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Enhanced Security Through Real-Time Face Recognition: A Deepfacenet Approach for Video Surveillance Systems

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Abstract: With the alarming rise in recidivism rates among violent offenders, including child sex offenders, there is an urgent and growing need for advanced security measures to safeguard vulnerable environments. Schools, childcare centers, and other high-risk areas are especially susceptible to potential threats, making it imperative to implement proactive solutions to ensure the safety and well-being of children and staff. Traditional surveillance systems, which rely heavily on manual monitoring by security personnel, are increasingly proving inadequate in identifying and responding to threats in real-time. Human oversight often suffers from limitations such as delayed reactions, and errors in judgment, leaving critical security gaps.
Our suggested work offers a novel video surveillance system that uses DeepFaceNet, a highly optimized and modular deep learning model intended for real-time face detection, to overcome these difficulties. Because this technology is primarily designed to handle live video feeds from surveillance cameras, it can identify and detect the faces of people who have a criminal background, especially those who have been classified as high-risk offenders. By leveraging state-of-the-art face recognition technology, our suggested system provides a strong and comprehensive threat detection solution. Along with improving public safety, it also acts as a disincentive to criminal conduct, which helps to avert such incidents. This system addresses and ensures a safer environment in the realm of security and surveillance by emphasizing high precision, real-time processing, and reliability.
Index Terms: Face recognition, Deep Learning, DeepFace, Surveillance, Security.

I. INTRODUCTION

The rapid expansion of surveillance infrastructure, in conjunction with the progressions in artificial intelligence, has revolutionized security and public safety endeavors worldwide. Facial recognition is one of the most revolutionary technologies in this field; it uses deep learning to recognize people by their faces. In complex environments, like identifying criminal faces in surveillance footage or wild videos, a term is used to describe unstructured, unconstrained video data captured in public settings: one of the state-of-the-art facial recognition techniques. DeepFace has shown immense promise in real-time, high-precision recognition tasks. Authorities need reliable systems that can rapidly scan live video streams, identify people of interest in real time, and notify law enforcement or security personnel about possible criminal activity in places like congested urban areas, airports, stadiums, and large-scale events. With thousands of faces potentially needing to be analyzed at once in real-time surveillance applications, this modification enables the algorithm to compare and identify faces with high accuracy. DeepFace's integration with surveillance systems promises a breakthrough in real-time criminal detection by guaranteeing that faces can be reliably identified and matched to sizable databases of known individuals even in chaotic and uncontrolled circumstances.

A. Research Domain

The proposed work falls within the domain of Artificial Intelligence (AI), specifically leveraging Deep Learning techniques for security surveillance. It focuses on utilizing real-time face recognition to enhance safety in vulnerable areas, employing advanced AI models like DeepFaceNet to accurately detect and identify known criminals, thereby preventing potential incidents and ensuring public safety. Deep Learning (DL) is a subset of Machine Learning (ML) and Artificial Intelligence (AI) that focuses on using artificial neural networks with many layers to model and solve complex problems. Inspired by the structure of the human brain, these networks are able to automatically identify patterns in vast amounts of data.

Advancements in computer vision, natural language processing, and speech recognition have been made possible by deep learning, which is the driving force behind technologies like virtual assistants, self-driving cars, and picture recognition.

B. Face Recognition

Face recognition is a biometric technology that identifies or verifies a person's identity by analyzing and matching facial features from images or video. Unlike face detection, which only locates and identifies the presence of faces, face recognition goes a step further to determine the identity of individuals. It is widely used in security, authentication, surveillance and personalization applications.

C. Working Of Face Recognition

Face recognition typically involves the following steps:

1) Face Detection: Identifying and separating the face or faces in a picture or video frame.
2) Face Alignment: Standardizing facial positions, which helps increase identification accuracy, and normalizing the face's orientation by aligning important features like the mouth, nose, and eyes.
3) Feature Extraction: Utilizing machine learning or deep learning models to extract distinctive features or embeddings from the face. In this process, important facial features are captured while extraneous details are ignored.
4) Face Matching: Comparing a database of recognized faces with the retrieved facial traits. As certain whether a match exists, similarity metrics or distances are computed.
5) Decision: The algorithm uses a threshold for similarity to determine whether a face is that of a known person or if it is a new or unknown face.

The main purpose of this paper is:

a) To develop an automated video surveillance system utilizing deep learning-based facial recognition for real-time monitoring of crime-prone areas.
b) To improve response time.
c) Overcome human limitations.
d) To enhance the reliability and accuracy of criminal identification by implementing a scoring mechanism based on face tracking.
e) To improve the processing speed of facial recognition by applying a down-sampling technique during the face detection phase.
f) To provide timely alerts to relevant authorities upon detecting known criminals, thereby enhancing public safety and preventing potential incidents.

II. LITERATURE SURVEY

In complex environments, like identifying criminal faces in surveillance footage or wild videos, a term used to describe unstructured, unconstrained video data captured in public settings, one of the state-of-the-art facial recognition techniques, FaceNet [1], has shown immense promise in real-time, high-precision recognition tasks. It blends facial embeddings, which translate a face into a distinct, high-dimensional vector space with convolutional neural networks (CNNs). In another study on lightweight models, Alansari et al. [4] proposed a face feature extraction network based on GhostNet, which duplicates duplicate features linearly.

Major tasks using computer vision related to crime prevention and investigation include license plate recognition, action and posture recognition, and facial recognition [5]. Video data can also be utilized by taking into account a dimension expansion from a temporal rather than a spatial standpoint. Videos typically undergo excessive lossy compression owing to the large storage space necessary for storing the videos. The three steps of face detection, face feature extraction, and face identification or verification are typically used by facial recognition systems. This method illustrates a pipeline that is comparable to the two-stage object detector. When dealing with face recognition issues, the 2-stage approach is unavoidable since training an FCN-based classifier concurrently, as with a 1-stage detector, is not practical. Conversely, PCA-based techniques allow for the fast modification of classifiers without requiring the network to be retrained. Furthermore, because surveillance film often contains low-quality data, it typically does not aid investigations. A generative adversarial network (GAN) formed the basis of a recent study to increase the resolution of surveillance footage [7]. The resolution of the primary objects in photos was enhanced by a super-resolution GAN (SRGAN)-based method, but the resolution of faces, which are sometimes incredibly small objects with delicate features, could not be recovered. Suggested a deep learning-based face detector and identifier for high-risk criminal identification in real-time. The system's goal is to prevent crimes by identifying a criminal through a comparison with criminal databases, detecting a face in video footage taken by image security devices like surveillance cameras, and then alerting a top manager or pertinent criminal institutions.

Both the general processes and the special processes suggested in this study make up the system. Face detector D, tracker T, face encoder E, and identifier I make up the suggested system, which is comparable to a broad facial recognition system [8]. Every frame of the recorded video data is processed instantly, allowing it to execute the analysis with the least amount of lag.

An enhanced SORT extension was also taken into consideration using deep SORT [10]. This approach can successfully address practical issues brought on by the occlusions that arise in the sort. A face detector, on the other hand, is not able to extract useful feature information for an intra-class classification between face instances because it is trained for binary detection. Therefore, the performance gain of adopting Deep SORT in the suggested system over SORT, at the expense of computation time, is negligible. The approach put forth by Schroff et al. [11] serves as the foundation for the face image encoder E and identifier I. The baseline model, FaceNet, is a metric learning-based method in the area of facial recognition. Consequently, while utilizing the FaceNet-based encoder and identifier instead of the basic encoder-identifier, the basic model of the suggested system shows a noticeably higher identification accuracy. Additionally, the detector needs to meet performance standards at a minimal level because an object tracker's operational performance is largely reliant on the performance of the detector. RetinaFace is a face instance identification system that uses a feature pyramid network [15] and a deformable convolutional network [14] to build a general deep CNN as the feature extractor, ensuring scale-invariant performance. While real-time facial recognition performance can be assessed using the video datasets in [9], they are not suitable for modeling the intended job. In this study, as specifics like face size and imaging format differ greatly. While some datasets contain videos, most datasets consist of fragmentary and discontinuous images. It is challenging to perform a matching experiment using mug shots that have been taken and processed in a fixed context. Furthermore, the video data provided in these files have very poor or inconsistent resolutions. To ascertain whether the system can manage real-time processing, an experiment with fixed input circumstances and FHD resolution must be carried out. Furthermore, the relevant datasets differ based on the particular goal, like face recognition, identification, or detection. This study aimed to investigate facial recognition ability in an environment that closely resembled a real-world application setting. To assess the overall performance, data had to be annotated as thoroughly as feasible. ArcFace [12] and [13] CosFace conducted tests on our video dataset, which showed a pedestrian approaching the camera, to evaluate the effectiveness of the suggested methodology against other frame-level techniques. Every film is captured from a variety of perspectives that reveal the face's front.

Table 1. Survey Table

S.NO	PAPER	TITLE	YEAR	AUTHORS	ALGORITHM & METHODS USED	ACCURACY	MERITS & DEMERITS
1	IEEE	Surveillance System for Real-Time High-Precision Recognition of Criminal Faces from Wild Videos	2023	Hyun-Bin Kim, Nakhoon Choi, Hye-Jeong Kwon, and Heeyoul Kim	FaceNet, ArcFace	Accuracy 0.900 and F-1 score 0.943	**Merits-** Robust, Scalable **Demerits-** Accuracy low, Complexity
2	Research Gate	TinaFace: Strong but Simple Baseline for face Face Detection	2020	Y. Zhu, H. Cai, S. Zhang, C. Wang, and Y. Xiong	FPN	92.40%	**Merits -** Simplicity, Efficient. **Demerits -** Model complexity
3	IEEE	SphereFace: Deep hypersphere embedding for face recognition	2017	W. Liu, Y. Wen, Z. Yu, M. Li, B. Raj, and L. Song	CNN	89.14%	**Merits -** Improved face recognition accuracy due to angularly discriminative features. **Demerits-** Computational complexity (depends on the specific CNN architecture). Sensitivity to hyperparameter tuning.
4	IEEE	GhostFaceNets: Lightweight Face Recognition Model From Cheap Operations	2023	M.Alansari, O. A. Hay, S. Javed, A. Shoufan, Y. Zweiri, and N. Werghi	GhostFaceNet	F Score is 0.900	Merits – Notifies relevant institutions about the appearance of criminals. Addresses blind spots of

							surveillance personnel. **Demerit** – Limited benchmark
5	AIP Conference Proceeding	Face Recognition for Criminal Identification: An implementation of principal component analysis for face recognition	2017	Nurul Azma Abdullah, Md. Jamri Saidi, Nurul Hidayah Ab Rahman, Chuah Chai Wen, and Isredza Rahmi A. Hamid	Principal Component Analysis (PCA), MatLab	80%	**Merits** – Automated Facial recognition, Complementary to thumbprint identification. **Demerits** – Limited Software, Dataset Size
6	Research Gate	Detection of violent behavior using neural networks and pose estimation	2022	K. B. Kwan-Loo, J. C. Ortiz-Bayliss, S. E. Conant-Pablos, H. TerashimaMarín, and P. Rad	CNN, LSTM	90%	**Merits** - Real-time detection of violent behavior. Focus on pose estimation, which extracts information regardless of the environment. Creation of a new video database (Kranok-NV) for research purposes. **Demerits** - Lack of explicit accuracy reporting. Dependency on pose estimation quality, which can be challenging in low-resolution videos.
7	IEEE	Multi scale-adaptive super-resolution person re-identification using GAN	2020	M. Adil, S. Mamoon, A. Zakir, M. A. Manzoor, and Z. Lian	ESRGAN	Variying upto 92.7%	**Merits** - Effective resolution enhancement for person re-identification. Mutual learning approach combining SR and re-identification. Superior performance compared to existing state-of-the-art methods. **Demerits** - Lack of explicit accuracy reporting in the paper

8	Springer	A discriminative feature learning approach for deep face recognition	2016	Yandong Wen, Kaipeng Zhang, Zhifeng Li, and Yu Qiao	CNN	76.50%	**Merits –** Center Loss. Joint supervision, MegaFace results. **Demerits -** Further research and experimentation are needed to explore potential limitations or challenges related to center loss and its impact on other tasks.
9	IEEE	Extended YouTube faces: A dataset for heterogeneous open-set face identification	2018	C. Ferrari, S. Berretti, and A. Del Bimbo	Open – set and closed – set identification and CNN	Varying 95%	**Merits** – Open set identification protocol, heterogeneous data, baseline result. **Demerits** – Limited. Size, data Bias
10	IEEE	Simple Online and Real Time Tracking with a Deep Association Metric	2017	Nicolai Wojke, Alex Bewley, Dietrich Paulus	CNN	45%	**Merits -** Pragmatic Approach, Appearance Integration, Deep Association Metric, identity Switch Reduction. **Demerits** – Dataset size, potential Biases

11	IEEE	FaceNet: A Unified Embedding for Face Recognition and Clustering	2015	Florian Schroff, Dmitry Kalenichenk,James Philbin	CNN	95.12%	**Merits –** Accuracy, Error deduction, Representational Efficiency. **Demerits –** Dataset Size, Biases
12	IEEE	ArcFace: Additive Angular Margin Loss for Deep Face Recognition	2019	Jiankang Deng, Jia Guo, Niannan Xue, Stefanos Zafeiriou	ArcFace	79.80%	**Merits –** Simplicity, Scalability **Demerits –** Overfit on small datasets, Cost
13	IEEE	CosFace: Large Margin Cosine Loss for Deep Face Recognition	2018	Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu	CosFace	90.30%	**Merits –** Versatile, State-of-the-art **Demerits** – Computational Complexity, Overfitting Risks
14	IEEE	Deformable Convolutional Networks	2017	Jifeng Dai, Haozhi Qi, Yuwen Xiong, Yi Li, Guodong Zhang, Han Hu, Yichen Wei	CNN	77.60%	**Merits –** Integration with existing architectures, overfitting reduction **Demerits –** Training complexity, Implementation complexity
15	IEEE	Feature Pyramid Networks for Object Detection	2017	Tsung-Yi Lin, Piotr Dollar, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie	FPN	77.60%	**Merits –** Modularity, Efficiency **Demerits –** Increased Complexity, Potential for overfitting

III. EXISTING SYSTEM

A. *Arcface Algorithm*

In our existing system, implementing the ArcFace-based approach offers a significant improvement by leveraging deep learning techniques for highly accurate face recognition, even in challenging conditions. ArcFace's advanced architecture enhances the system's ability to differentiate between individuals with subtle facial variations, providing a more reliable solution for detecting high-risk ex-convicts in real-time.

1) Angular Margin: To improve the face embeddings' discriminative power, ArcFace adds an angular margin to the softmax. It transfers features onto a hypersphere and maximizes the angular distances between embeddings of various identities rather than simply comparing feature vectors.
2) Function of Loss: Through the addition of an angular margin m to the cosine similarity formula, the ArcFace loss function alters the softmax loss:

$$L = -\frac{1}{N}\sum_{i=0}^{N} \log \frac{e^{s.(\cos(\theta y + m))}}{e^{s.(\cos(\theta y + m))} + \sum_{j \neq y} e^{s.\cos(\theta j)}}$$

θ_y: The angle formed by the weight vector and the appropriate class's input feature.
s: Factor of feature scaling.
m: The angular margin and N: Batch size

3) Geometric Interpretation: By limiting embeddings to lie on a unit sphere, the technique works on a hypersphere. Robustness and distinct identity separation are guaranteed by this geometric restriction.
4) 2D Alignment: 2D alignment uses transformations such as translation, scaling, and rotation in a 2D plane to align a face to a canonical location. This approach is easier since it presumes that the face is primarily in the same plane.

a) *Input:* Real-time processing is done on surveillance camera video frames. For initial face detection, down-sampling is used to lower frame resolution.
b) *Detection and Tracking:* To prevent redundancy and preserve continuity, faces are identified and tracked across frames. For the best feature extraction, bounding boxes for faces that are detected are modified.
c) *Encoding and identification:* High-resolution face photos are cropped and encoded into embeddings. A database of criminal faces is compared to these embeddings.
d) *Score Accumulation:* By handling forecast reversals and minimizing false positives, scores are computed and saved for every tracked face, guaranteeing accurate predictions.

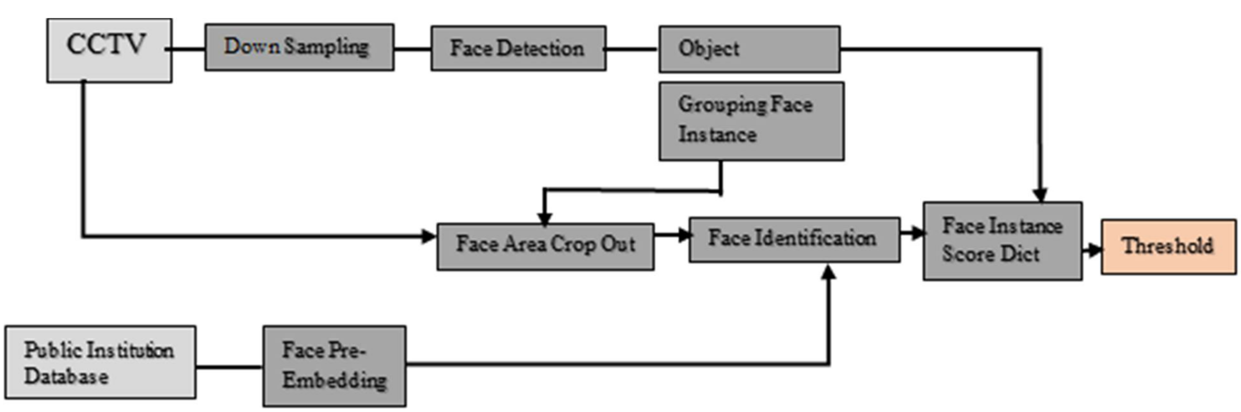

Fig 3.1 Existing System Architecture

e) *Output:* Administrators receive alerts using a web-based interface or push messages when matches are found that surpass the score criteria.

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B. Disadvantages

1) ArcFaceNet's reliance on high-quality, well-lit images for optimal performance can be a limitation in scenarios with poor lighting or significant facial occlusions, potentially reducing its effectiveness.
2) The computational complexity required for real-time processing.
3) Sensitivity to pose and illumination variations under harsh lighting conditions or with significant stance changes; performance may suffer.
4) Vulnerability to adversarial attacks like most deep learning models, ArcFace is susceptible to adversarial examples that could mislead recognition systems.

IV. PROPOSED SYSTEM

The proposed video surveillance system utilizes DeepFace, a deep learning model optimized for real-time face recognition, to enhance security in vulnerable areas such as schools and childcare centers. By processing video feeds from surveillance cameras, the system detects and identifies the faces of known criminals with high accuracy. It employs a down-sampled image approach to boost processing speed and a scoring mechanism based on face tracking to improve the reliability of identifications. Upon detecting a threat, the system immediately alerts security personnel, thereby providing a robust solution for early detection and prevention of potential incidents, enhancing public safety. Fig 4.1 is the proposed architecture which has processes:

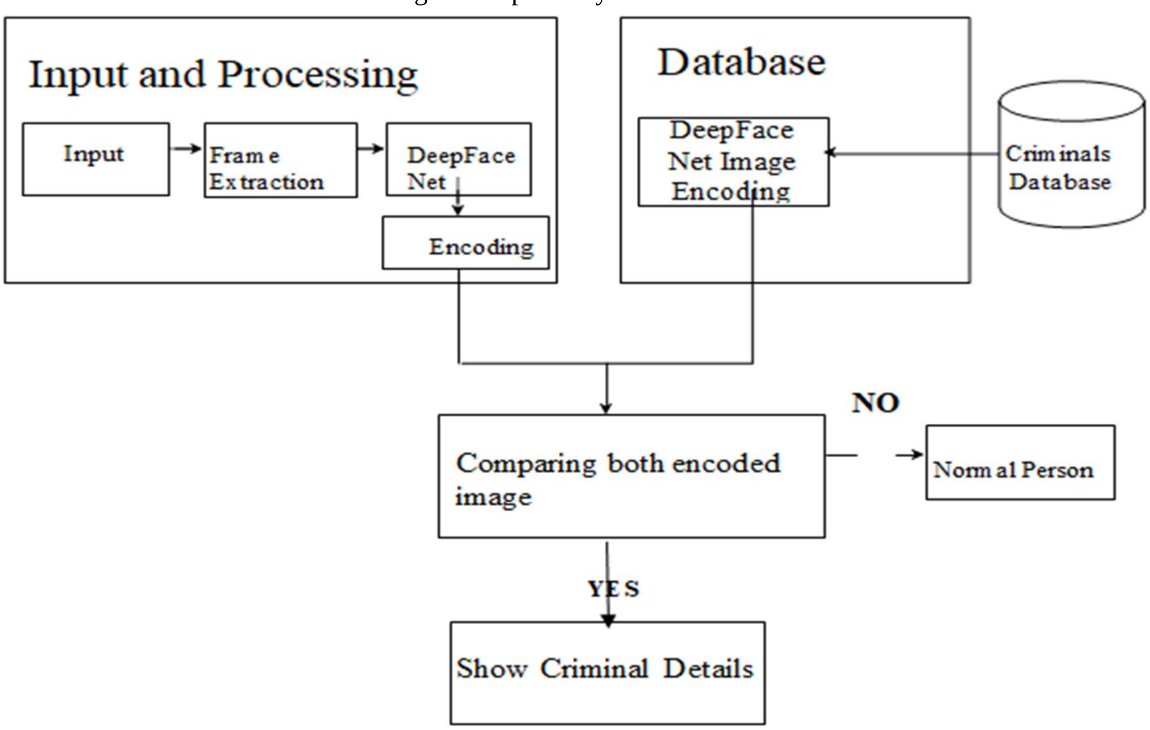
A. Crime Database

Users or law enforcement agencies can input images of criminals into the system. The system uses the DeepFace algorithm to identify and isolate faces from the input images. The extracted facial features with vectors, along with relevant metadata (e.g., criminal name, crime details), are stored in the crime database for future reference.

B. Input and Processing

Input Video: The system accepts video footage as input (e.g., custom datasets or created video recordings).
Frame Extraction: The video is processed frame by frame to extract individual images.
Face Encoding: The system detects faces in each video frame by using DeepFace algorithm.

Fig 4.1 Proposed System Architecture



The important facial features will be converted into vector form, which is numerical representation.

C. Comparison with Crime Database

The facial feature vectors extracted from both the encoding process, which is database stored and the input are compared. If a match is found between the facial feature vector of a detected face and a vector in the crime database.

D. Criminal Identification Output

Once a criminal is identified, the system provides the matching face, along with any related details from the database, enabling authorities to take appropriate action, or otherwise it shows a normal person with no match found.

1) Deepface Algorithm

Facebook uses a facial recognition algorithm called DeepFace to tag photos. It was initially forth at the 2014 IEEE Computer Vision and Pattern Recognition Conference (CVPR) by researchers from Facebook AI Research (FAIR). One of the key innovations in DeepFace was its face alignment technique. Traditional methods used 2D alignment, which was not robust to pose variations. DeepFace introduced a 3D

alignment process: faces were aligned to a frontal view by applying a 3D transformation. This made the model more robust to different head poses (e.g., side profiles). The alignment was based on a 3D model of the human face, which helped in rectifying the variations in rotation, scale, and angle. Deep Convolutional Neural Network (DCNN): The core of DeepFace is a deep convolutional neural network with 9 layers.

There are 4 steps:

- Detect
- Align
- Represent
- Classify

a) Face Detection

Detects faces in an image.

b) 3D Face Alignment

Aligns the detected faces to a frontal pose using 3D modeling techniques. This alignment reduces the variability caused by different head poses. The suggested technique extracted the frontal face by 3D frontalization of faces based on the fiducial (facial feature points). The alignment procedure is finished by following these steps:

- First, we use six fiducial points to identify the face in an input image.
- Utilizing six fiducial points, create a 2D cropped face picture from the original image.
- Then, apply the 67 fiducial point map to the matching 2D-aligned cropped image.
- Using a generic 2D to 3D model generator, we also create a 3D model in this stage, and we manually plot 67 fiducial points on it.
- Frontalization of alignment is the last phase.

c) Representation and Classification

- DeepFace is trained for multi-class face recognition, i.e., to classify the images of multiple people based on their identities.
- It takes input into a 3D-aligned image of 152*152. This image is then passed through the convolution layer with 32 filters and a size of 11*11*3 and a 3*3 max-pooling. A second convolution layer with 16 filters and a dimension of 9*9*16 comes next. These layers are used to extract low-level features from the textures and edges of images.
- The following three layers are locally connected layers, which are a subset of fully connected layers with various filter types in distinct feature maps. This helps in improving the model because different regions of the face have different discrimination abilities, so it is better to have different types of feature maps to distinguish these facial regions.
- Classification Layer during the training phase, the model is trained to classify faces using a softmax layer. During testing, the feature vectors (face embeddings) are used for verification or identification by comparing the similarity between embeddings.

2) *Advantages*

- It enhances security by providing real-time detection and identification of known criminals, enabling quicker responses to potential threats.
- The use of DeepFace ensures high accuracy in face recognition, even in challenging conditions, reducing the likelihood of false positives.
- Lower computational cost.
- The scoring mechanism increases the reliability of identifications by aggregating recognition results across multiple frames.

V. IMPLEMENTATION

i) Using Anaconda Prompt the code file location is opened by using jupyter notebook which is named as CrimeFaceIdentification.

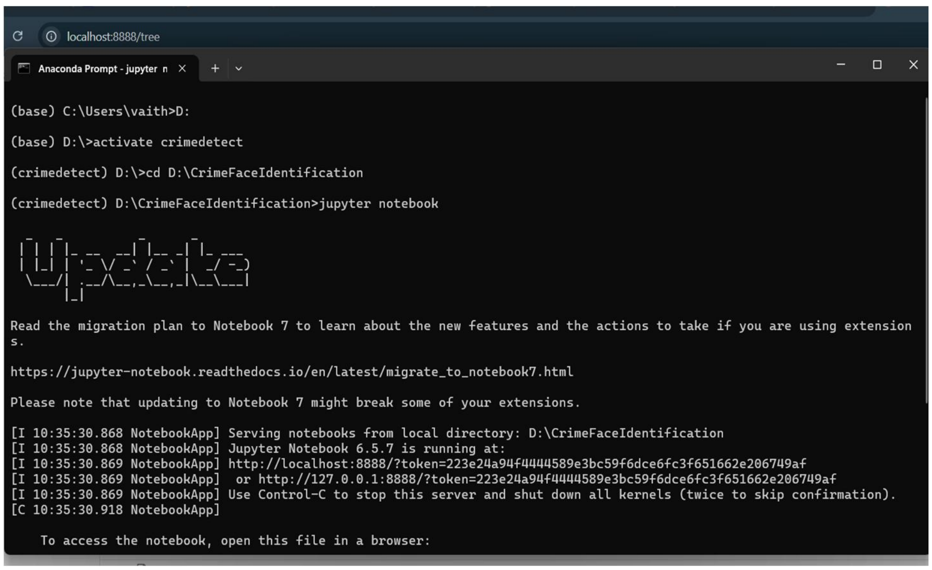


Fig 5.1 Anaconda Prompt Running

ii) This is the datasets stored folder location. (e.g., custom datasets or created video recordings or images).

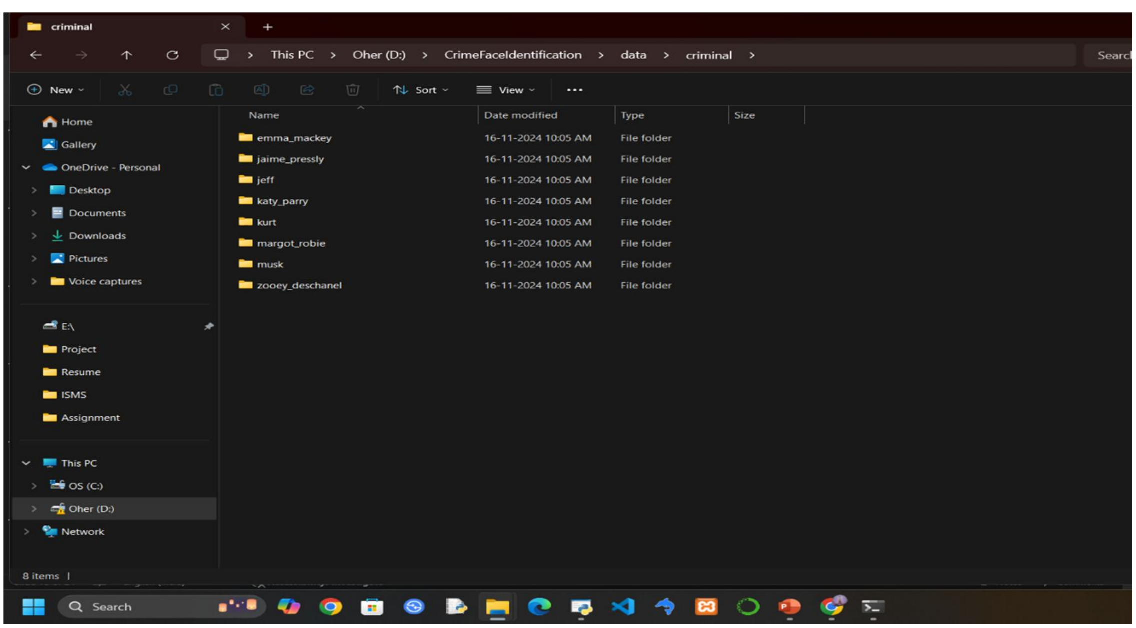


Fig 5.2 Dataset Storage

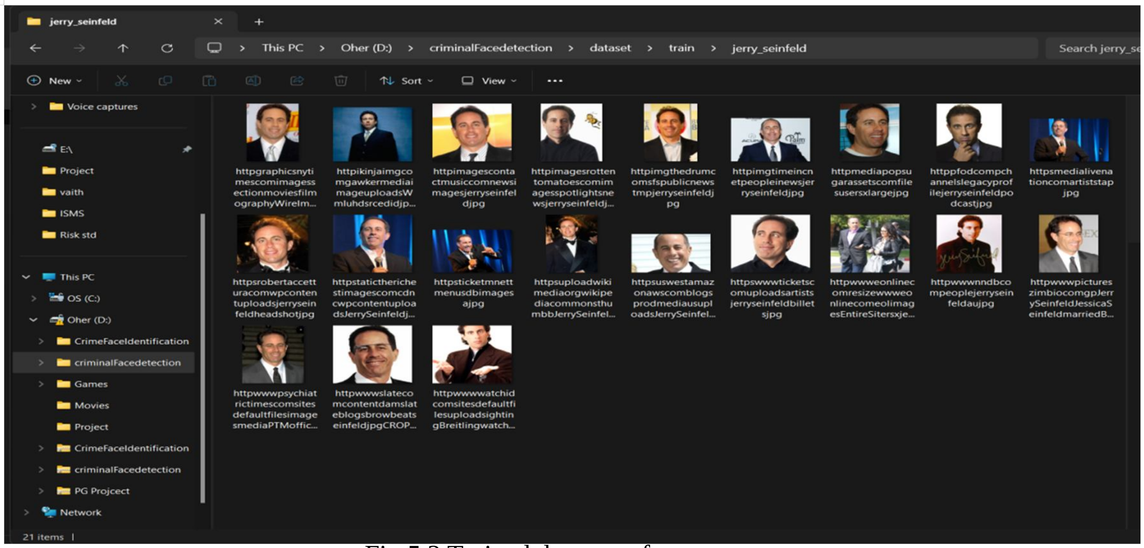


Fig 5.3 Trained datasets of a person

iii) Preprocessing of datasets that is processing the data for the algorithm to use it for the identification.

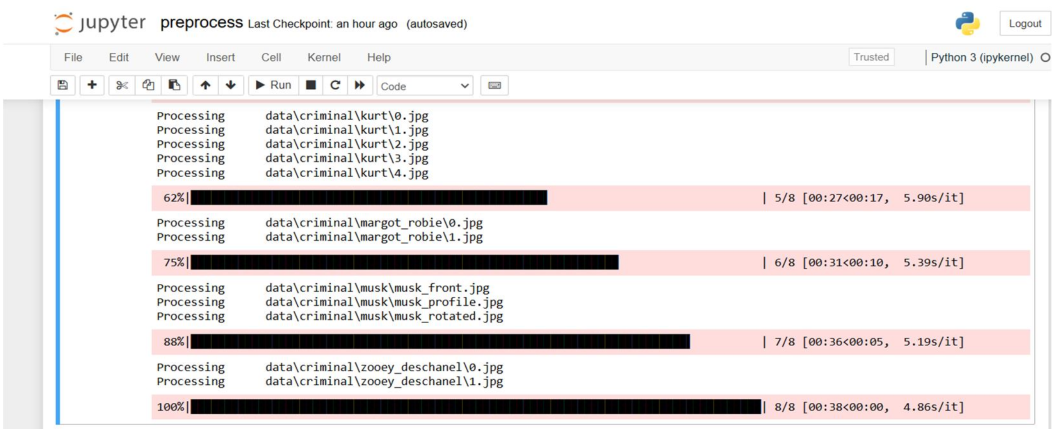


Fig 5.4 Preprocessing

iv) Example input and output process

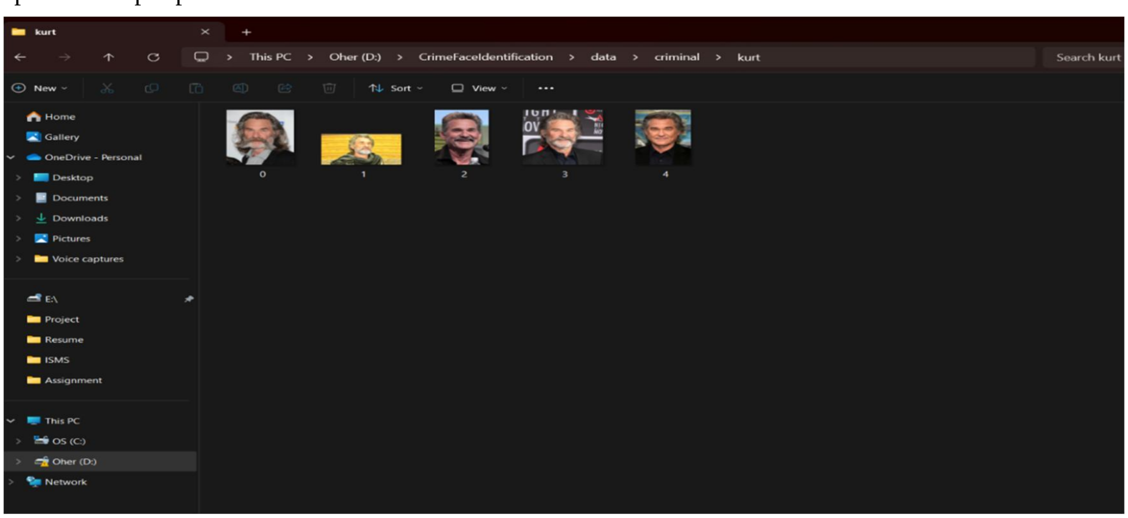


Fig 5.5 Input example: Kurt

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```
'''
[86 79 84]
[87 80 85]
[88 81 86]]] | Matched Person: kurt | Similarity: 1.00
```

Fig 5.6 Output person identified as Kurt with the vector values

VI. CONCLUSION

In conclusion, deploying a DeepFace-based video surveillance system shows a notable improvement in real-time security for locations that are prone to crime. The suggested technique improves the detection and identification of known criminals with high accuracy by utilizing deep learning for facial recognition. This system addresses the latency and reliability issues of traditional surveillance by maintaining high

processing rates and providing timely alerts with down-sampling techniques and a face tracking scoring mechanism. All things considered, this approach offers to improve public safety by proactively preventing events and providing law enforcement and security workers in crucial, high-risk situations with reliability.

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