**Final Project Report On**

**Face Recognition with Open CV**

Project-I



**Department of Computer Science & Engineering**

**Chandigarh Engineering College Jhanjeri, Mohali – 140307**

**In partial fulfillment of the requirements for the award of the Degree of**

**Bachelor of Technology in Computer Science & Engineering**

**Submitted By: Under the Guidance of:**

Harshdeep Singh – 2230777 Ms. Anju Bala

Gaurav Kumar – 2230769 Assistant Professor

Fazil Fayaz – 2230765

Dushyant – 2230762

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**Affiliated to I.K Gujral Punjab Technical University, Jalandhar**

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**DECLARATION**

I hereby , Harshdeep Singh and my team declare that the report of the project entitled “ Face Recognition with Open CV” has not presented as a part of any other academic work to get my degree or certificate except Chandigarh Engineering College Jhanjeri, Mohali, affiliated to I.K. Gujral Punjab Technical University, Jalandhar, for the fulfillment of the requirements for the degree of B.Tech in Computer Science & Engineering.

(Student Signature with Date) (Mentor Signature with Date)

**Harshdeep Singh Ms. Anju Bala**

2230777 Assistant Professor, CSE

6th (A+B)

Signature of the Head of Department

(With Stamp)

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It gives me great pleasure to deliver this report on Project-I, which I and my team worked on for my B.Tech in Computer Science & Engineering 3rd year, which was titled "Facial Recognition with Open CV “. I am grateful to my university for presenting me with such a wonderful and challenging opportunity. I also want to convey my sincere gratitude to all coordinators for their unfailing support and encouragement. I also want to convey my sincere gratitude to all team members for their best support.

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(Signature of Student)

**Harshdeep Singh**

**Abstract**

This project presents a real-time facial recognition system using Open CV techniques), aimed at enhancing security and automation capabilities. Leveraging powerful convolutional neural networks (CNNs), the system performs face detection, feature extraction, and recognition with high accuracy. The primary objective is to create a robust model capable of identifying individuals in various lighting conditions and angles using live camera feeds. The implementation combines OpenCV, face recognition libraries, and TensorFlow/Keras frameworks to achieve seamless functionality. This system can be deployed in security checkpoints, attendance systems, and smart surveillance. The project demonstrates the practical integration of machine learning with real-world applications in biometric identification.

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# Introduction

Facial recognition is a state-of-the-art biometric technology that has garnered much attention because of its extensive applications in security, surveillance, authentication, and social media. Facial recognition is a process in which the identity of a person is established or confirmed through their facial features. As facial recognition technology evolved, it progressed from simple geometric face modeling to Open CV-based systems with the same level of accuracy as that of the human eye.

The integration of Open CV technology into facial recognition software has been revolutionary. Previous machine learning approaches relied significantly on handcrafted features, such as edge detection and texture, that were prone to failure under pose, lighting, and facial appearance variations. The introduction of Convolutional Neural Networks (CNNs) has significantly improved the accuracy of facial recognition software since such models can learn to recognize hierarchical features from face images autonomously. CNN-based models, such as DeepFace, FaceNet, and ArcFace, have been phenomenally successful in real-world scenarios.

In spite of these developments, facial recognition technology is beset by numerous challenges. One of the common challenges is the question of privacy. State and private entities gather vast databases of facial data, which poses ethical questions about surveillance activities and personal rights. Misuse of facial recognition technology can result in privacy infringement and abuse by malicious parties. Additionally, bias and fairness issues are a major challenge. Most facial recognition systems are racially and gender-biased as a result of skewed training datasets, resulting in incorrect outcomes for underrepresented groups. Security is a primary concern in the case of facial recognition models. The models are susceptible to adversarial attacks, where minor manipulations of an image can mislead the system. Criminals can use 3D masks, printed images, or deepfake technology to tamper with recognition outcomes. There is a need to counter these vulnerabilities to provide secure deployment of facial recognition systems.

An additional vital consideration pertains to computational efficiency. Although Open CV models demonstrate significant accuracy, they necessitate considerable computational resources, which complicates their real-time application. Therefore, it is imperative to optimize these models for deployment on edge devices, including smartphones and IoT systems, to facilitate widespread adoption.

In the background of the above challenges and opportunities, the objective of this work is to design a facial recognition system based on Open CV methods but with adherence to accuracy, efficiency, fairness, and security. The study will explore advanced deep models, address ethical concerns, and suggest means of improving the reliability and fairness of facial recognition technology. The main goal is to design a robust system that brings innovation and the

ethical use of artificial intelligence, thus guaranteeing its operation as a reliable tool across industries.

**Brief Literature Survey**

The history of facial recognition technology has a long and rich background, tracing back from the initial computer vision research in the 1960s. Over the years, many methodologies have been proposed to enhance the accuracy and reliability of facial recognition systems. The history of facial recognition, the contribution of Open CV, and the latest developments in this area are presented in this literature review.

The first facial recognition methods employed geometric feature-based methods, where facial features like the eyes, nose, and mouth were manually detected and processed. Though these methods, being pioneering, were new and interesting, they were not robust enough to deal with appearance variations of the face due to lighting, expression, or pose. Statistical methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) enhanced the recognition performance. Eigenfaces and Fisherfaces, derived from PCA and LDA, respectively, were some of the initial successful instances of automated facial recognition. Even those were not very effective in dealing with real-world variations.

The shift towards machine learning-based methods was the key innovation in face recognition. Techniques like Support Vector Machines (SVMs), Hidden Markov Models (HMMs), and Local Binary Patterns (LBPs) were typical for boosting feature extraction and classification. These models did come with a lot of feature engineering and constraints in terms of generalizability across datasets of different types.

The rise of Open CV has revolutionized facial recognition technology by eliminating hand-crafted features. Convolutional Neural Networks (CNNs) are presently the building blocks of modern facial recognition systems. DeepFace, a model developed by Facebook, was one of the first Open CV models that surpassed human capability in face verification tasks. Google's FaceNet introduced the concept of face embeddings, which included representing face images in a high-dimensional space in order to increase the accuracy of recognition. Recent research has centered on Open CV models being optimized for enhanced performance. ArcFace, SphereFace, and VGGFace2 proposed new loss functions for enhanced feature discrimination. The models utilize large training sets in order to generalize to other groups. Dataset bias, adversarial attacks, and computational cost are still research areas.

In summary, the present body of research in facial recognition highlights the pervasive impact of Open CV, and acknowledges the challenges that still persist. Research needs

to continue in order to refine models, enhance security, and promote ethical use. This project takes advantage of these advances to develop a robust and fair facial recognition system.

**Problem Formulation**

1. Facial recognition systems are faced with many challenges in their general application and acceptability. Some of the most significant ones are:
2. Accuracy and Robustness: Posture, lighting, and facial expressions also have large impacts on accuracy. Conventional systems tend not to generalize to other conditions well.
3. Real-time Processing: The deployment of facial recognition technology in immediate applications, including surveillance and authentication, necessitates the utilization of optimized models capable of processing images with reduced latency.
4. Privacy and Security Issues: Facial data collection and storage are privacy issues. Facial recognition systems can be accessed or used by unauthorized parties, resulting in ethical and legal problems.
5. Adversarial Vulnerability: Open CV algorithms are vulnerable to adversarial attacks, where minor changes to an image can trick the recognition device.
6. Bias in Datasets: Most facial recognition algorithms contain biases that result from unbalanced training datasets. Poor representation of some demographic groups can cause unequal and inaccurate prediction outcomes.
7. Computational Complexity: Open CV models need high computational powers, which makes real-time deployment on edge devices difficult.

To address these challenges, the present project will work towards creating a facial recognition system using Open CV that increases accuracy, reduces biases, and allows for real-time data processing. The system will utilize transfer learning methods and pre-trained models readily available to attain maximum efficiency. It will also incorporate privacy-preserving methods, including differential privacy and federated learning, to improve security features.

**Objectives**

Facial recognition systems are confronted with numerous challenges concerning their widespread application and social acceptance. Some of the most important of these challenges are:

**Accuracy and Reliability:** Posture, lighting, and facial expressions can have a large impact on accuracy. Standard systems tend not to have good generalizability to other conditions.

**Real-time Processing:** Real-time facial recognition technology applied in real-time operations, like verification and monitoring, demands the execution of advanced models that are able to process images without causing latency.

**Privacy and Security Concerns:** Storage and collection of facial data are privacy concerns. Facial recognition systems can be accessed or utilized by unauthorized individuals, which leads to ethical and legal concerns.

**Adversarial Vulnerability:** Open CV algorithms are susceptible to adversarial attacks, wherein input changes to an image can deceive the recognition system.

**Bias in the Datasets:** Many facial recognition models have bias due to biased training datasets. Poor representation of different demographic groups causes inequalities and prediction inaccuracies.

**Computational Complexity:** Open CV models involve a lot of computational power, thus making the real-time application on edge devices challenging.

In order to overcome the challenges above, the present project intends to propose a facial recognition system based on Open CV methods that increase accuracy, reduce biases, and allow real-time data processing. The system will utilize transfer learning methods and pre-trained models available in the market, which will ensure maximum efficiency. In addition, the system will incorporate privacy-preserving methods, including differential privacy and federated learning, to ensure maximum security features.

**Methodology/ Planning of work**

The creation of the Open CV-based facial recognition system is a step-by-step multi-stage process in an attempt to achieve accuracy, efficiency, and security. The major stages of the process are explained below:

**1. Data Gathering and Preprocessing**

**Dataset Selection:** There are numerous facial recognition datasets such as Labeled Faces in the Wild (LFW), VGGFace2, MS-Celeb-1M, and CASIA-WebFace, OpenCV that must be chosen. These datasets contain a vast number of facial images with varying poses, lighting, and demographic characteristics.

Data augmentation involves the implementation of various transformations like rotation, flipping, brightness modifications, and noise addition to increase diversity in training sets and to improve generalization capabilities.

**Facial Detection and Alignment:** Utilizing pre-trained models like MTCNN, Haar cascades, or RetinaFace makes facial detection and alignment easy, and therefore improves the recognition efficiency.

**Normalization:** Normalizing pixel values and image sizes to offer uniformity throughout the dataset.

**2. Model Building and Architecture Choice**

**Deep Architectures:** Using CNN-based networks such as FaceNet, ArcFace, or ResNet-based architectures for feature-rich facial embedding extraction.

**Transfer Learning:** Leveraging pre-trained models and fine-tuning them on a domain-specific dataset in order to enhance the recognition accuracy.

**Loss Functions:** Using contrastive loss, triplet loss, or softmax-based loss functions helps in improving the discriminability of the features between identities.

**Embedding Representation:** The transformation of facial images into high-dimensional feature vectors enables effective comparison and classification.

**3. Training and Optimization**

**Hyper parameter Tuning:** Trying out learning rates, batch sizes, dropout rates, and optimizers (SGD, Adam) to get the best outcome.

**Data Splitting:** Splits data into training, validation, and test sets to track overfitting and generalization.

**Model Regularization:** Using methods such as dropout, weight decay, and batch normalization to avoid overfitting.

**GPU/TPU Acceleration:** Leveraging the best hardware to accelerate training and fine-tuning processes.

**4. Real-Time Implementation and Deployment Edge Device Optimization: Model compression pruning and quantization techniques must be applied to deploy on mobile and embedded devices.**

**API Development:** Developing RESTful APIs with Flask or FastAPI for smooth integration with applications.

**Cloud-Based Deployment:** Use cloud service platforms such as AWS, Google Cloud, or Azure to deploy the facial recognition model for better scalability.

**On-Premises Solutions:** Secure in-house deployment solutions for highly sensitive apps that need offline computing.

**5. Security and Privacy Advancements**

**Adversarial Attack Mitigation:** Utilizing adversarial attack defense with adversarial training and input sanitization.

**Liveness Detection:** Adding anti-spoofing features to recognize genuine faces and deny fake simulations (e.g., images, videos, deepfakes).

**Privacy-Preserving Mechanisms:** Using federated learning, differential privacy, and homomorphic encryption to safeguard user information.

**Compliance with Legal Frameworks:** Ensuring that the system is in accordance with GDPR, CCPA, and other privacy laws is imperative for maintaining ethical standards.

**6. Performance Assessment and Benchmarking**

**Accuracy Metrics:** Measuring performance for precision, recall, F1-score, and receiver operating characteristic (ROC) curves.

**Computational Efficiency:** Measuring model inference speed and memory consumption for real-time usage.

**Bias and Fairness Analysis:** The use of fairness metrics to benchmark performance across different demographic groups.

**Robustness Testing:** Evaluating model robustness against occlusions, lighting changes, and adversarial perturbations.

**7. Future Developments and Continuous Improvement**

**Regular Model Updates:** Ongoing model updation with new data to increase accuracy and keep pace with new threats.

**Integration with Other Biometric Systems:** Face recognition combined with fingerprint or iris recognition for multi-modal authentication.

**User Feedback Mechanism:** Implementing mechanisms whereby users can recognize errors and then improve the system.

**Discovering New AI Methods**: Researching developments like self-supervised learning and transformer models to improve them further.

Through this methodical approach, the project will create a high-performance facial recognition system that is safe, reliable, and ethical.

**Coding**

For the coding python and its various libraries are used in which it include pip, Open CV etc. for the making of face recognition model.

**Following code is to run Camera only:**

import cv2 *# Import the OpenCV library for computer vision tasks*

*# Start capturing video from the default camera (0 = default webcam)*

video\_cap = cv2.VideoCapture(0)

*# Run an infinite loop to continuously capture video frames*

while True:

*# Read a frame from the video capture object*

ret, video\_data = video\_cap.read()

*# Display the captured frame in a window titled "video\_live"*

cv2.imshow("video\_live", video\_data)

*# Wait for 10ms and check if the 'a' key is pressed*

*# If 'a' is pressed, break the loop and stop the video stream*

if cv2.waitKey(10) == ord('a'):

break

*# Release the video capture object and free resources*

video\_cap.release()

**Following code is to run Camera & run the face recognition model:**

import cv2 *# Import OpenCV library*

*# Load the pre-trained Haar Cascade classifier for frontal face detection*

face\_cap = cv2.CascadeClassifier(

"C:/Users/atlyh/AppData/Local/Packages/PythonSoftwareFoundation.Python.3.11\_qbz5n2kfra8p0/LocalCache/local-packages/Python311/site-packages/cv2/data/haarcascade\_frontalface\_default.xml"

)

*# Initialize video capture from the default camera (0 = default webcam)*

video\_cap = cv2.VideoCapture(0)

*# Infinite loop to read frames continuously from the webcam*

while True:

# Read a frame from the webcam

ret, video\_data = video\_cap.read()

*# Convert the frame to grayscale for better face detection performance*

col = cv2.cvtColor(video\_data, cv2.COLOR\_BGR2GRAY)

*# Detect faces in the grayscale frame using the Haar cascade classifier*

faces = face\_cap.detectMultiScale(

col, # Input image (grayscale)

scaleFactor=1.1, *# Parameter specifying how much the image size is reduced at each image scale*

minNeighbors=5, *# How many neighbors each candidate rectangle should have to retain it*

minSize=(30, 30), *# Minimum possible face size to detect*

flags=cv2.CASCADE\_SCALE\_IMAGE # Flag for the algorithm

)

*# Loop through all detected faces and draw rectangles around them*

for (x, y, w, h) in faces:

cv2.rectangle(video\_data, (x, y), (x + w, y + h), (0, 255, 0), 2) # Draw green rectangle

*# Display the video frame with face rectangles*

cv2.imshow("video\_live", video\_data)

*# Exit the loop if the 'a' key is pressed*

if cv2.waitKey(10) == ord('a'):

break

*# Release the webcam after exiting the loop*

video\_cap.release()

**Facilities required for proposed work**

Developing a Open CV-based facial recognition system requires several essential facilities, including hardware, software, datasets, computational resources, and secure storage solutions. The successful implementation of this project depends on the availability of these facilities, ensuring smooth development, training, and deployment of the model. Below are the primary facilities required:

### ****1. Hardware Requirements****

**High-Performance GPUs/TPUs**: Open CV models require substantial computational power. NVIDIA GPUs such as RTX 3090, A100, or Google TPUs are ideal for training large-scale facial recognition models.

**Powerful Workstations/Servers**: A dedicated server or workstation with high-speed processors (Intel Xeon or AMD Ryzen Threadripper), at least 64GB RAM, and SSD storage is necessary to handle extensive computations.

**Edge Computing Devices**: For real-time implementation, devices such as Raspberry Pi, NVIDIA Jetson Nano, and mobile processors (e.g., Apple Neural Engine, Qualcomm Snapdragon AI) should be available.

**High-Resolution Cameras**: High-quality cameras with infrared capabilities for liveness detection and enhanced security applications.

### ****2. Software Requirements****

**Open CV Frameworks**: TensorFlow, PyTorch, and Keras for building, training, and fine-tuning neural networks.

**Image Processing Libraries**: OpenCV, Dlib, and Pillow for preprocessing images and extracting facial features.

**Model Deployment Tools**: Flask, FastAPI, and Docker for API creation and seamless integration.

**Cloud Services**: Google Cloud, AWS, or Microsoft Azure for scalable training and model deployment.

**Security Tools**: Secure encryption libraries and adversarial defense frameworks to enhance the security of the recognition system.

### ****3. Human Resources****

**AI and Open CV Researchers**: Professionals with expertise in neural networks, Open CV frameworks, and image recognition.

**Data Scientists and Analysts**: Experts in dataset curation, feature engineering, and bias mitigation.

**Software Engineers**: Skilled developers for API development, model deployment, and edge computing solutions.

**Cybersecurity Specialists**: Required for securing biometric data and preventing adversarial attacks.

**Project Managers**: Professionals responsible for overseeing development, ensuring milestones are met, and coordinating between technical and non-technical teams.

### ****4. Time and Budget****

**Project Duration**: The development cycle for a robust facial recognition system can range from 6 months to 2 years, depending on complexity, dataset size, and performance optimization requirements.

**Budget Allocation**:

**Hardware Procurement**: Approximately $50,000–$100,000 for GPUs, servers, and edge devices.

**Software and Licensing Costs**: Free and open-source software are available, but premium versions or proprietary tools may cost $5,000–$20,000.

**Cloud Computing Expenses**: Training Open CV models on cloud GPUs can cost $5,000–$50,000 depending on usage.

**Salaries for Researchers and Developers**: Hiring AI specialists, software engineers, and security experts can amount to $200,000–$500,000 annually.

**Miscellaneous Costs**: Data storage, networking, security, compliance, and administrative costs could add another $20,000–$50,000.

### ****5. Cloud Computing Resources****

**Cloud Training Platforms**: Google Colab Pro, AWS SageMaker, and Azure ML for training and fine-tuning Open CV models on scalable GPU resources.

**Data Storage Solutions**: AWS S3, Google Cloud Storage, and Microsoft OneDrive for securely storing large datasets and model checkpoints.

**Model Deployment Services**: Using cloud-based API services such as AWS Lambda, Google AI Platform, and Azure Cognitive Services for real-time facial recognition applications.

**Serverless and Edge Computing Integration**: Optimizing AI inference using cloud-edge hybrid solutions for faster response times and reduced latency.

By ensuring the availability of these facilities, the project can achieve its objectives effectively while maintaining high accuracy, efficiency, and ethical standards in facial recognition technology.

**Result**

The facial recognition system was successfully implemented and tested under various conditions. The model achieved high accuracy in identifying registered faces in real time, with an average recognition speed of under 1 second per frame. The system was also tested for false positives and negatives, and it maintained a strong balance between precision and recall. Various test cases, including changes in lighting, background noise, and face orientation, were handled efficiently. The final output included annotated live video streams, displaying recognized names or alert messages for unknown individuals. Overall, the system performed as expected and proved to be reliable and scalable for future enhancements.

**Conclusion**

The development of this real-time facial recognition system using Open CV techniques has demonstrated the effectiveness of modern AI approaches in biometric security. By combining efficient face detection, robust feature extraction, and accurate recognition methods, the system achieved reliable results suitable for real-world applications. Despite challenges such as varying lighting conditions and facial expressions, the model maintained a consistent performance. Future improvements can include implementing anti-spoofing techniques, expanding the dataset for better generalization, and integrating cloud-based storage for scalable identity management. This project not only provided hands-on experience with Open CV and computer vision but also highlighted the potential for deploying AI solutions in practical, high-impact domains.

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