramavath Ganesh, Chilukuri Srija, Bhuriwale Devesh, Mrs.Harikakoormala, Finding a Missing Person Using Al, IRJAEH, 2025.

[21] Aswani T., Gorli Lakshmi Sai Amalodbhavi, Pindiga Urmila, Sanathan Reddy P., Mohammed Mosim Ali, Face Recognition and Tracking of Missing Person Using AI, IRO Journals, 2025.

[22] M Mounika, Mohan R, Kiran Kumar M ,Daruru Tharaka Rathna,K Padma Priy, A SURVEY PAPER ON MISSING PERSON IDENTIFICATION SYSTEM, JETIR, 2025.

[23] Deepa M, Missing Persons Identification Using Deep Learning, IJARSCT, 2025.

[24] B. Venkateswara Reddy, Duggirala Chandra Sena, Goddanti T N Lakshmana Sai,Ch. Srihari, Ch. Vishnu Teja, Real-Time Face Recognition in Policing:Implementing YOLO for Accuracy and Efficiency, IARJSET, 2025.

[25] Aidana Zhalgas,BeibutAmirgaliyev and Adil Sovet, Robust Face Recognition Under Challenging Conditions: A Comprehensive Review of Deep Learning Methods and Challenges, MDPI Applied, 2023.

[26] Harshil Ketankumar Champaneria, Vector Embedding Spaces and the Paradigm Shift of FaceNet in Modern Facial Recognition Systems, ResearchGate, 2025.

[27] Shriyash Kapse, Pradip Ghadge, Vikas VirkarPrasad Shinde, Krishna Patil, Finding Missing People Using ML