TraceFusion: Precision AI for Missing and Wanted Person Detection

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***Abstract*—With the advent of advanced technologies, which has paved the way for critical social challenges. One such social challenge is the identification of missing and wanted individuals in day-to-day basis. Manual identification is time consuming and less efficient to tackle this challenge.TraceFusion leverages Machine Learning(ML) to enhance efficiency in identification. The system features a Web based application that allows its users to register missing persons with image uploads,facilitating real time searches.The MTCNN model and the InceptionResNetV1 model processes live camera feeds as well as recorded videos to match faces against a database of missing and wanted persons which upon detection can assist the authorities in response actions. A flask based server performs real-time face recognition, while Firestore is used to store and retrieve images for matching. Using TraceFusion, public safety can be enhanced and investigations be fastened up.**

***Index Terms*—Face Recognition, Missing Person Detection, Wanted Person Identification, Artificial Intelligence, Machine Learning, MTCNN, InceptionResNetV1, Firestore, Flask.**

1. INTRODUCTION

Identifying missing individuals and wanted persons is crucial for public safety and law enforcement. Traditional methods of searching for missing persons rely heavily on manual searching, which mostly leads to delays and inefficiencies. With the advancement in Artificial Intelligence(AI) and Machine Learning (ML), face recognition has emerged as a powerful tool for automating and subsequently enhancing the identification process.

Despite these advancements , challenges persist, including real time search and system capabalities,low data storage , lesser accuracy etc..Additionally, many existing systems lack integration with databases, which reduces their effectiveness in real time.

To address these issues, we present TraceFusion, a face recognition system designed to assist in detection of missing and wanted persons. The system uses a Flask based inference server for face recognition and the Firebase Firestore database for storing and retrieving images for matching. The key parts of the system include a Web based application for reporting missing persons, the MTCNN for face detection, and InceptionResnetV1 for feature extraction and matching. The system also incorporates a real-time notification system that alerts the persons who reported the case upon a positive match, enabling faster response times.

TraceFusion bridges the gap between technology and law enforcement,making the identification process more efficient. This paper explores the system's architecture , the face recognition model and its potential impact on public safety.

2. LITERATURE SURVEY

The identification of missing persons and wanted individuals has historically relied on manual methods, inclusive of public awareness campaigns and traditional surveillance techniques. However, with the advent of more advanced technology , more efficient and automated approaches which enables faster and more accurate identification is realizable.

A. Face Recognition and Biometric Identification

Face recognition has become one of the most widely used biometric identification techniques due to its non intrusive nature and greater level of accuracy. It plays a crucial role in applications ranging from security and surveillance to identity verifications using standard cameras.Earlier biometric methods such as fingerprint and iris recognition require more specialized

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equipment, whereas face recognition systems can operate using standard cameras.

Several deep-learning approaches were proposed to attain higher accuracy and robustness in face recognition systems. Schroff et al. [1] introduced FaceNet, which used deep convolutional network to generate face embeddings.Parkhi et al. [2] developed a large-scale VGG-Face model, which was trained on an extensive dataset, which demonstrated superior performance in face recognition tasks. These models leverage deep learning techniques for creating highly discriminative face representations, making them suitable for real-world applications.

B. Challenges in Person Identification

Despite rapid advancements in face recognition, many issues still remain in real world application of missing person and wanted criminals identification systems.

1) Aging and Appearance Issues: Facial features of a person change over time due to aging and various unavoidable issues such as accidents. Zhang et al. [3] explored age-invariant face recognition models which progessed facial images to improve matching accuracy.

2) Occlusions and Partial Visibility: Faces are often partially not visible due to occlusions caused by clothing,face masks,camera angle etc. Jafri et al. [4] proposed the landmark based face completion model to reconstruct missing facial features which improve the accuracy in incomplete images.

3) Scalability and Real-Time Processing: Efficient face recognition requires handling large datasets while ensuring real-time processing.Traditional systems are generally less scalable and less computationally efficient while performing face matching on large databases.

C. AI and ML in Face Detection

1) Convolutional Neural Networks (CNNs) for Face Recognition: CNNs are commonly used for person identification using facial and gait analysis. These networks learn from the spatial heirarchies from the image data. CNNs handle variations in lighting, pose, and facial expressions, which makes it suitable for surveillance footages where ideal conditions are unattainable.In the case of gait recognition, CNNs analyze walking patterns unique to individuals which serve as a robust identifier when faces are not properly visible. This technique is particularly useful in low-resolution or crowded scenes where facial recognition struggles. [6], [5].

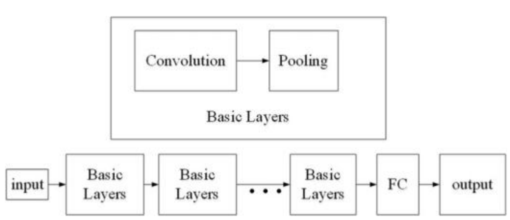

Fig. 1: CNN-based Gait and Face Recognition [6].

2) Siamese Neural Networks for Face Verification: Siamese networks are effective when the goal is to compare two images and verify whether they belong to the same individual. These networks consist of twin subnetworks that learn to output similar embeddings for identical images and dissimilar embeddings for different ones. It is robust against changes in lighting, pose, and image quality, which makes it an excellent tool for facial verification in dynamic surveillance conditions and is especially useful to recognize partially occluded faces or in cases where subjects appear at different angles. [8]

3) Mask R-CNN for Person Detection and Segmentation: Mask R-CNN is a deep learning model that is used for object detection and instance segmentation.It can be used to accurately detect and segment individuals from video frames. The segmentation mask allows the system to isolate a person from the background, which improves the accuracy of subsequent facial or gait recognition. This technique is particularly effective in complex scenes where multiple individuals are present, which ensures that the system focuses only on the relevant subjects present. [7]

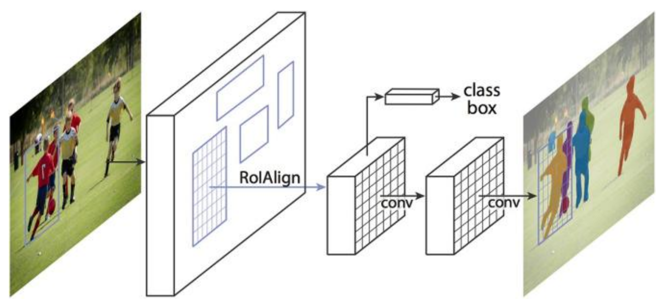

Fig. 2: Detection and Segmentation using Mask R-CNN [7].

4) Semantic Part Detection for Facial Recognition: Accurate identification of individuals when parts of the face are obscured is a challenge. Semantic part detection focuses on extracting and analyzing specific facial regions, such as the eyes, nose, mouth, and jawline, to improve recognition accuracy.Using this approach is particularly beneficial in low-resolution footages where the faces are not fully visible. This type of detection is also valuable in forensic settings, where a partial facial image might be the only available evidence. [9], [10]

5) Image Quality Assessment: Surveillance footages often suffer from quality inconsistencies, such as blur, low contrast, or noise, which degrades the performance of identification models. Image quality assessment helps to evaluate and filter out low-quality images that may affect recognition accuracy. These systems assess key quality indicators like sharpness, brightness, and contrast at the pixel level, which ensure that only high-quality images are processed for recognition. This enhances the reliability of identification models, reducing false positives and improving the overall robustness of surveillance systems, especially in uncontrollable environments. [10]

6) Multi-Task Learning for Combined Identification: Multi-task learning (MTL) is a deep learning paradigm where a single model is trained to perform multiple related tasks simultaneously. By sharing information between tasks, MTL improves generalization which reduces the need for task-specific data. MTL enables a single model to handle both facial and non-facial identification methods, switching between them as needed depending on the video quality or the visibility of the individual. This flexibility enhances the system's ability to identify individuals even when one method fails making it suitable for real-time applications. [11]

3. METHODOLOGY

A. System Architecture

The system architecture of TraceFusion shown in figure 3 comprises multiple interconnected components, integrating AI and ML technologies with a user-friendly interface for efficient missing and wanted person detection. The core modules include Face Recognition, Image Storage & Retrieval, Real-Time Notification System, and Web-Based User Interface. The architecture follows a client-server model, with a web-based front end communicating with a Flask-based inference server. The face recognition model is deployed on the Flask backend, which handles real-time image processing. Firebase Firestore serves as the database for storing user-submitted images and metadata, enabling fast retrieval and matching.

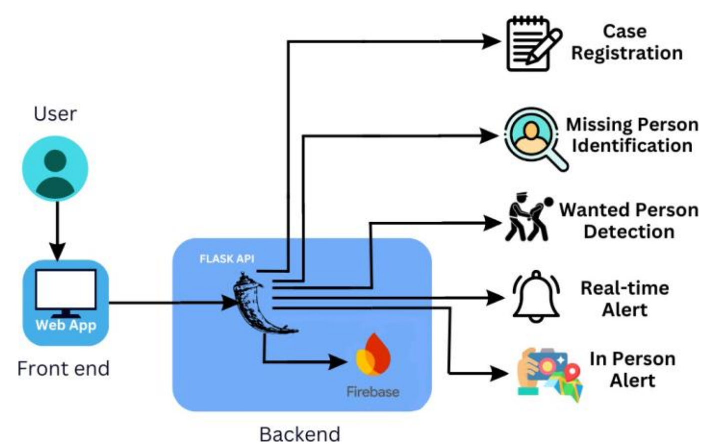

Fig. 3: System Architecture of TraceFusion

B. Web-Based User Interface

The web application allows users to report missing persons and then upload their images alongside other information, and receive real-time alerts if they are detected. The interface is designed keeping in mind ease of use, which ensures that both the public and administration can quickly interact with the system. Users can submit reports, view matched cases, and receive notifications when a missing or wanted person is identified.

C. Face Recognition and Matching

The main part of TraceFusion is the face recognition model, which processes images from both live camera feeds as well recorded videos. TraceFusion employs MTCNN (Multi-task Cascaded Convolutional Networks) for face detection and the InceptionResNetV1 model for feature extraction.

1) Model Development and Training:

- **Face Detection:** MTCNN is used to identify facial landmarks and aligns faces for improved recognition. MTCNN consists of three neural network cascades, which are P-Net, R-Net, and O-Net. In order to achieve face recognition on a unified scale, the original image is scaled to different scales inorder to form an image pyramid before using these networks. P-Net, is a fully convolutional network which is employed in candidate windows and border regression vectors generation. Candidate boxes are corrected using bounding box regression, and then Non-Maximum Suppression (NMS) is used to consolidate highly overlapping candidates.
  The outputs from P-Net are further tuned by R-Net. R-Net is similar to P-Net in structure but is more precise. It takes candidate windows from P-Net, eliminates most of the false positives, and applies bounding box regression and NMS to improve detection accuracy.
  Lastly, O-Net is employed to generate the final face bounding boxes and position the feature points. O-Net further refines the candidates and produces five important facial feature points, improving detection accuracy even further.

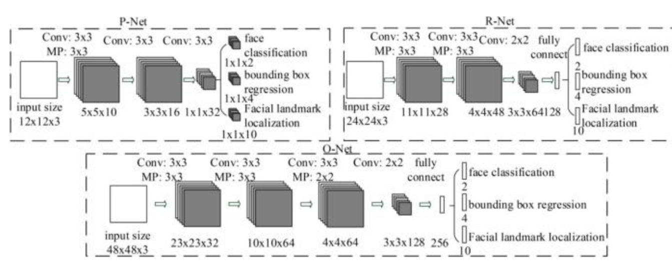

Fig. 4: Architectures of P-Net, R-Net, O-Net [12]

- **Feature Extraction:** InceptionResNetV1 generates the face embeddings for comparison.
- **Matching Algorithm:** The algorithm compares the embeddings based on Euclidean distance, with the identity being determined by a set threshold.
- **Preprocessing:** Images are resized and normalized for uniformity. Data augmentation methods like cropping and contrast changes are done to ensure enhanced model resilience.

D. Image Storage and Retrieval

The system stores all reported images in Firebase Firestore, which ensures secure and scalable storage. Each image is indexed with corresponding metadata, such as timestamps, location details, and reporter information.The system utilizes optimized Firestore queries for faster retrieval, reducing search latency and ensuring quick matches.

E. Real-Time Notification System

When a match is detected, an instant alert is sent to the reporting user and the concerned authorities incase of wanted person detection. Alerts are sent through email, or even SMS to ensure that action can be taken immediately. The system gives priority to real-time alerts to ensure maximum efficiency in missing person recovery.

F. Security and Access Control

In order to ensure that the data is not remote only and also to ensure privacy of data and free from unauthorized access,it is intended to enforce:

- **Role-Based Access Control (RBAC):** Role Based Access Control can be used to deny access to sensitive information for authorized staff,i.e, every authorized person has a level of authorization.
- **End-to-End Encryption:** End to end encryption is helpful in keeping all information including images and metadata safe.
- **Firestore Security Rules** Firebase Firestore can be used to implementing stringent access policies depending on user roles.

4. Results and Discussions

Dataset: The datasets used for training and evaluating our face recognition model play a crucial role in ensuring accurate identity matching. For face detection and recognition, we created our own dataset for training and testing the face recognition model, which comprised of a variety of facial images taken under different conditions such as the lighting, angles etc. which is done to very much model the real world. The then obtained images were preprocessed for enhanced model generalization.

1) **Face Detection:** The TraceFusion system employs MTCNN for face detection, which achieved higher accuracy in identifying facial landmarks for face recognition with fewer false positives. The accuracy of MTCNN was seen to increase with more training data, ensuring accurate detection in challenging situations.
2) **Feature Extraction:** TraceFusion used InceptionResNetV1 for feature extraction, generating 512-dimensional embeddings for detected faces. The Euclidean distance algorithm was applied to compare the embeddings, allowing effective identity verification. The system demonstrated an accuracy of over 98% in recognizing individuals within the dataset.
3) **Live Detection and Processing Speed:** The main motive of TraceFusion is real time processing. The system was highly responsive for real-time applications with optimized performance and reduced latency, which ensured live recognition in dynamic environments.
4) **Database and Storage Efficiency:** The processed face embeddings are stored in Firebase, which enables faster retrieval for identity verification. The use of optimized storage solutions has minimized memory usage which ensures quick access to stored facial representations.

5. Conclusion

TraceFusion successfully combines MTCNN with Inception-ResNetV1 for accurate face detection and feature extraction with highly accurate identity verification. TraceFusion could handle diverse facial variations efficiently, achieving over 98% recognition accuracy. The live detection and video processing capabilities enhanced its usability, making it suitable for real-world applications of Missing and Wanted Person detection, which could assist the society in safety. Further improvements would focus on the dataset expansion for better generalization and model optimization fir faster inference.

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