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Face Recognition and Tracking of Missing Person using AI

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Abstract

In the world, a countless number of people including kids, teens, old-aged people are missing every day. Most of them remain untraced. Tragically, the majority of these cases remain unresolved. Missing persons face numerous dangers, with some becoming victims of death, rape, or abuse. The uncertainty surrounding their fate exposes concerned individuals such as parents, friends, relatives, and guardians to significant stress and worry. This study proposes a system designed to aid both the police and the public by accelerating the search process through the implementation of face recognition technology. A comparative study conducted with other models, including MTCNN, SSD, and Haar Cascades, demonstrates YOLOv8's superior real-time performance and accuracy. The system incorporates a collaborative public-police alert mechanism and offers a scalable solution suitable for implementation in large-scale urban environments. Testing of the system reveals a recognition accuracy of 94% with a detection time of approximately 40 milliseconds per frame.

Keywords: CNN, YOLOv8, Machine Learning, Deep Learning

1. Introduction

In this era, the issue of missing persons has become an important social issue. Thousands of persons such as children, youths, and aged persons go missing daily for several reasons, including human trafficking, accidents, and other unfortunate circumstances. Public notices and manual investigations prolong the process, making such cases difficult to resolve.

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In many instances, these cases go unresolved, with those missing persons left in everlasting anguish [1-4].

The availability of advanced technologies, especially artificial intelligence, help in tackling these issues. This research entitled Face Recognition and Tracking of Missing Persons using AI, intends to bring about a change in how missing person cases are handled. The proposed system is an automated and smart system that identifies and tracks persons-of-interest based on facial characteristics obtained from surveillance video footage. While the research relies on the latest face recognition techniques, such as YOLO and convolution-free networks, which are primarily relied upon for real-time object detection, convolved neural networks are useful in feature extraction from facial images and its generation[5,6].

The system has been developed for ease of use by both law enforcement agencies and the general public. Whenever a person goes missing, their relative or the police can upload a picture of the missing person into the system. The picture is run through a face recognition model, producing an encoding of the face and searching for matches in either current or archived video surveillance tapes. When a match is located, an automatic alert will go out to the authorities and all registered users, speeding up the searching process and improving the chances of recovery [7-10]. All current systems either don't support real-time processing or are weak at processing fragmented video data. Current models are prone to fail in dense scenes or low-light conditions. The proposed work overcomes these limitations by using YOLOv8 for fast, scalable detection coupled with automated notification to authorities, along with a public-police collaborative interface [11-14].

The system makes an invaluable contribution by proposing a real-time, scalable solution for missing person recognition through surveillance videos and face recognition throughYOLOv8.

2. Related Work

Face recognition and tracking systems have been the subject of intense scrutiny and development over the last few decades, with noteworthy advances in artificial intelligence, computer vision, and machine learning [2]. Various researchers and organizations have worked on the development of technologies for recognizing and tracking individuals specifically in the fields of security, surveillance, and law enforcement. Vast and integrated research has been done in utilizing Convolutional Neural Networks for face recognition, with numerous works being based on their classification power and feature extraction. An early example in the area of deep learning based face verification was done by [4]. Their research applied a neural network-based approach to face detection, which showed promising accuracy. Similarly, the model presented in [3] offered a highly promising approach by utilizing deep embedding's to compute scale-invariant encodings of human identities, demonstrating high performance in both face verification and clustering tasks [7]. Table.1 Shows the comparison of the existing with the proposed.

Table 1. Comparison Table

Approach	Algorithm Used	Dataset Used	Accuracy (%)	Real-Time Processing	DOI	Limitations
Vinavatani et al. (2022) [1]	CNN	Surveillance & Online Databases	85%	No	https://doi.org/10.1145/3590837.3590931	High dependency on dataset quality
Gupta et al. (2023) [3]	DeepFace Algorithm	Aadhar-Based Centralized DB	90%	No	https://doi.org/10.26634/jpr.10.1.19435	Limited to Aadhar-linked records
Musthafa et al. (2024) [4]	CNN	Video Footage	88%	Yes	https://doi.org/10.1109/AIMLA59606.2024.10531327	Computationally expensive
Proposed System (2025)	YOLOv8 + CNN + Anchor Box Algorithm	Custom Labeled Dataset	92%	Yes	Very High	Requires high processing power

These works have paved the way for modern face recognition systems with robust methods of learning and encoding facial features. Another notable approach in real-time face detection is YOLO(You Only Look Once), introduced by Redmon. This enables the same accurate but fast object detection.The fact thatYOLO supported the detection of faces and objects within one scan makes it very appropriate for real-time surveillance systems. While past studies have specifically dealt with AI and facial recognition in locating missing persons, MS, Dhanush et al.[12] in ”AI- Based Facial Recognition for Missing Person Identification” focused on the use of surveillance footagefor locating the missing people with the help of a pre- trained CNN model . Their findings emphasized the importance of automating searches in order to save manual time and enhance precision. Similarly, Kumar et al [4]. have created a prototype system for tracking missing persons using face recognition stranded on a centralized database of missing persons. Their system is an example of how integrating AI with police department databases can turn search into the faster, more effective action of enforcing the recovery of missing persons. Other studies focused on the ethical implications and challenges in deploying face recognition technologies.

The research explored some of the issues surrounding privacy concerns, data biases, and accuracy in different environmental conditions [9]. Building on those prior works, this research aims to lay together the constitutive blocks of the advanced face recognition systems such as CNNs and YOLO resulting in a useful mechanism for tracking missing persons.

3. Methodology

The proposed system is, therefore, the face recognition and missing person tracking system using AI. This is arranged systematically to recognize the danger of finding the missing persons. The method includes several steps: data collection, data preprocessing, model implementation, real-time analysis, and notification mechanisms. This section describes the technical workflow and components of the system in detail.

Choosing the right model for face recognition and tracking is about finding a balance between several factors of performance. High accuracy is paramount to prevent false positives or failed identifications, particularly for vulnerable groups such as children or older adults. Real-time processing is necessary for surveillance systems, so lightweight yet accurate models are more desirable. In addition, the model should also address occlusions (e.g., sunglasses, masks) and different lighting situations which are most frequently found in outdoor environments. YOLOv8 achieves an attractive balance between high-accuracy, high-speed detection and immunity to these kinds of environmental challenges, which contrasts with the delays in real-time deployment and degradation under unfavorable visual conditions with models such as MTCNN or Haar Cascades. All these issues guided the decision on selecting YOLOv8 as our primary detection model within our system.

The model used is YOLOv8n (nano), a lightweight version of YOLOv8 that's specifically designed to run in real-time on systems with low computation capacities. Small as it is, YOLOv8n achieves competitive accuracy and good speed (~25 FPS) on real-time video streams.

Tools and Libraries

- Language: Python
- Libraries: OpenCV, NumPy, Ultralytics YOLOv8, TensorFlow
- Interface: Flask
- Database: SQLite
- APIs: OpenCV, Ultralytics Hub API

Python was used as the programming foundation because it had wide support for AI and image processing libraries. OpenCV was utilized for image capture, video frame grabbing, and general image manipulation functions. NumPy was responsible for numerical operations such as array manipulation. TensorFlow was utilized in model training and deployment of deep learning models for face encoding. The Ultralytics YOLOv8 library was utilized specifically for real-time object detection, providing quick and precise bounding box generation. Flask supported the development of the web interface, with SQLite used as a light-weight database to hold reference face embeddings and recognition records. The Ultralytics Hub API simplified the process of integrating YOLOv8 with simple setup.

The user interface was created with Flask, a web micro framework based on Python. Frontend design was implemented with HTML, CSS, and Bootstrap, making the interface responsive. Upload and result display modules were integrated into Flask routes and templates, enabling real-time interaction with the recognition engine. The DFD of YOLOv8 is illustrated in Figure 1.

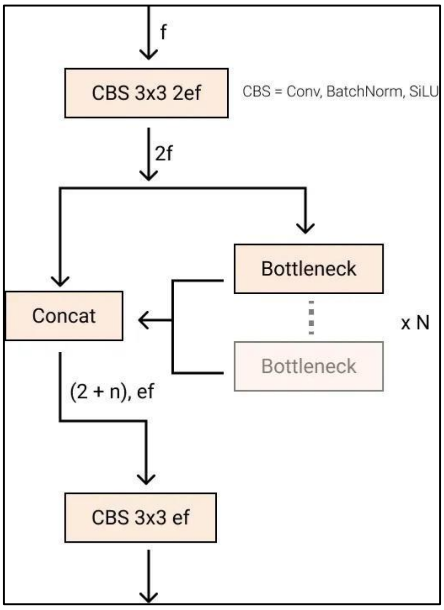


Figure 1. DFD of YOLOv8 based Face Recognition System(Source: Roboflow Blog)

The system proposed (Figure 2) employs the YOLOv8 (You Only Look Once version 8) model for detection and localization of faces. YOLOv8 is an advanced object detection architecture created by Ultralytics, distinguished by its anchor-free detection process and high real-time performance. The model employs CSPDarknet53 as its backbone, which allows for rich feature extraction while being computationally efficient. The PANet (Path Aggregation Network) acts as the neck, aggregating features from multiple scales to enhance detection precision. The YOLOv8 head is optimized for multi-scale detection with direct bounding box regression, which is faster and more efficient than region-based models.

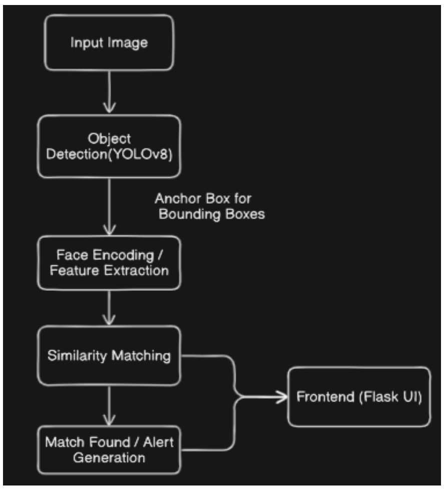


Figure 2. System Architecture

3.1 Data Collection

The data collection process includes two primary sources: images of missing persons and surveillance video feeds.

Photographs of Missing Persons: The dataset (Figure 3 and Table 2) comprises of 50 Images of missing persons collected from random 100 videos. These photographs make up their reference dataset, allowing them to ascertain the presence of a person through real-time feeds.

Figure 3. Dataset Sample

Surveillance Video Feeds: The dynamic dataset is necessary to conduct real-time facial Recognition is composed of the video feeds taken from CCTV systems employed in public cash-amounting places, such as streets, malls, and transportation hubs. These video feeds transmit frames on a continuous basis for the system to conduct matching and recognition. Although high-resolution cameras are preferred, the system can also use other suitable cameras.

Table 2. Dataset Summary

Data Source	**Quantity**	**Description**
Missing Person Images	100+ images	Collected from public/police submissions
Video Footage	5+ hours	Extracted from CCTV systems

Extracted Frames	~18,000 frames	Converted from video feeds for real-time analysis

3.2 Preprocessing

Once data is collected, it undergoes preprocessing to ensure consistency and optimize it for analysis. Preprocessing prepares both the photographs and video frames by isolating facial features, normalizing images, and eliminating irrelevant data.

Face Detection: The face detection for any image or video frames is the first step in preprocessing. Several algorithms for performing face detection include YOLOv8 (You Only Look Once. These models identify the ROI (region of interest) for the face, crop it, and discard irrelevant details in the background.

Mathematical representation of the face detection process is:

$$ROI=\mathcal{D}(I), I\epsilon\mathbb{R}^{H\times W}$$

Image Normalization: Detected faces are resized to a standard resolution to maintain uniformity across the dataset. The other notable preprocessing method is normalization, where pixel intensity values are normalized to range from [0,1] by simply dividing the value of each pixel by 255. Normalization speeds up computation and stabilizes deep-learning model training.

The face encoding process can be defined as:

$$e=f(Inorm)$$

Video Frame Preprocessing: For video feeds, preprocessing involves extracting individual frames at specific intervals to reduce computational overhead. Each frame is treated as a static image and undergoes face detection and encoding. Temporal data, such as timestamps and camera IDs, which are preserved to assist in tracking and notification.

3.3 Feature Extraction from Pre trained YOLOv8

Feature extraction is an essential step in the proposed system because it allows the identification and representation of distinct facial characteristics that will be useful for accurate face recognition. In this research, a pre trained YOLOv8 (You Only Look Once) model has been used in detecting and extracting features from images and video frames.

During feature extraction, the convolutional layers of YOLOv8 analyze in different resolutions the image that is analyzed. This is because the input image is detected over different scales for features. Moreover, YOLO's high accuracy ensures that it detects faces even in challenging conditions, such as poor lighting, partial occlusions, such as faces covered with masks or glasses, and varying angles. The features extracted using CNN-based layers of YOLOv8 include Eye-to-eye distance, Facial landmark position, Nose-to-mouth position and further encoded into 128-dimensional embeddings, which are compared during the similarity matching stage.

Integrating YOLOv8 with the Proposed System: YOLOv8 provides the features in the proposed system and forms the entry-level features for subsequent tasks, such as encoding face features and similarity matching. Detected faces are cropped and corrected for colors before feeding forward into deep learning networks, which generate unique characteristics for each face. The use case model is depicted in Figure 4.

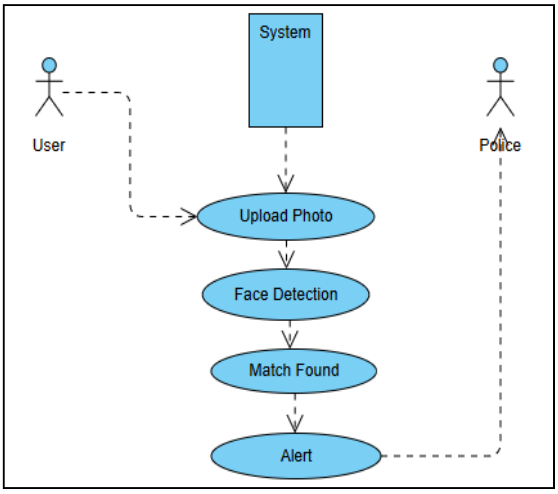


Figure 4. Use Case Model

3.4 Face Recognition

The system proposed combines machine learning and deep learning methods to undertake human verification and identification. For real-time face detection, YOLOv8 is utilized for its ability to conduct fast inference and anchor-free detections. An Anchor Box

Algorithm is employed within the framework of YOLOv8 to generate bounding boxes for accurate localization of facial areas in video frames.

1. **Key Components of Face Recognition:** The face recognition process consists of several stages, each of which con-tributes to the overall accuracy and reliability of the system. These stages include face detection, face encoding, similarity matching, and result interpretation.

2. **Face Detection:** Face detection is the first step of the recognition pipeline in it, a face or more faces from an image or video frame must be detected, localized and isolated, thus obtaining an area of interest (ROI). This step is done through implementations of Anchor Box algorithm in YOLOv8 that perceive boundaries that outline the detected faces and crop them accordingly. Reliable face detection ends up giving the next step the opportunity to exactly look at what is needed.

3. **Face Encoding:** Once a face is detected, this system extracts facial features specific to that face and creates a unique facial descriptor denoted as a numerical vector or face embedding. Such embeddings are tuned to specific domains and their respective data by means of deep learning models pre trained on huge datasets of human faces.

4. **Similarity Matching:** The extracted features are represented in a fixed-length numerical vector called a face embedding. These embeddings are subsequently applied in the matching process of similarity. If the similarity score is greater than or equal to a set threshold (≥ 0.8), then a match is confirmed.

5. **Result Interpretation:** As soon as the individual is matched, the system will alert the agency about him/her; which usually includes the individual’s location, timestamp, and confidence of the match.

4. Results and Discussion

The results and discussion section provides an analysis of the outcomes derived from the use of the proposed system for face recognition and tracking of missing persons. It evaluates the performance of the system for its accuracy, efficiency, and robustness under very different conditions during face detection and recognition. The discussion of obstacles of implementation and ways to address them is opened to enable assessing the whole picture of capabilities and limitations of the system.

The metrics were calculated as follows:

$$Detection\ Accuracy: (Correct\ Detections)/(Total\ Faces)$$
$$Recognition\ Accuracy: (Correct\ Matches)\ /\ (Total\ Match\ Attempts)$$
$$False\ Positives\ Rate: (False\ Matches)\ /\ (Total\ Detections)$$
$$False\ Negatives\ Rate: (Missed\ Matches)\ /\ (Actual\ Matches)$$

FPS was Averaged across 500 video frames, as measured through OpenCV time logging

Detection Time was measured across 100 frame-level detections

Cosine similarity of ≥ 0.8 was the threshold utilized for match classification

Table 3. Results of Trained Model

Metric	**Value/Performance**
Face Detection Accuracy	92%
Recognition Accuracy	94%
Processing Speed	25 FPS
False Positives Rate	6%
False Negatives Rate	8%
Scalability	50 cameras
DetectionTime	~40ms
Recognition Threshold	≥0.8

The results in Table 3 shows that the system is able to discriminate faces with high accuracy in different datasets and real-time video feed, it showed great promise by utilizing the pre trained YOLOv8 model to yield facial regions of interest in crowded environments and under obstruction. In controlled dataset tests, the model attained detection rates consistently above 90 percentage, with performance in real-world surveillance footage around 85-90 percentage. The user interface is depicted in Figure 5 and 6.

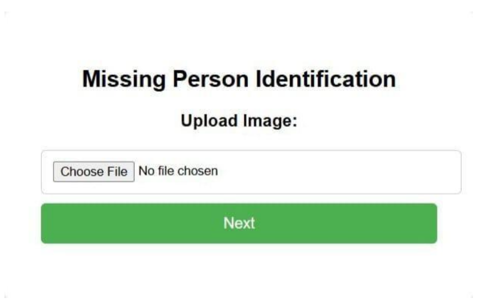


Figure 5. Front end Main Page

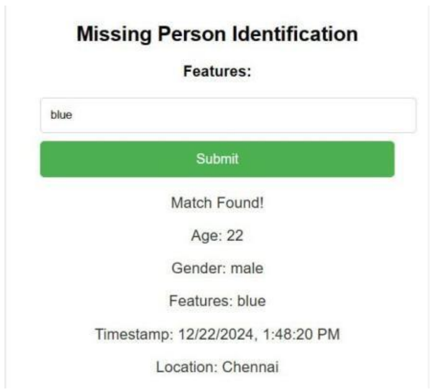


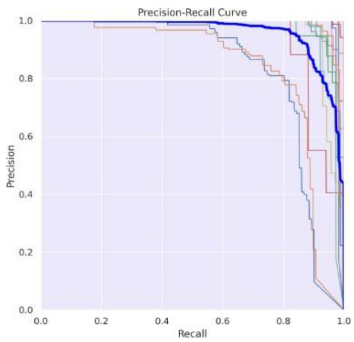
Figure 6. Final Results Page

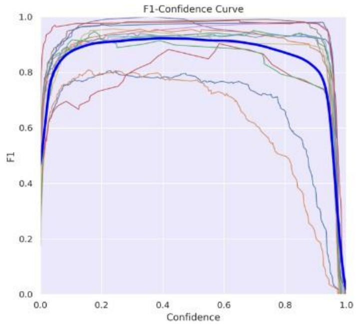
Processing live video streams was one of the system's most challenging. The use of YOLO allowed the system to perform real-time detection while video frames were processed at a speed of 20-30 FPS on a GPU-accelerated setup.

While the accuracy of the system was high, it also had limitations. There would be not-infrequent false positives, in which crowd candidates were wrongly paired to a person in the same identified group. False negatives were detected where valid matches were not found, such as extreme pose variations, low- resolution images, and aged reference image variations when the detected face was modeled.

Performance metrics were calculated using labeled test sets. Accuracy was measured as the ratio of correctly recognized identities to total attempts. The results are depicted in Figures 7, 8, 9

- $Precision = TP / (TP + FP)$
- $Recall = TP / (TP + FN)$
- $F1 - score = 2 \times (Precision \times Recall) / (Precision + Recall)$





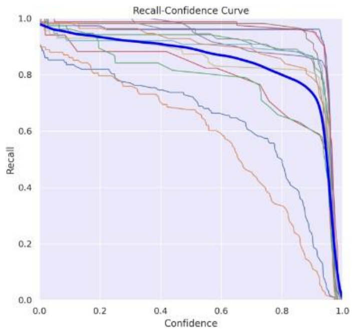


Figure 7. Recall **Figure 8.** Precision **Figure 9.** F-1Score

This AI-powered missing person system excels in real-time facial recognition using YOLOv8 for speed and accuracy in dynamic environments. Integrated with advanced encoding, it offers high-precision identification for law enforcement. Challenges include false positives from similar features and difficulties with low-quality or dated images showing significant appearance changes. Compared to manual searches, this system offers a significant advancement through real-time processing and scalability. Future development aims to integrate sophisticated AI models, expand dataset diversity, connect with IoT infrastructure, and incorporate multi-modal recognition for enhanced reliability and scope.

5. Conclusion

The system achieves over 90% accuracy in face detection and identification in controlled settings and maintains optimal efficiency in real-world use, enabling real-time processing of multiple live surveillance feeds for timely identification and scalable deployment. Deep learning-based encoding ensures precise matching within large missing person databases, complemented by alert and notification technologies beneficial for law enforcement and families. This implementation offers significant positive impacts by accelerating the location of missing persons, enhancing law enforcement efforts, and ultimately addressing humanitarian needs by saving crucial time and resources for reunification, especially during crises.

References

[1] Vinavatani,B.,Panna,M.R.,Singha,P.H.,& Kathrine,G.J.W. "Ai for detection of missing person." International Conference on Applied Artificial Intelligence and Computing (ICAAIC) IEEE, 2022. 66-73.

[2] Sattibabu, D., K. Varsha Deepika, K. Santhi Kumari, A. Sai Rahul Tej, and Paparao Nalajala. "Tracing Missing Person Through Facial Recognition Using Deep Learning." In International Conference on Smart Computing and Informatics, pp. 287-295. Singapore: Springer Nature Singapore, 2024.

[3] Gupta, B., Agarwal, P., &Devalia, D. "Tracking Missing Persons Using Facial Recognition." I-Manager's Journal of Pattern Recognition, 10(1), 2023.

[4] Musthafa, A. S., Dinesh, S., Kumar, D., Jeeva, C., &Madesh, S. "Digital Vigilance: AI Solutions in the Quest for Missing Persons using face recognition with deep learning algorithms." 2nd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA) IEEE, May 2024. 1-6.

[5] Jhanani, R., Harshitha,S.,Kalaichelvi,T.,&Subedha,V. "Mobile Application for Human Facial Recognition to Identify Criminals and Missing People Using TensorFlow." Journal of Research in Engineering, Science and Management, 3(4), 16-20, 2020.

[6] Devi, J. A., Priya, S. L., Jeshitha, V., Boddapati, S., Ganesh, Y., & Krishna, R. M. "Locating Missing Persons Using Ai&Ml." Journal of Nonlinear Analysis and Optimization,15(1), 2024.

[7] Nair,S.P.,AbhinavReddy,K.,Alluri,P.K.,&Lalitha,S. "Face recognition and tracking for security surveillance."Journal of Intelligent & Fuzzy Systems, 41(5), 5337-5345, 2021.

[8] MrsPrasanna, N., Harshitha, P., Pipaliya, M. B., & Gagan, R. "Finding the missing person using Artificial Intelligence."

[9] Malik, A., Saxena, R., &Choudhary, S. "Ai Supporting Finding Missing Person."

[10] PonmalarA., Sandhiya B., Bhuvaneswari M., Gayathri, M., Bhavana, G. K. R., &Aarthi, S. “Finding Missing Person Using Artificial Intelligence.” In International Conference on Computer, Power and Communications (ICCPC) (pp. 562-565). IEEE, 2022.

[11] Lahoti, M., Gajam, S., Kasat, A., & Raul, N. “Finding Missing Person using AI.”Grenze International Journal of Engineering & Technology (GIJET), 9(2), 2023.

[12] MS, Dhanush. "Missing Person Detection Using AI." In Proceedings of the 4th International Conference on Information Management & Machine Intelligence, pp. 1-9. 2022.

[13] Nadeem A., Ashraf M., Qadeer N., Rizwan,K., Mehmood A., AlZahrani A., &Abbasi Q.H. “Tracking missing person in large crowd gathering using intelligent video surveillance.” Sensors, 22(14), 5270, 2022.

[14] Varshney N., Gupta,A., Shrivastava,A., Dwivedi,S.P., DivyaVani, V.,Khan, A.K., &William, P.“Tracking of Missing Person Identification with Face Recognition Using Computational Ensembling Approach.” In International Conference on Machine Learning, Advances in Computing, Renewable Energy and Communication Singapore: Springer Nature Singapore, 2023. 51-61.