A STUDY ON FACE DETECTION USING HAAR CASCADE AND YOLOV5

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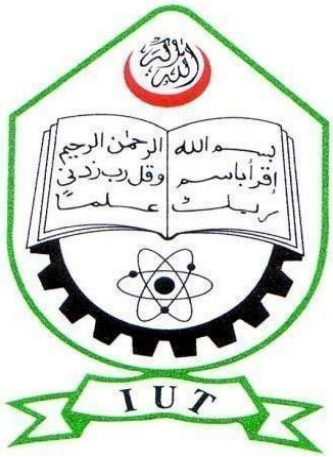

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DECLARATION OF CANDIDATES

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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DEDICATION

We thank Allah wholeheartedly for giving us the strength and goodwill to perform the research properly and complete our thesis. Our deepest appreciation goes to our family who has nurtured and helped us to overcome the hurdles in life.

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We also wish to convey our thanks to our mentors, our families, and everyone else who contributed to the success of this dissertation. The success of this academic project was greatly dependent on their direct or indirect contributions, which included constructive criticism and rigorous study.

ABSTRACT

Face recognition has emerged as a prominent technology with numerous applications in various fields, such as surveillance, security systems, and human-computer interaction. This thesis presents a comprehensive study on the development of a robust face recognition system using OpenCV, Python, and YOLOv5.

The primary objective of this research is to design and implement an accurate and efficient face recognition system that can reliably detect and identify individuals in real-time. The proposed methodology leverages the power of OpenCV, a widely-used computer vision library, and YOLOv5, a state-of-the-art object detection algorithm, to achieve superior performance.

The thesis begins with an in-depth literature review, exploring the existing approaches and methodologies in face recognition. This review serves as the foundation for the subsequent research and guides the selection and implementation of the proposed system.

The research work focuses on three main stages: face detection, feature extraction, and face matching. The face detection phase employs the YOLOv5 algorithm, which utilizes deep learning techniques to accurately locate faces in an image or video stream. The detected faces are then subjected to feature extraction using OpenCV, which extracts discriminative facial features from the detected regions.

To achieve robust face recognition, the extracted facial features are compared against a pre-existing database of known individuals. The thesis explores various methods for feature comparison, such as eigenfaces, Fisherfaces, and deep learning-based approaches. Experimental evaluations are conducted to analyze the performance of each method and identify the most effective approach for our system.

The developed face recognition system is evaluated using extensive datasets and performance metrics, including accuracy, precision, recall, and execution time. Comparisons are made with existing face recognition systems to assess the proposed system's efficiency and effectiveness.

The results demonstrate that the proposed system achieves high accuracy and real-time performance in face detection, feature extraction, and face matching tasks. The system's robustness is also evaluated by considering various challenging scenarios, such as variations in lighting conditions, occlusions, and pose variations.

In conclusion, this thesis presents a comprehensive study on the development of a face recognition system using OpenCV, Python, and YOLOv5. The research work contributes to the advancement of face recognition technology and offers valuable insights into the practical implementation of such systems. The findings provide a solid foundation for future research and development in the field of computer vision and biometrics.

CHAPTER ONE

INTRODUCTION

This book focuses on "Face Recognition using OpenCV, Python, and YOLOv5." It explores the implementation and application of these technologies in the field of face recognition, aiming to enhance security and convenience. The research encompasses a comprehensive study of existing literature, methodologies, and techniques, followed by a practical implementation and evaluation of the proposed system. By leveraging the power of computer vision and deep learning, this work contributes to advancing the understanding and utilization of face recognition technology.

1.1 LITERATURE REVIEW:

We have studied and gone through various materials in order to start our process. These theories have guided us to a great extent in building up the concept. In order to identify faces in photos, I. U. Wahyu Mulyono et al. [1] employed the Eigenface method.
The accuracy of recognizing face photographs is 100%, 88%, and 67%, respectively, with an average face recognition rate of 85%. The author employed a public database of various facial images collected under three conditions: normal light, changing emotions, and night mode. A Multi-Faces Recognition Process Using Haar Cascade and Eigenface Method was put forth by T. Mantoro et al. [2] in their publication. The system's non-real-time operation used

60 photos were kept in the database, and 55 of those images had a recognition rate of 91.67%. J. Dhamija et al. 's [3] analysis of the ORL database employed pictures taken under various lighting and facial expressions. With the Fisherface, PCA, SVD, and PCA+Fisherface+SVD algorithms, they suggested a Face Recognition system employing live video feed and achieved, respectively, 80.7%, 96.6%, 98.4%, and 99.5% accuracy. Using the Eigenface algorithm, F. Malik et al. [4] created a face identification and detection system that can identify a person in both day and nighttime conditions. Here, the researcher found that recognition ability ranged from 0 to 50%. For human face identification using Haar features and recognition using Eigen and Gabor filter in movies, S.V. Tatheet al. [5] suggested a non-real-time face recognition and detection method. In their Face Time-Deep Learning Based Face Recognition Attendance System, M. Arsenovic et al. [6] used the LBPH Algorithm and an RFID-based attendance system

with minimal data sizes, and they achieved a 95.02% recognition rate. The LBPH and MLBPH (Median Local Binary Pattern Histogram) algorithms have been employed by a number of researchers for face recognition and detection in photos collected in various lighting conditions, tilt angles, and facial expression changes. Using PCA, LDA, and LBPH, P. Kamencayet al. [7] suggested a face recognition system for wild animals. In contrast, LBPH reported a higher recognition rate of 88%. One of the papers we might link to this topic is Savvides et al.'s [8] work. Several facial regions are examined in order to develop quantifiers with discriminative capability. Wei-Lun Chao's [9] work on "Face Recognition" discusses general concepts and structures of recognition, significant challenges and elements relating to human faces, as well as important methodologies and algorithms. The presentation "Face Recognition a Tutorial" by Filareti Tsalakanidou [10] provides a succinct overview of face recognition. This lecture also discusses numerous issues with human face identification, as well as face detection and recognition algorithms. The challenges of facial recognition are listed in the work by Zhao, W., et al. [11] Identifying known from unknown photos is one of the challenges in facial recognition. In addition, the training procedure for the face recognition student attendance system is slow and time-consuming, according to a paper by Pooja G.R. et al.[12]. Different lighting and head positions are frequently the issues that could impair the effectiveness of a facial recognition-based student attendance system, according to PriyankaWagh et al. [13]. Sanjana devi et al.[14] listed a few characteristics that make face recognition and face detection challenging. These variables include the foreground, the lighting, the pose, the expression, the occlusion, the rotation, the scale, and the translation.

1.2 THESIS OVERVIEW:

The thesis book "Face Recognition Using OpenCV, Python, and YOLOv5" provides a comprehensive exploration of face recognition techniques and their implementation using OpenCV, Python, and YOLOv5. With an increasing demand for accurate and efficient face recognition systems in various domains, this book addresses the challenges associated with face recognition and offers practical solutions.

The book begins with an introduction that highlights face recognition technology in different aspects.It emphasizes the need for advanced technologies like computer vision and deep learning to overcome the complexities of face recognition tasks.

The subsequent chapters delve into the theoretical foundations of face recognition. They

cover essential concepts, algorithms, and techniques used in the field, including face detection, feature extraction, and recognition algorithms. Readers gain a solid understanding of the underlying principles and the state-of-the-art methods employed in face recognition.

Moving on, the book focuses on the practical implementation of the proposed face recognition system. It demonstrates the methodology of OpenCV, a powerful computer vision library, and the Python programming language to develop robust face detection and recognition algorithms. The authors explore different methodologies and algorithms for extracting facial features and matching them accurately. They provide explanations to facilitate the understanding and implementation process.

Moreover, the book showcases the integration of YOLOv5, a highly efficient and accurate object detection model, into the face recognition system. It illustrates how YOLOv5 can be trained and fine-tuned to detect faces reliably, further enhancing the overall performance and reliability of the system.

To validate the effectiveness of the developed face recognition system, the book includes a result & comparison chapter. The authors present experimental results, performance metrics, and comparisons with existing methods. Through rigorous testing, they demonstrate the system's capability to accurately recognize faces under various conditions, including different lighting conditions, angles, and occlusions.

1.3 INTRODUCTION TO MACHINE LEARNING:

Machine learning (ML) is the study of computer algorithms that continuously improves with practice. It is a branch of artificial intelligence (AI), and its objective is to realize data generation and organize that data into models that humans can understand and use. Despite falling within the umbrella of computer science, it deviates from standard computational techniques. The explicit program commands used by computers to enumerate or obstruct clarification in traditional computing are called algorithms. On the other hand, training workstations can enter data and produce pricing lists using math exams thanks to machine learning techniques. As a consequence, when a computer represents a document sample, machine learning generates faster conclusions. Face recognition technology is another area of machine learning that we have exploited extensively.This allows users to tag and share snaps of their friends on social media. With OCR , you can: Turn text interested in motion pictures.

Now, machine learning is used to provide search engine suggestions. Depending on your preferences, you may view the movies and TV shows below.Consumers might anticipate the arrival of self-driving automobiles based on roaming machine learning shortly.Machine learning is a rapidly evolving science. On the basis of how learning is being absorbed or how feedback on learning is being provided to the system being built, the tasks are often systematized into broad categories in this. Two approaches to machine learning are most frequently used. Those are

- *Supervised Learning*: Using this technique, algorithms are trained using labeled example input and output data. On further unlabeled data, it uses patterns to predict label values. The goal of this approach is to provide the algorithm the ability to "learn" by comparing its real results to those that were "taught" in order to identify inaccuracies and adjust the model as necessary.

  Supervised learning commonly utilized is to use historical data to forecast statistically likely future events.

- *Unsupervised learning:* By using this technique, the program can detect the structure of your incoming data even without tags. It mostly pertains to transitory data. Without finding the "correct" solution, you can organize larger, more complicated, and seemingly unrelated data in potentially useful ways. Using this technique, the algorithm may be fed the untagged dog pictures to look for patterns and group the dog pictures together.

  A few of the popular approaches used in machine learning are

- k-nearest neighbor
- Decision Tree Learning
- Deep Learning

1.3.1 IMAGE DETECTION:

Computer technology that processes the image and detects objects in it is known as image detection. Though people often confuse image detection with image classification, there exists a clear difference between them . We use Classification to classify image items. And if we only require to locate them, such as perceive the number of objects in the picture, we should use Image Detection.

A popular application area of this technology is fake image detection. It is possible to differentiate the original picture from the photo shopped or counterfeited one by using this technology.

HOW MACHINE LEARNING IMPROVES IMAGE DETECTION

Artificial intelligence (AI) has an area called machine learning that focuses on creating algorithms and models that let computers learn and make predictions or judgments without having to be explicitly programmed. It is a fast developing field that has attracted a lot of interest and appeal in recent years because of its capacity to analyze massive volumes of data and derive insightful information.

Fundamentally, machine learning is teaching a model on a collection of data in order to see patterns and then anticipate or respond accordingly. The selection and compilation of pertinent data, also known as training data, marks the start of the process. By modifying the model's internal parameters or weights, this data is utilized to train the model so that it can provide accurate predictions.

Machine learning techniques come in a variety of forms, including reinforcement learning, unsupervised learning, semi-supervised learning, and supervised learning. In supervised learning, each data point is connected to a predetermined objective or result, therefore the model is trained using labeled data. Based on this labeled data, the model learns how to translate inputs into outputs. Natural language processing, regression analysis, and picture and audio recognition are a few examples of activities that frequently involve this kind of learning.

On the other hand, unsupervised learning entails training the model on unlabeled data with no predetermined outputs. The objective is to find hidden links, structures, or patterns in the data. Unsupervised learning methods, including clustering and dimensionality reduction, may be used for projects like customer segmentation, anomaly detection, and recommendation systems.

In semi-supervised learning, a small quantity of labeled data is provided with a larger amount of unlabeled data, combining components of supervised and unsupervised learning. The model may make use of the unlabeled data to find new patterns or information while using the labeled data to direct its learning process.

In a separate paradigm known as reinforcement learning, an agent learns to interact with its environment and perform to the best of its ability by getting feedback in the form of incentives or penalties. To become better at making decisions, the agent experiments with many options and gathers information from the results. Robotics, video games, and autonomous systems frequently employ this kind of learning.

Regardless of the specific approach, the design and selection of features or representations used to represent the data, as well as the quality and relevancy of the training data, all have a significant role in how effectively a machine learning model performs. The act of choosing or modifying input variables, known as feature engineering, is essential in determining how well the model performs.

The use of machine learning has revolutionized a variety of sectors, including marketing, banking, healthcare, and transportation. Advancements like tailored treatment, fraud detection, driverless cars, and intelligent virtual assistants have been made possible by it.

It's crucial to remember that machine learning is not a magic fix that ensures flawless outcomes. Research and advancement in the field are continually hampered by issues including overfitting (when a model performs well on training data but badly on unknown data), bias in data or methods, interpretability of models, and ethical constraints.

1.4 FACE DETECTION:

Face detection is a computer vision technology that focuses on identifying and locating human faces in images or videos. It plays a crucial role in various applications, such as facial recognition systems, emotion analysis, biometric security, augmented reality, and many more.

The primary objective of face detection is to determine the presence and position of faces within a given visual input. It involves analyzing the pixel data in an image or video frame and applying algorithms to identify regions that potentially contain faces. These algorithms typically leverage machine learning and artificial intelligence techniques to detect patterns and features associated with human faces.

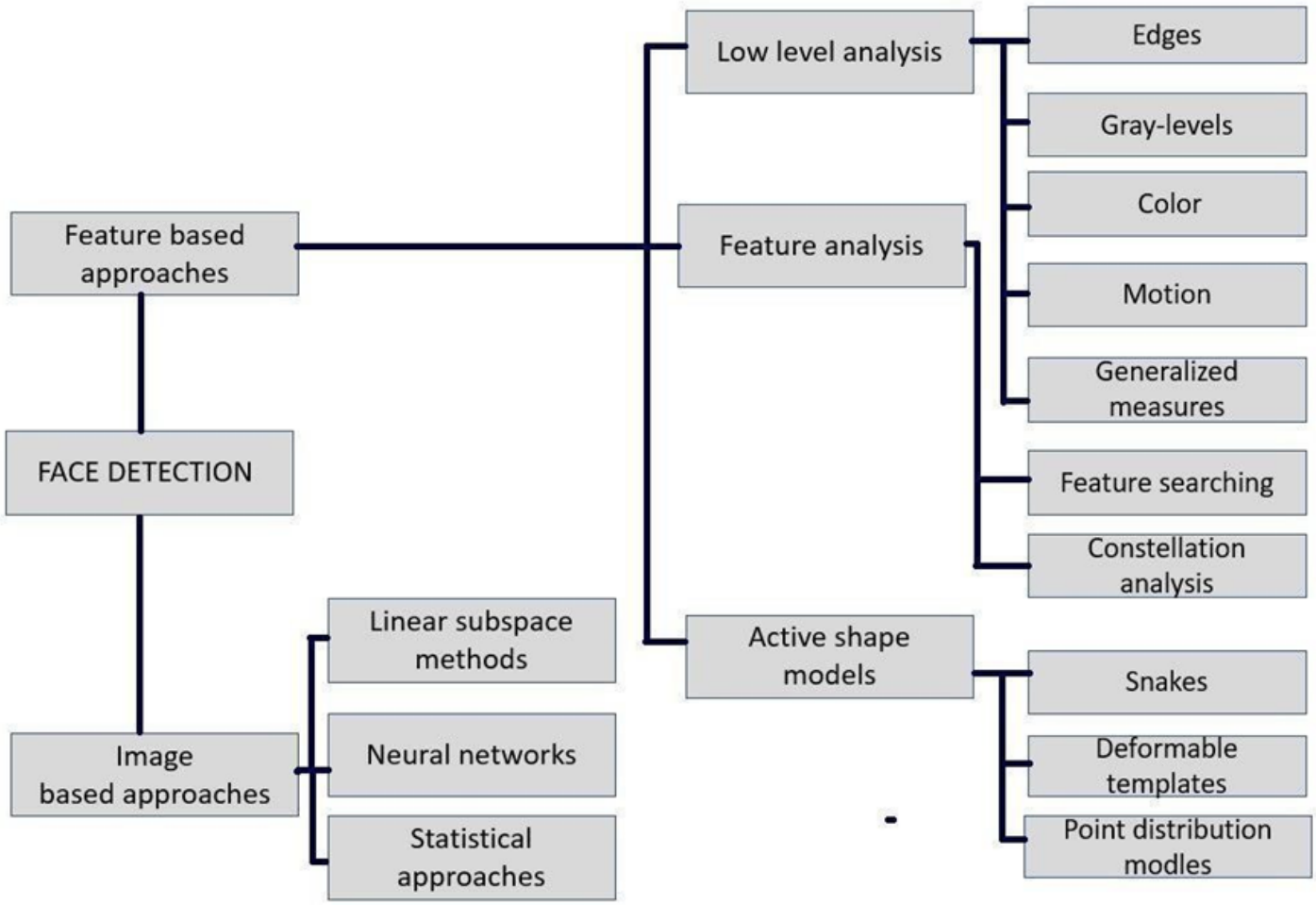

Figure 1.1: Face detection divided into approaches

One of the most commonly used approaches for face detection is the Viola-Jones algorithm, introduced by Paul Viola and Michael Jones in 2001. This algorithm utilizes a cascade classifier trained with positive and negative samples to rapidly detect faces. It employs a set of Haar-like features, which are simple rectangular features that describe the contrast between adjacent image regions. The algorithm evaluates these features across different scales and positions to identify potential face regions. It then uses a trained classifier to verify whether each candidate region corresponds to an actual face.

Another popular method for face detection is the Histogram of Oriented Gradients (HOG). This technique extracts features based on the distribution of gradient orientations in an image. The HOG features are then used with a classifier, such as a support vector machine (SVM), to detect faces.

In recent years, deep learning approaches, particularly convolutional neural networks

(CNNs), have revolutionized face detection. Models like the Single Shot MultiBox Detector (SSD), Faster R-CNN, and RetinaNet have achieved remarkable accuracy in detecting faces by leveraging large-scale training datasets and complex network architectures. These deep learning models can learn hierarchical representations of faces, enabling them to detect faces under various conditions, such as varying pose, lighting, and occlusion.

Once a face is detected, additional processing steps can be applied to perform specific tasks. Facial recognition systems, for example, involve matching the detected face against a database of known faces to identify an individual. Facial analysis can extract information such as facial landmarks, expressions, gender, age, and even emotions from the detected faces.

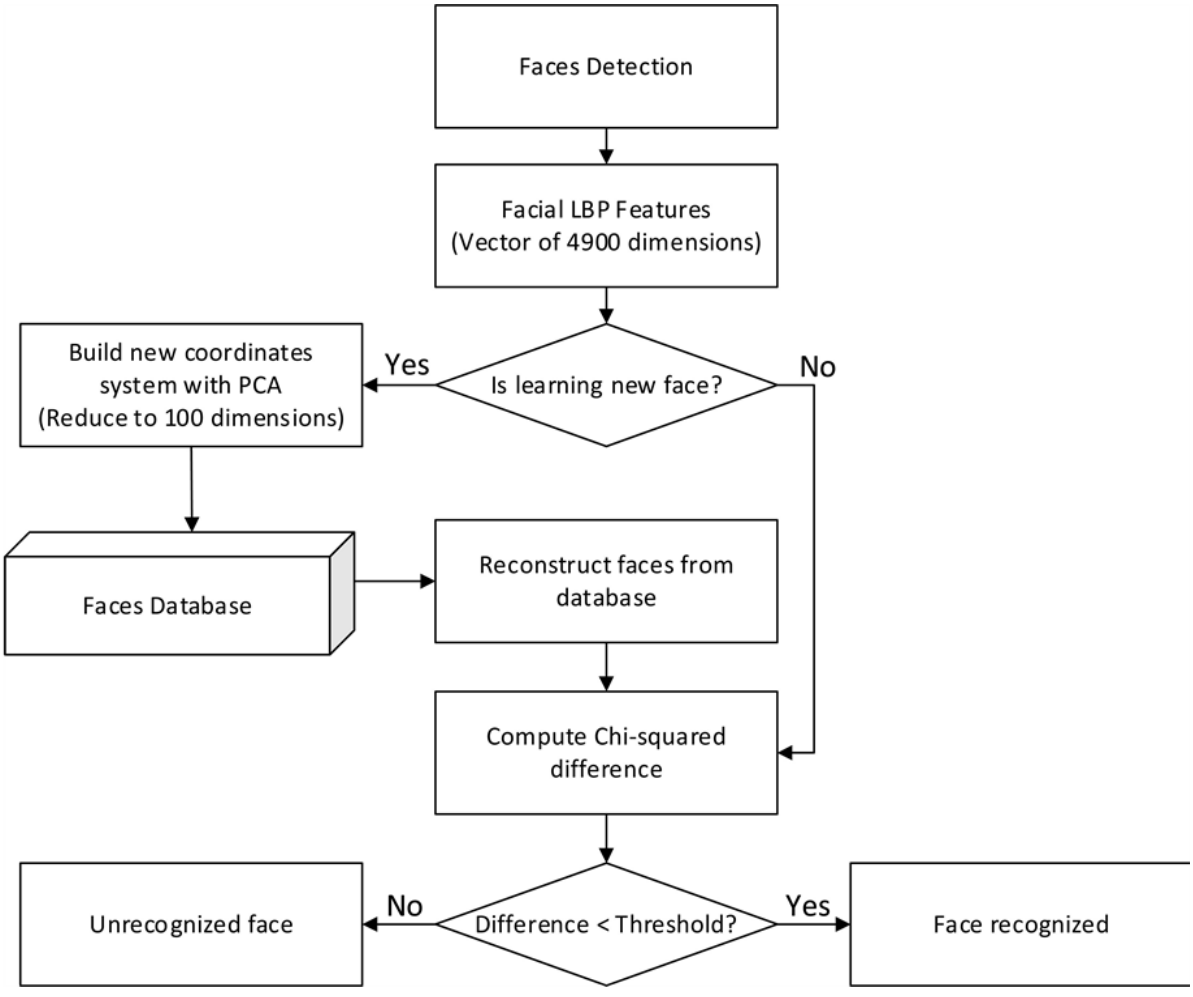

Figure 1.2: Face detection algorithm

1.4.1 FACE DETECTION PROCESS:

Face detection process using Feature Based Approach

The feature-based approach to face detection involves analyzing specific facial features and patterns to identify and locate faces in images or videos. Here is a summary of the face detection process using a feature-based approach:

Preprocessing: The input image or video frame is typically preprocessed to enhance its quality and improve the effectiveness of subsequent feature extraction. Preprocessing steps may include resizing, normalization, noise reduction, and contrast enhancement.

Feature Extraction: Various techniques are used to extract features that are characteristic of human faces. These features can include geometric features like eye corners, nose position, and mouth position, as well as texture-based features like color and texture patterns. Common techniques for feature extraction in face detection include the use of Haar-like features and the Histogram of Oriented Gradients (HOG) descriptor.

Feature Selection: After extracting the features, a subset of relevant features is typically selected to reduce computational complexity and improve accuracy. This step involves evaluating the importance or discriminative power of each feature and selecting the most informative ones for face detection.

Classifier Training: A machine learning algorithm is trained using positive and negative samples to classify whether a given image patch contains a face or not. The positive samples are typically images with annotated faces, while negative samples can be non-face images or background patches. Common classifiers used in feature-based face detection include decision trees, support vector machines (SVM), and ensemble methods like AdaBoost.

Face Localization: Once the classifier is trained, it is applied to sliding windows or image regions at multiple scales to detect potential face regions. The classifier evaluates each window or region based on the selected features and outputs a probability or confidence score indicating the presence of a face. High-scoring regions are considered as candidate face regions.

Post-processing: The candidate face regions obtained from the previous step are refined and filtered to improve accuracy and eliminate false detections. Techniques like non-maximum suppression, geometric constraints, and template matching can be applied to remove overlapping or inconsistent face detections and refine the final face bounding boxes.

Additional Analysis or Applications: Depending on the specific requirements, additional processing steps can be performed on the detected faces. This may include facial recognition, facial landmark detection, emotion analysis, age estimation, gender classification, or other facial attribute extraction.

The feature-based approach to face detection has been widely used and has demonstrated good performance in various applications. However, it may face challenges when dealing with variations in pose, illumination, occlusion, and scale. Recent advancements in deep learning-based approaches have achieved remarkable improvements in face detection accuracy, but feature-based methods still provide a valuable and interpretable solution in certain scenarios.

Face detection process using Image Based Approach

The image-based approach to face detection involves directly analyzing the pixel values and patterns in an image to detect and locate faces. Here is a summary of the face detection process using an image-based approach:

Preprocessing: The input image is typically preprocessed to enhance its quality and improve the effectiveness of face detection. Preprocessing steps may include resizing, grayscale conversion, noise reduction, and contrast enhancement.

Skin Color Segmentation: Skin color segmentation techniques are applied to identify regions in the image that are likely to contain skin tones. This helps narrow down the search space for potential face regions since human faces typically have distinct skin color characteristics.

Edge Detection: Edge detection algorithms are used to detect the edges or boundaries of objects in the image. Faces often exhibit specific edge patterns, such as the edges of the eyes, nose, and mouth, which can aid in face detection.

Feature Extraction: Various image features, such as texture, shape, and color, are extracted from the image or the segmented skin regions. These features capture the unique characteristics of faces and are used to distinguish them from other objects or background elements.

Classifier or Template Matching: A classifier or template matching technique is employed to identify whether the extracted features correspond to a face or not. This step involves comparing the extracted features against a set of predefined face patterns or using a trained classifier to determine the likelihood of a face being present.

Face Localization: Once a potential face region is identified, additional steps are taken to refine and accurately localize the face. This may involve adjusting the size and position of the detected region based on the facial features or employing geometric constraints to ensure that the region corresponds to an actual face.

Post-processing: The detected face regions are often post-processed to eliminate false detections and improve accuracy. Techniques such as non-maximum suppression, geometric verification, or additional contextual analysis may be applied to refine the final set of detected faces.

The image-based approach to face detection is relatively simpler compared to feature-based or deep learning-based methods. It relies on analyzing the visual characteristics of faces directly from the image. While it may not achieve the same level of accuracy as more advanced approaches, it can still be effective in certain scenarios and applications where computational resources or complexity constraints are a concern.

1.4.2 FACE DETECTION ALGORITHM:

Face detection algorithms are designed to identify and locate human faces within images or video streams. These algorithms utilize various techniques and approaches to achieve accurate and efficient face detection. Here are explanations of some popular face detection algorithms:

Haar Cascade Classifiers: Haar cascade classifiers are based on the concept of Haar-like features and are commonly used for face detection. They use a trained model that consists of cascaded stages, each containing a set of weak classifiers. These classifiers evaluate specific features at different scales and positions in the image to determine whether a region contains a face or not. Haar cascade classifiers provide real-time face detection and have been widely used in applications.

Viola-Jones Algorithm: The Viola-Jones algorithm is a variant of the Haar cascade classifiers and is known for its speed and accuracy. It utilizes integral images and a method called the AdaBoost algorithm to select and combine a set of weak classifiers into

a strong classifier. The algorithm efficiently scans the image at multiple scales, quickly eliminating non-face regions, and focuses on potential face regions.

Figure 1.3 : Face recognition method

Histogram of Oriented Gradients (HOG): The HOG algorithm focuses on detecting object boundaries and local texture patterns in an image. It computes the gradients and orientations of image pixels and represents the distribution of gradient orientations as a feature vector. This vector is then used with a machine learning classifier, such as Support Vector Machines (SVM), to detect faces. HOG-based face detection algorithms are effective in capturing facial features but may be slower compared to other methods.

Convolutional Neural Networks (CNN): CNN-based face detection algorithms leverage deep learning techniques to detect faces. These algorithms use a convolutional neural network architecture that has been trained on large datasets containing annotated face images. The network learns to recognize facial features and detects faces by analyzing the image at different scales and locations. CNN-based algorithms have shown impressive accuracy in face detection but may require more computational resources.

Multi-task Cascaded Convolutional Networks (MTCNN): MTCNN is a popular face detection algorithm that combines CNN and cascaded networks. It consists of three stages: face proposal network, bounding box regression network, and facial landmark localization network. MTCNN first proposes potential face regions, refines the bounding boxes, and then locates facial landmarks. It achieves accurate face detection along with

facial landmark localization, making it useful for applications like facial analysis and recognition.

These are some of the commonly used face detection algorithms. Each algorithm has its strengths and may be suitable for different scenarios depending on factors such as speed, accuracy, and computational resources available. Researchers and developers can choose the algorithm that best fits their requirements and application needs.

1.4.3 FACE DETECTION USING HAAR CASCADE:

The Haar Cascade classifier is a machine learning-based approach for object detection, specifically designed for face detection. It works by utilizing a set of Haar-like features and a cascade of weak classifiers.

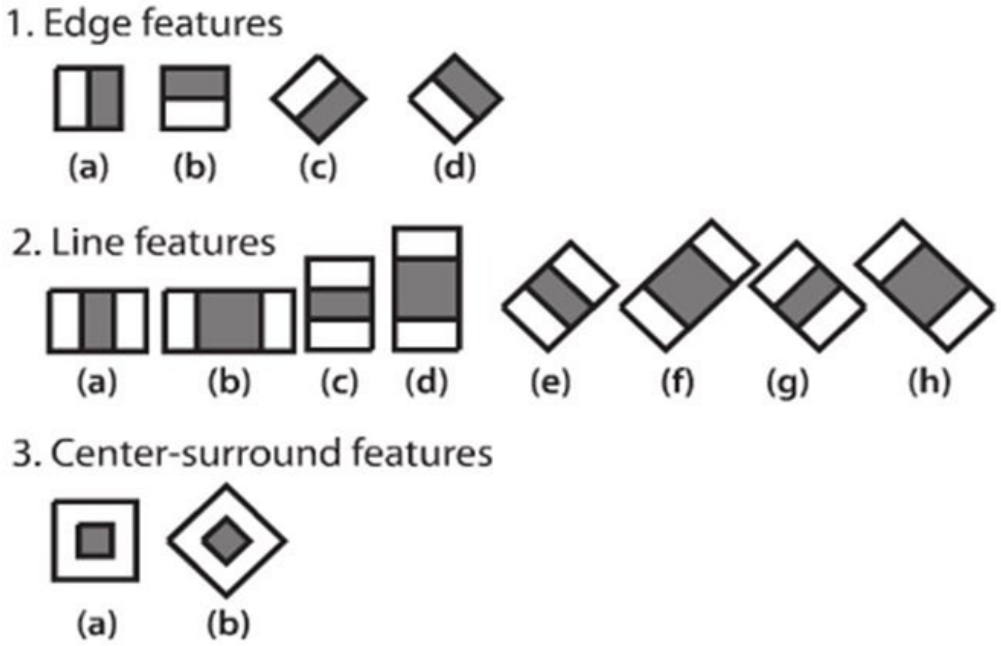

Figure 1.4 : Features of a Haar cascade classifier

Here is a step-by-step explanation of how the Haar Cascade classifier works:

Haar-like Features: Haar-like features are simple rectangular filters that are used to capture local image properties. They are named after the Hungarian mathematician

Alfred Haar, who introduced the concept. Haar-like features are calculated by subtracting the sum of pixel intensities within a white rectangle from the sum within a black rectangle.

Training Stage: The Haar Cascade classifier is trained using a large dataset of positive and negative images. Positive images contain the object of interest (e.g., faces), while negative images do not. During the training stage, the classifier learns to differentiate between positive and negative samples by selecting and combining a subset of Haar-like features.

Integral Image Representation: To efficiently calculate Haar-like features, the integral image representation is used. The integral image is created by summing up the pixel intensities of the original image in a way that allows quick computation of the sum of intensities over any rectangular region.

Cascade of Weak Classifiers: The Haar Cascade classifier consists of multiple stages, each containing a set of weak classifiers. A weak classifier is a simple decision rule based on a single Haar-like feature and a threshold value. It evaluates whether a region of the image contains the object of interest (e.g., a face) or not.

Adaptive Boosting (AdaBoost): During the training process, the AdaBoost algorithm is used to select the most informative Haar-like features and assign weights to them. AdaBoost focuses on the misclassified samples and gives them higher weights in subsequent iterations. It iteratively creates a strong classifier by combining the weak classifiers, with more weight given to the ones that perform better on the training data.

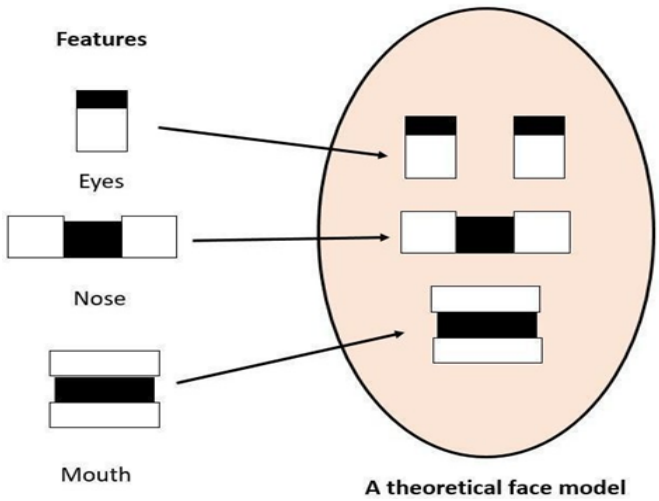

Figure 1.5 : A theoretical face model

Cascade Structure: The cascade structure of the classifier is formed by organizing the weak classifiers into multiple stages. Each stage consists of several weak classifiers that are applied sequentially. The purpose of the cascade structure is to quickly reject non-face regions in the image. Regions that pass one stage are further evaluated by subsequent stages, increasing the confidence in the detection.

Sliding Window Technique: During the detection phase, the Haar Cascade classifier applies the set of weak classifiers to different regions of the image at different scales and positions. This is done using a sliding window technique, where a window is moved across the image, evaluating the presence of the object in each window.

Non-Maximum Suppression: To eliminate duplicate or overlapping detections, a non-maximum suppression technique is often applied. It selects the most confident detection among overlapping bounding boxes and discards the rest.

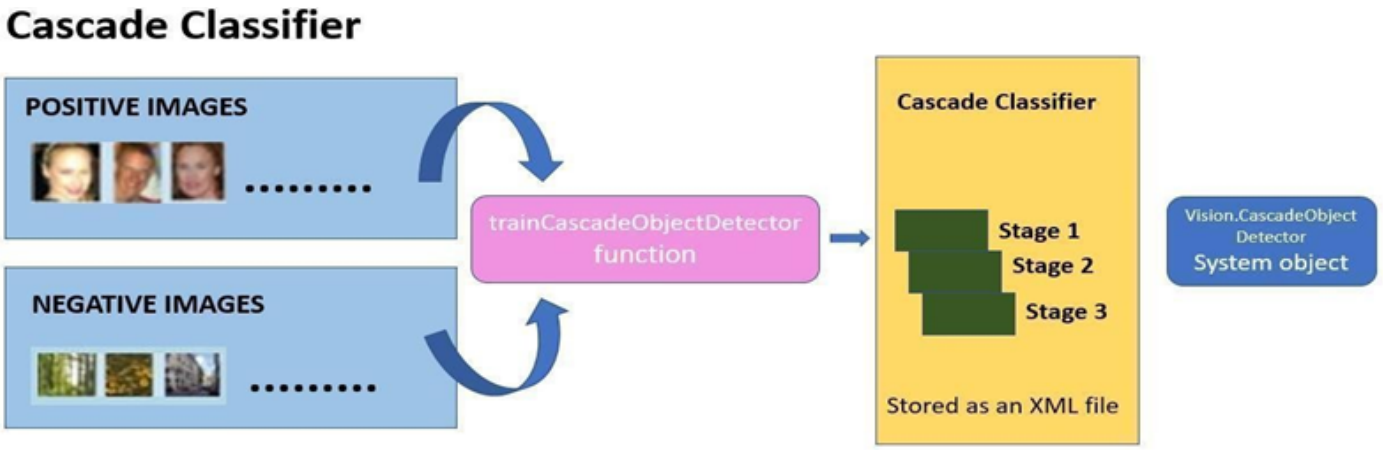

Figure 1.6 : How Haar cascade classifier works

By combining the strengths of Haar-like features, AdaBoost, and the cascade structure, the Haar Cascade classifier can efficiently detect objects, such as faces, in images or video streams. It provides a balance between accuracy and speed, making it suitable for real-time applications.

Figure 1.7 : Haar Cascade features

1.4.4 FACE DETECTION USING YOLOV5:

YOLOv5 is a state-of-the-art object detection algorithm, and it can be used to detect faces as well.

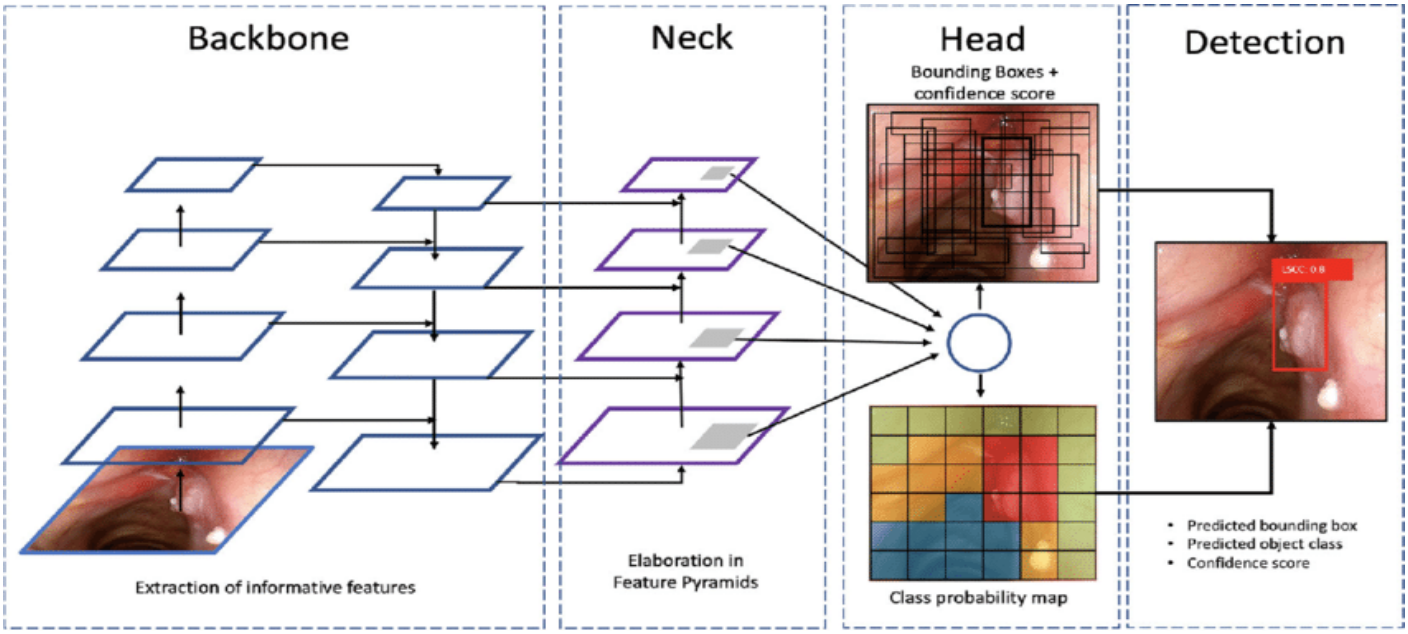

Figure 1.8 : Detection Process using Yolov5

Here's an overview of how YOLOv5 detects faces:

Architecture: YOLOv5 follows a one-stage object detection approach. It consists of a

backbone network, often based on a convolutional neural network (CNN) architecture like ResNet or CSPNet, and a detection head.

Training: YOLOv5 is trained on a large dataset with annotated images that contain face bounding box annotations. During training, the network learns to detect faces by optimizing the loss function, which measures the discrepancy between predicted bounding boxes and the ground truth annotations.

Input Preparation: To detect faces using YOLOv5, you need to provide an input image or a video frame to the network. Typically, the input image is resized to a fixed size to match the network's requirements.

Forward Pass: The input image is passed through the YOLOv5 network, where a series of convolutional layers extract features at different scales. These features capture the visual information necessary for detecting faces.

Anchor Boxes: YOLOv5 uses anchor boxes, which are predefined bounding boxes with different aspect ratios and sizes. The network predicts offsets and scales for each anchor box to match the detected faces.

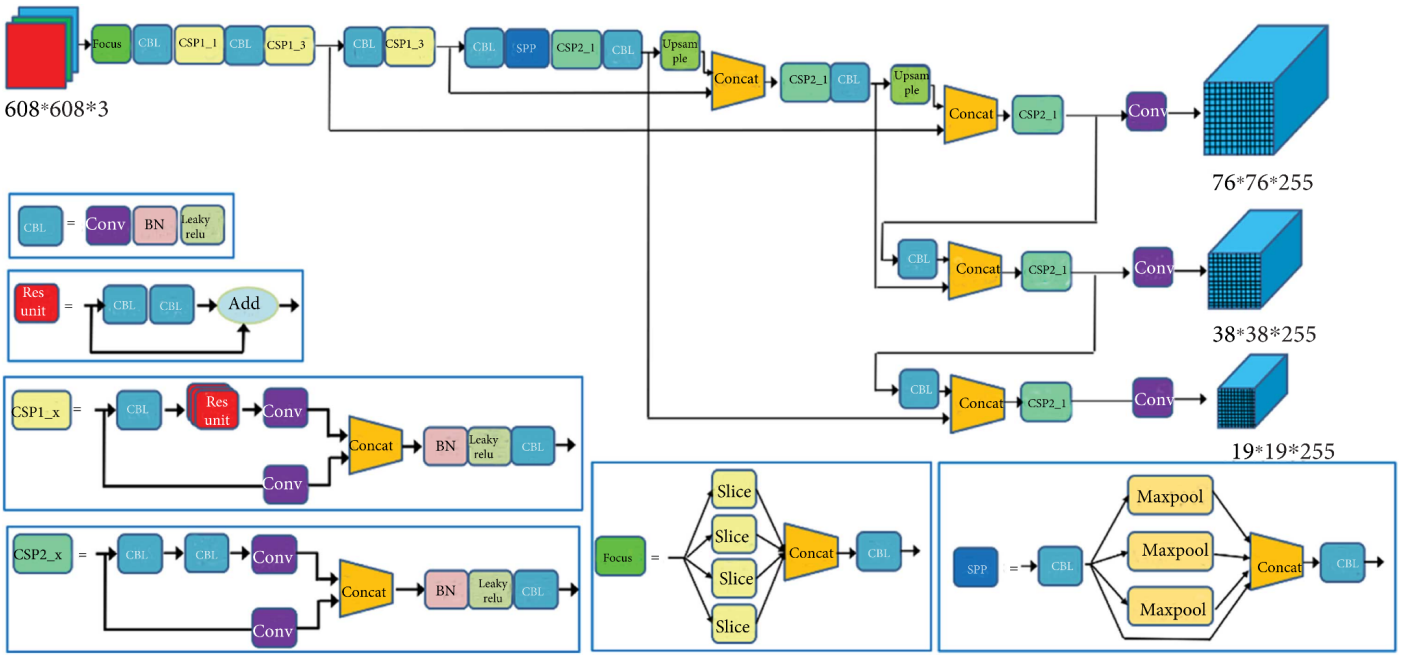

Figure 1.9 : Structures of YOLOv5

Prediction: The network predicts bounding boxes and class probabilities for various objects, including faces, at different locations and scales in the image. These predictions are made based on the features extracted from the previous layers.

Non-Maximum Suppression: To eliminate duplicate or overlapping detections, a post-processing step called non-maximum suppression (NMS) is applied. NMS selects the most confident detection among overlapping bounding boxes and suppresses the rest.

Thresholding: To filter out low-confidence detections, a threshold is applied to the predicted class probabilities. Only the detections with probabilities above the threshold are considered as valid detections.

Output: The final output of YOLOv5 for face detection is a list of bounding boxes that represent the detected faces, along with their associated confidence scores.

YOLOv5 offers accurate and efficient face detection capabilities, and it has been widely used in various computer vision applications. However, it's important to note that YOLOv5 is primarily designed for generic object detection and may not perform as well as specialized face detection algorithms in certain scenarios.

1.5 REAL TIME FACE DETECTION:

Real-time face detection is a crucial technology in the field of computer vision that allows the automatic identification and localization of human faces in images or video streams. It plays a pivotal role in numerous applications, ranging from security and surveillance to biometrics, augmented reality, emotion recognition, and more. This essay explores the significance, challenges, and advancements in real-time face detection, highlighting its impact on modern technologies.

Importance of Real-Time Face Detection: Real-time face detection has revolutionized various industries by enabling sophisticated applications that rely on facial analysis. In the realm of security and surveillance, it aids in identifying individuals in crowded areas, detecting unauthorized access, and enhancing public safety. It also finds applications in human-computer interaction, where it enables hands-free control, facial authentication, and personalized user experiences. Moreover, real-time face detection plays a crucial role in biometric systems, enabling identity verification, access control, and forensic analysis.

Challenges in Real-Time Face Detection: Real-time face detection poses unique challenges due to the complexity of the task and the need for efficient and rapid processing. Some of the key challenges include:

Real-Time Processing: Face detection algorithms must process video frames or image streams in real-time to provide instantaneous results. This requires optimizing the computational efficiency of the algorithms and leveraging hardware acceleration, such as GPUs or dedicated neural network accelerators.

Variability in Appearance: Faces exhibit significant variability in terms of pose, illumination, facial expressions [1], distance between person from camera [2], Angel [3], occlusions, and scale. Robust face detection algorithms should be able to handle these variations and accurately detect faces under different conditions.

Complex Backgrounds: Real-world environments often contain complex backgrounds, clutter, and distractions. Face detection algorithms need to differentiate between faces and other objects, ensuring accurate and reliable detection in challenging scenarios.

Advancements in Real-Time Face Detection: Over the years, significant advancements have been made in real-time face detection, driven by the evolution of machine learning and computer vision techniques. Some notable advancements include:

Haar Cascade Classifiers: The Haar Cascade classifier, introduced by Viola and Jones, was one of the pioneering methods for real-time face detection. It utilizes Haar-like features and a cascade of weak classifiers to efficiently detect faces. This method provides a balance between accuracy and speed and remains popular today.

Deep Learning Approaches: Deep learning has revolutionized face detection by leveraging neural networks and large datasets. Convolutional Neural Networks (CNNs) and architectures like YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector) have achieved remarkable accuracy and real-time performance by learning complex features directly from the data.

Real-Time Face Detection APIs: Frameworks and libraries like OpenCV, Dlib, and TensorFlow provide pre-trained models and APIs specifically designed for real-time face detection. These resources offer a user-friendly interface, allowing developers to

incorporate face detection capabilities into their applications with ease.

Real-time face detection has transformed the way we interact with technology and has opened doors to numerous innovative applications. Its impact spans across industries, from security to entertainment, healthcare to marketing. With advancements in machine learning and computer vision techniques, real-time face detection continues to evolve, offering higher accuracy, improved speed, and enhanced robustness. As technology progresses, we can expect further innovations in real-time face detection, enabling even more sophisticated and intelligent applications that leverage the power of facial analysis.

1.6 OBJECT DETECTION:

Object detection is a fundamental task in computer vision that involves identifying and localizing objects within images or video streams. It plays a pivotal role in a wide range of applications, from autonomous driving and surveillance to augmented reality and robotics. This essay explores the significance, techniques, advancements, and applications of object detection, highlighting its impact on various domains.

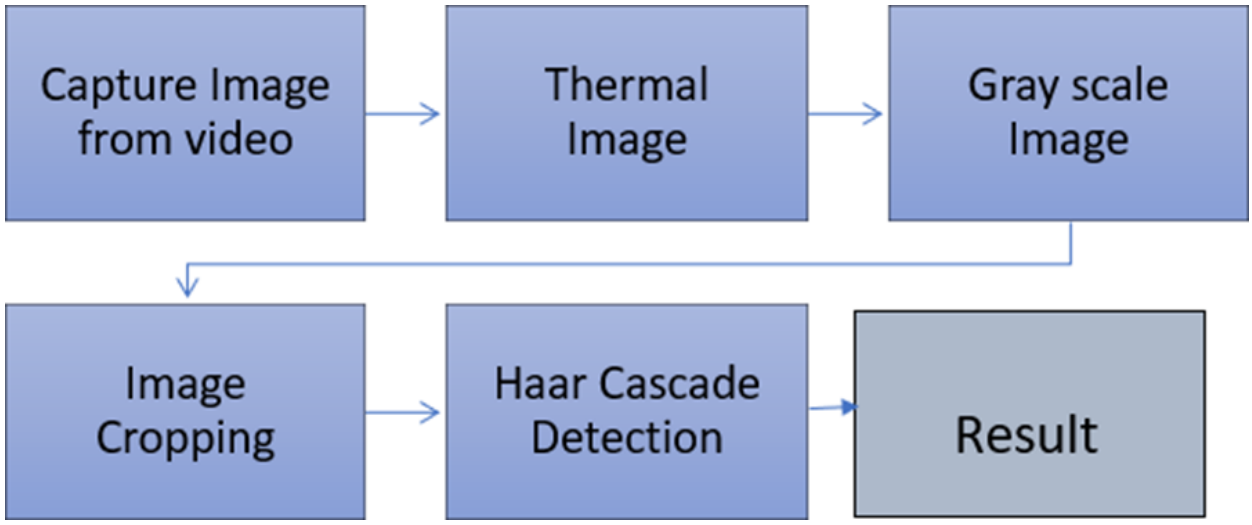

Figure 1.10 : Object detection

Importance of Object Detection: Object detection enables machines to perceive and understand their surroundings, allowing them to interact intelligently with the environment. It provides crucial information about the presence, location, and category of objects, which is vital for decision-making in many applications. Object detection has

revolutionized industries such as autonomous driving, where it enables the identification of pedestrians, vehicles, and obstacles. It also plays a vital role in surveillance systems, allowing for the detection of suspicious activities or unauthorized objects. Moreover, object detection is utilized in medical imaging, retail analytics, robotics, video analysis, and many other domains.

Techniques for Object Detection: Various techniques have been developed for object detection, ranging from traditional methods to advanced deep learning approaches. Some popular techniques include:

Sliding Window: This approach involves scanning an image with a fixed-size window at different scales and positions. Classifiers are applied to each window to determine if it contains an object. While effective, this method can be computationally expensive.

Region Proposal: These methods generate potential object regions (region proposals) and then classify them. Examples include Selective Search and EdgeBoxes, which extract region proposals based on heuristics or low-level image features.

One-Stage Detectors: One-stage detectors, such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), directly predict object bounding boxes and class probabilities in a single pass. They offer real-time performance and have gained popularity due to their efficiency.

Two-Stage Detectors: Two-stage detectors, including the R-CNN (Region-based Convolutional Neural Networks) family, such as Fast R-CNN and Faster R-CNN, employ a region proposal network to generate potential object regions. These regions are then classified and refined. Two-stage detectors often achieve high accuracy but can be slower.

Advancements in Object Detection: Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have significantly improved object detection performance. CNN-based models leverage deep architectures to learn complex features directly from the data, enabling accurate and efficient detection. Models like Faster R-CNN, RetinaNet, and EfficientDet have achieved remarkable results in terms of accuracy and speed, pushing the boundaries of object detection.

Applications of Object Detection: Object detection has numerous practical applications across various domains. Some notable applications include:

Autonomous Driving: Object detection is essential for autonomous vehicles to detect and track pedestrians, vehicles, traffic signs, and obstacles in real-time, ensuring safe navigation.

Surveillance and Security: Object detection enables the monitoring of public spaces, identifying suspicious activities, detecting intruders, and enhancing security systems.

Retail Analytics: Object detection is utilized for customer behavior analysis, product recognition, inventory management, and shelf optimization in retail environments.

Augmented Reality: Object detection allows virtual objects to be overlaid onto the real world, enhancing user experiences in gaming, advertising, and interactive applications.

Medical Imaging: Object detection aids in the detection and localization of abnormalities in medical images, assisting in the diagnosis of diseases like cancer and assisting in surgical planning.

Object detection Flowchart:

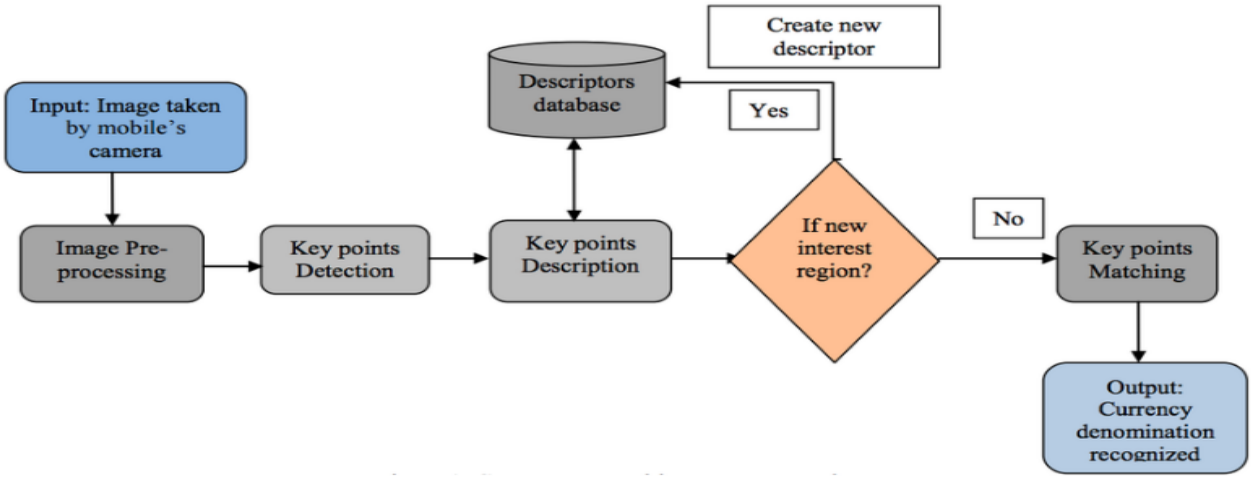

Figure 1.11 : Object detection flowchart

CHAPTER TWO

HISTORY & MOTIVATION

2.1 HISTORY OF FACE DETECTION BY PYTHON OPENCV USING HAAR CASCADE:

The history of face detection using Python and OpenCV with Haar Cascade classifiers traces back to the early 2000s when Viola and Jones introduced the Haar Cascade algorithm for rapid object detection. While the algorithm was not initially designed specifically for face detection, it quickly gained popularity in the computer vision community due to its efficiency and effectiveness in detecting faces.

In 2001, Viola and Jones published their groundbreaking paper titled "Rapid Object Detection using a Boosted Cascade of Simple Features," which outlined the Haar Cascade algorithm. The algorithm was designed to detect any type of object by utilizing a cascade of simple classifiers, each based on Haar-like features. Haar-like features are rectangular patterns that capture the differences in intensities between adjacent image regions.

The Haar Cascade algorithm uses a machine learning approach called Adaboost to train the classifiers. Adaboost iteratively selects a subset of Haar-like features that are most discriminative for object detection. These features are combined into a cascade of classifiers, where each classifier is trained to discriminate between the object and the background.

Haar Cascade classifiers are trained using positive and negative samples. Positive samples are images containing the target object, in this case, faces, while negative samples are images without the object. The algorithm adjusts the weights of the Haar-like features during training to optimize the discrimination between positive and negative samples.

OpenCV, an open-source computer vision library, integrated the Haar Cascade algorithm and provided a user-friendly interface for face detection. OpenCV's implementation of Haar Cascade classifiers simplifies the process of face detection by offering pre-trained models for immediate use. These pre-trained models are trained on

large datasets and can detect faces in real-time with high accuracy.

The availability of pre-trained Haar Cascade models in OpenCV enabled researchers and developers to easily incorporate face detection capabilities into their Python applications. The Haar Cascade-based face detection approach gained widespread adoption due to its real-time performance, ease of use, and robustness to variations in pose and lighting conditions.

Since its introduction, face detection using Haar Cascade classifiers has been widely utilized in various domains and applications. It has become an integral part of facial recognition systems, surveillance systems, human-computer interaction, and more. Over the years, researchers and developers have continued to explore and enhance the Haar Cascade algorithm, incorporating improvements such as more robust feature selection, cascaded classifiers, and better training techniques.

While the Haar Cascade algorithm remains a popular choice for face detection, newer deep learning-based methods, such as convolutional neural networks (CNNs), have emerged and achieved state-of-the-art performance in recent years. These methods have demonstrated superior accuracy and can handle more complex scenarios, but they often require larger computational resources.

2.2 MOTIVATION OF FACE DETECTION BY PYTHON OPENCV USING HAAR CASCADE:

The motivation behind face detection using Python, OpenCV, and Haar Cascade classifiers is driven by the increasing demand for automated facial analysis and recognition systems in various domains. Faces are essential visual cues that carry valuable information about individuals, and their detection plays a crucial role in numerous applications, including security, surveillance, biometrics, human-computer interaction, and entertainment.

One of the primary motivations for face detection is in the field of biometrics. Biometric systems utilize unique physical or behavioral characteristics, such as facial features, for identification and verification purposes. Face detection serves as the initial step in these systems, allowing the extraction and analysis of facial features for further processing, such as face recognition or emotion analysis

In security and surveillance applications, face detection is essential for monitoring public spaces, identifying potential threats, and enhancing safety. Automated face

detection enables real-time monitoring of crowds or specific areas, alerting security personnel to the presence of individuals of interest. It facilitates the identification of suspects, enhances forensic investigations, and aids in crime prevention and detection.

Moreover, face detection has become a key component in human-computer interaction systems. By accurately detecting and tracking faces, computers can respond to users' facial expressions, gestures, and movements, enabling more intuitive and natural interactions. This technology has found applications in gaming, virtual reality, augmented reality, and robotics, enhancing user experiences and enabling new modes of interaction.

Another motivation for face detection using Haar Cascade classifiers is the widespread availability and ease of use of the OpenCV library. OpenCV provides a comprehensive set of computer vision algorithms and tools, including pre-trained Haar Cascade models for face detection. Its Python interface allows developers to leverage the power of OpenCV and integrate face detection capabilities into their Python applications with ease.

Furthermore, the Haar Cascade algorithm's real-time performance makes it particularly suitable for applications that require fast processing, such as video surveillance or interactive systems. Its ability to handle variations in pose, lighting conditions, and occlusions further adds to its appeal.

Overall, the motivation behind face detection using Python, OpenCV, and Haar Cascade classifiers stems from the increasing need for automated facial analysis and recognition systems in various domains. The ability to detect and locate faces accurately and efficiently enables a wide range of applications, contributing to improved security, enhanced human-computer interaction, and advancements in biometrics and surveillance technology. The availability of OpenCV and its user-friendly interface makes it accessible to developers, empowering them to incorporate face detection capabilities into their Python-based projects seamlessly.

2.3 HISTORY OF FACE DETECTION BY YOLOV5:

The history of face detection using YOLOv5 begins with the development of the YOLO (You Only Look Once) family of object detection algorithms. YOLO was introduced by Joseph Redmon et al. in 2016, and it quickly gained attention for its real-time object detection capabilities.
YOLO initially consisted of several versions, including YOLOv1, YOLOv2 (also known as YOLO9000), and YOLOv3. These versions achieved impressive object detection results, but they were not specifically tailored for face detection.

In 2020, Ultralytics, an AI research company, released YOLOv5, which focused on further improving the speed, accuracy, and usability of the YOLO algorithm. YOLOv5 introduced several significant changes and enhancements, making it particularly well-suited for face detection tasks.

One of the key advancements in YOLOv5 is its architecture, which features a more streamlined and efficient design. YOLOv5 adopts a single-stage detector approach, eliminating the region proposal network used in previous versions. This change allows for faster inference and reduces computational complexity while maintaining high accuracy.

YOLOv5 also introduced a novel focus on smaller object detection, which is especially relevant in face detection scenarios. By incorporating a PANet (Path Aggregation Network) as the feature fusion module, YOLOv5 enhances the network's ability to detect small objects, such as faces, with higher precision.

Another crucial aspect of YOLOv5's success is the availability of large-scale, annotated datasets. These datasets, such as WIDER Face and CelebA, provide extensive training data specifically curated for face detection tasks. Training YOLOv5 on these datasets enables the algorithm to learn and generalize effectively for face detection.

Additionally, YOLOv5 benefits from advancements in hardware and deep learning frameworks, such as NVIDIA GPUs and the PyTorch framework. These technologies enable efficient training and inference, making real-time face detection using YOLOv5 achievable on a wide range of hardware platforms.

The release of YOLOv5 has sparked significant interest and adoption within the

computer vision community. Researchers and developers worldwide have utilized YOLOv5 for various face detection applications, including facial recognition systems, video surveillance, emotion analysis, and more. Its combination of high performance, ease of use, and flexibility has made YOLOv5 a popular choice for face detection tasks.

It's developing everyday!

2.4 MOTIVATION OF FACE DETECTION BY YOLOV5:

The motivation behind face detection using YOLOv5 stems from the need for accurate, real-time, and efficient detection of faces in various applications. YOLOv5, with its advanced features and capabilities, has gained significant motivation and adoption in the computer vision community. Here are some key motivations for using YOLOv5 for face detection:

Accuracy: YOLOv5 offers high accuracy in face detection due to its advanced architecture and training techniques. It can effectively detect faces in different poses, orientations, and lighting conditions, making it suitable for diverse real-world scenarios. The accuracy of YOLOv5 enables reliable face recognition, emotion analysis, and other facial analysis tasks.

Real-time Performance: Real-time face detection is crucial in many applications, especially those requiring live video analysis or interactive systems. YOLOv5 is optimized for speed, allowing it to process video streams or image sequences in real-time. Its efficient architecture and implementation enable fast inference on various hardware platforms, making it ideal for applications that demand low latency.

Versatility: YOLOv5 is a versatile object detection algorithm, capable of detecting multiple object classes, including faces. Its flexibility allows it to handle complex scenes with multiple objects, making it suitable for applications where face detection needs to coexist with other object detection tasks. This versatility opens up opportunities for multi-object tracking, crowd analysis, and scene understanding.

Deep Learning Advancements: YOLOv5 takes advantage of the advancements in deep learning, specifically convolutional neural networks (CNNs). CNNs have revolutionized computer vision tasks by learning intricate features directly from the data. YOLOv5 leverages CNNs to extract discriminative features for face detection, enabling better accuracy and robustness.

Training on Large Datasets: The availability of large-scale face detection datasets, such as WIDER Face, has driven the motivation to use YOLOv5 for face detection. Training YOLOv5 on these datasets allows the model to learn from a diverse range of face examples, improving its ability to generalize and detect faces accurately in various conditions.

Open-source and Community Support: YOLOv5 is an open-source project, which means it benefits from a vibrant community of developers and researchers. This community-driven development fosters innovation, continuous improvement, and the availability of resources and tutorials, making it easier for developers to adopt and customize YOLOv5 for their specific face detection needs.

In summary, the motivation behind using YOLOv5 for face detection lies in its high accuracy, real-time performance, versatility, and leveraging the advancements in deep learning. The ability to detect faces accurately and efficiently opens up opportunities for various applications, including security, surveillance, human-computer interaction, and biometrics. YOLOv5's open-source nature and community support further enhance its appeal, making it a popular choice for face detection tasks.

CHAPTER THREE

ADOPTED METHODOLOGY

The used Python modules OpenCV, numpy, pillow, OS and LBPH recognizer.

3.1 PYTHON MODULES:

Python modules are files that contain Python code and provide additional functionality to your programs. They allow you to organize your code into reusable and modular components, making your programs more efficient and easier to maintain. Here are some key points about Python modules:

Definition: A module is a file with a .py extension that contains Python code, including variables, functions, and classes. It serves as a container for related code and provides a way to encapsulate functionality for easy reuse.

Importing Modules: To use code from a module, you need to import it into your program. Python provides several ways to import modules, including the import statement, import...as, and from...import. By importing a module, you can access its functions, classes, and variables in your program.

Standard Library Modules: Python comes with a vast collection of standard library modules that provide a wide range of functionality. These modules cover areas such as file handling, mathematical operations, network communication, data serialization, regular expressions, and more. They are readily available for use in your programs without requiring any additional installation.

Third-Party Modules: In addition to the standard library, Python has a rich ecosystem of third-party modules developed by the community. These modules extend the functionality of Python and cater to specific domains and tasks. Popular third-party modules include NumPy for numerical computing, Pandas for data analysis, Matplotlib for data visualization, Requests for HTTP requests, and many more. Third-party modules are typically installed using package managers like pip.

Creating Custom Modules: You can create your own custom modules by writing Python code in a separate .py file. This allows you to encapsulate related functionality,

making it easier to organize and reuse your code across multiple programs. By defining functions, classes, and variables within a module, you can import and use them in other Python scripts.

Module Hierarchy: Modules can be organized in a hierarchical structure using packages. A package is a directory that contains multiple modules and an additional init.py file. This file indicates that the directory is a Python package. Packages help organize related modules into a coherent structure, allowing for better code organization and separation of concerns.

Namespaces: Modules provide a way to create separate namespaces, which help avoid naming conflicts. Each module has its own namespace, preventing clashes between variables, functions, and classes with the same name in different modules. Namespaces promote code modularity and prevent unintended side effects.

3.1.1 OPENCV:

The term OpenCV, short for "Open Source Computer Vision Library," is a popular open-source library for computer vision and image processing tasks. It provides a comprehensive set of functions and tools that enable developers to perform various operations on images and videos. Here are some key points about OpenCV:

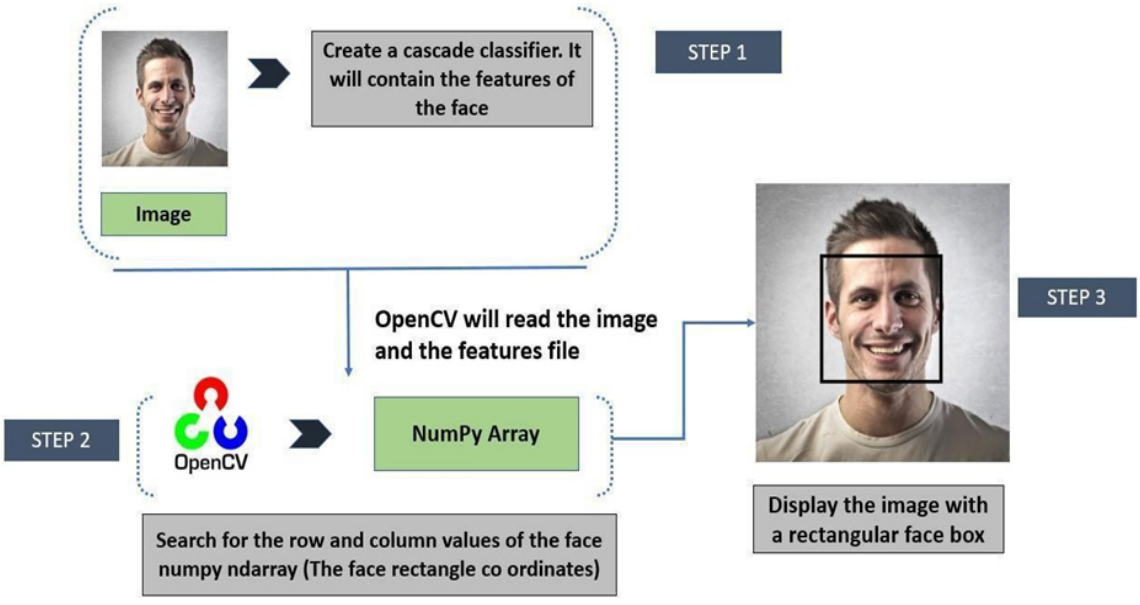

Figure 3.1: How OpenCV works

Image and Video Processing: OpenCV offers a wide range of functions for image and video processing, including reading and writing image files, resizing, cropping, rotating, and applying various filters and transformations. It provides tools for color manipulation, histogram analysis, edge detection, contour detection, and many other image processing tasks.

In Computer Vision Algorithms: OpenCV includes a collection of computer vision algorithms for tasks such as feature detection and extraction, object recognition, object tracking, camera calibration, and 3D reconstruction. These algorithms enable applications like face detection, optical character recognition (OCR), gesture recognition, motion tracking, and more.

In Machine Learning Integration: OpenCV seamlessly integrates with machine learning frameworks, including TensorFlow and PyTorch. It provides functions for training and applying machine learning models on images and videos, allowing developers to build complex computer vision systems using the power of deep learning.

Cross-platform and Language Support: OpenCV is cross-platform and can be used on various operating systems, including Windows, Linux, macOS, iOS, and Android. It supports multiple programming languages, including C++, Python, Java, and MATLAB, making it accessible to a wide range of developers.

Real-time Vision Applications: OpenCV is widely used for real-time vision applications, where high-performance processing is required. It leverages hardware acceleration, multi-threading, and parallel processing techniques to achieve real-time performance, making it suitable for applications like object detection and tracking in video streams, augmented reality, robotics, and autonomous systems.

Open-source Community: OpenCV is an open-source project with a large and active community of developers. The community contributes to the development and improvement of OpenCV by providing bug fixes, new features, and tutorials. The availability of extensive documentation, code samples, and online resources makes it easier for developers to learn and use OpenCV.

Integration with Other Libraries: OpenCV can be easily integrated with other libraries and frameworks for additional functionality. It works well with libraries like NumPy for efficient array operations, SciPy for scientific computing, and Matplotlib for data

visualization, enabling developers to build comprehensive computer vision systems.

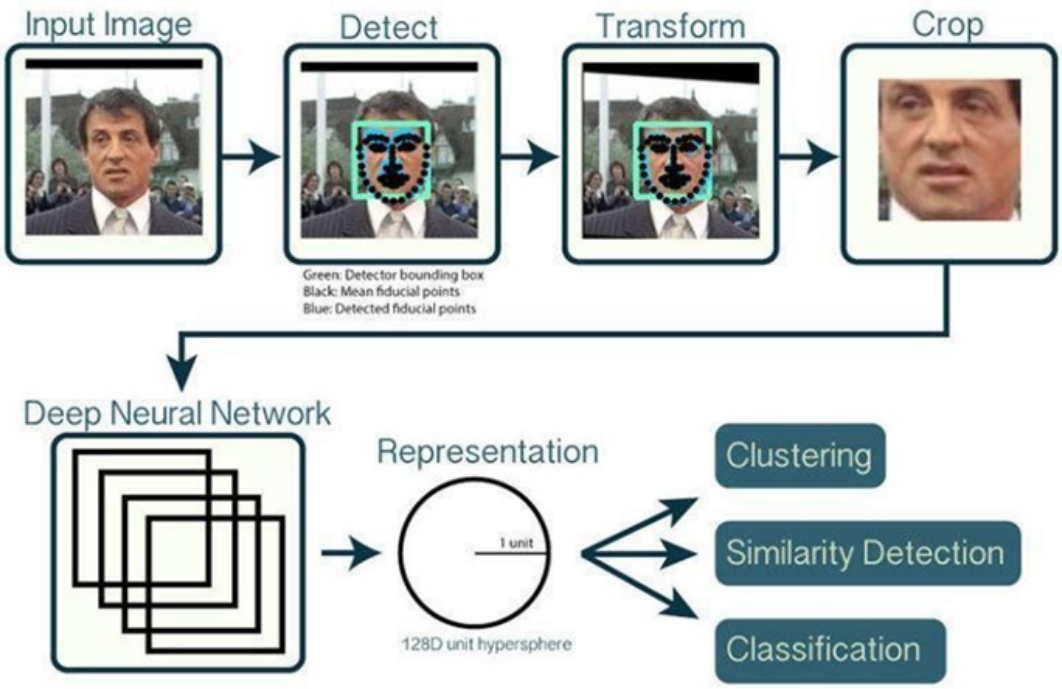

Figure 3.2 : OpenCV in facial recognition system

Thus OpenCV is a powerful and versatile library for computer vision and image processing tasks. Its wide range of functions, algorithms, and platform support makes it a go-to choice for developing applications in various domains, including robotics, healthcare, surveillance, automotive, and entertainment. The active community and continuous development ensure that OpenCV stays at the forefront of computer vision technology.

3.1.2 NUMPY

NumPy, short for Numerical Python, is a fundamental library in Python for scientific computing. It provides a powerful multi-dimensional array object, along with a collection of functions and tools for working with arrays. NumPy is widely used in various domains, including mathematics, physics, engineering, data science, and more.

Here are some key features and aspects of NumPy:

Multi-dimensional Arrays: The core feature of NumPy is the ndarray (n-dimensional

array) object, which allows efficient storage and manipulation of homogeneous data. These arrays can have any number of dimensions and are highly optimized for numerical operations.

Mathematical Operations: NumPy provides a wide range of mathematical functions that operate element-wise on arrays. These functions include basic arithmetic operations, logarithms, trigonometric functions, linear algebra operations, statistical calculations, and more. NumPy's vectorized operations enable faster and more concise code execution compared to traditional loops.

Broadcasting: NumPy allows for broadcasting, which is a powerful mechanism for performing operations on arrays with different shapes. Broadcasting automatically aligns the arrays' dimensions to perform element-wise operations efficiently, eliminating the need for explicit looping.

Integration with other Libraries: NumPy seamlessly integrates with other scientific computing libraries such as SciPy, Pandas, Matplotlib, and scikit-learn. This integration enables a comprehensive ecosystem for data analysis, visualization, machine learning, and scientific research.

Efficiency: NumPy is implemented in C and provides highly efficient array operations. It leverages optimized routines, which significantly enhance the performance and speed of numerical computations compared to pure Python implementations.

To use NumPy, you need to import the library in your Python program using the following statement:

```
import numpy as np
```

NumPy has become a foundational library for many scientific and data analysis tasks in Python, providing efficient array manipulation and numerical operations. Its versatility, performance, and extensive community support make it an essential tool for anyone working with numerical data in Python.

3.1.3 PILLOW

Pillow is a popular Python library for handling and manipulating digital images. It serves as a powerful tool for tasks such as opening, creating, editing, and saving

various image file formats. Pillow is a fork of the Python Imaging Library (PIL) and offers an easy-to-use interface along with extensive functionality for image processing.

Here are some key features and aspects of Pillow:

Image Manipulation: Pillow provides a comprehensive set of functions to perform basic image operations like cropping, resizing, rotating, and flipping. It also allows for more advanced tasks such as applying filters, adjusting colors, enhancing images, and working with image metadata.

Support for Image Formats: Pillow supports a wide range of image file formats, including common formats like JPEG, PNG, GIF, BMP, and TIFF. It allows you to read and write images in these formats, making it versatile for working with different types of image data.

Image Enhancement and Filtering: Pillow offers numerous image enhancement techniques, such as adjusting brightness, contrast, and sharpness. It also provides a variety of filters like blurring, edge detection, noise reduction, and more. These features enable you to improve the quality and appearance of images.

Image Data Transformation: Pillow facilitates the conversion between different image modes and color spaces. You can easily convert images from grayscale to RGB, apply alpha compositing, convert between indexed and true-color images, and handle transparency.

Image Drawing and Text: Pillow allows you to draw shapes, lines, and text on images using various drawing primitives. You can annotate images, add captions, overlay graphics, and create simple visualizations directly on the image data.

To use Pillow, you need to install it first using pip:

pip install pillow

After installation, you can import the library in your Python program using the following statement:

from PIL import Image

Pillow provides a user-friendly API, making it relatively straightforward to work with images in Python. Its extensive functionality, support for multiple image formats, and ease of use have made it a popular choice for image processing tasks in various domains, including computer vision, web development, and digital media.

3.1.4 OS & LBPH RECOGNIZER

OS (Eigenface-based Face Recognition):

Eigenface-based face recognition is a popular approach in computer vision for recognizing and identifying individuals based on their facial features. The main idea behind eigenface-based recognition is to represent faces as a linear combination of eigenfaces, which are the principal components extracted from a training set of facial images.

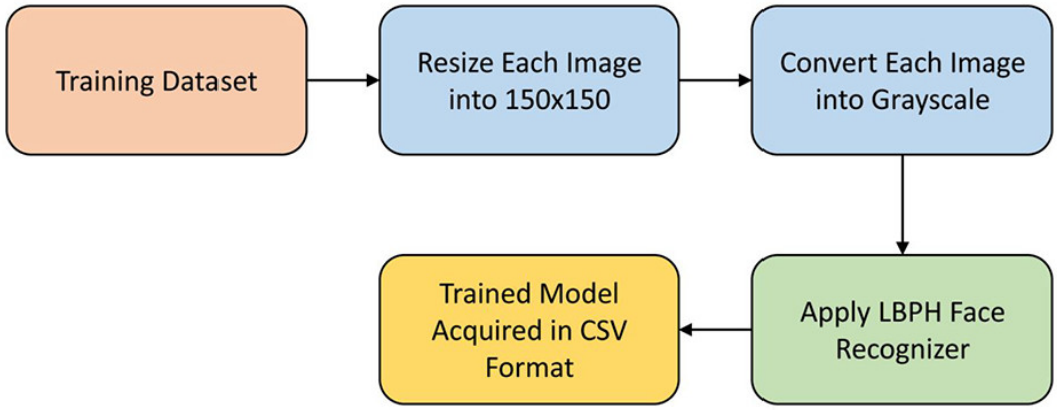

Figure 3.3 : Working procedure of a LBPH recognizer

The process involves the following steps:

Data Collection: A set of facial images is collected for training the recognition system. These images should capture variations in facial expressions, lighting conditions, and pose.

Preprocessing: The collected facial images are preprocessed to normalize factors such as illumination, scale, and alignment. Techniques like histogram equalization, resizing, and

face alignment may be applied.

Feature Extraction: Principal Component Analysis (PCA) is performed on the preprocessed facial images to extract the eigenfaces. PCA identifies the principal components that capture the most significant variations in the face dataset.

Recognition: To recognize a face, an input image is preprocessed in the same manner as the training images. The face is projected onto the eigenface subspace, and the projection coefficients are calculated. The recognition is performed by finding the closest match between the input face and the faces in the training set based on these coefficients.

LBPH (Local Binary Patterns Histograms):

Local Binary Patterns (LBP) is a texture descriptor used in computer vision for various tasks, including face recognition. LBPH is an extension of LBP specifically designed for face recognition. It encodes local texture patterns of a face and represents them using a histogram-based approach.

The process involves the following steps:

Data Collection: A set of facial images is collected for training the recognition system. These images should capture variations in facial expressions, lighting conditions, and pose.

Image Preprocessing: The collected facial images are preprocessed to enhance the quality and normalize factors such as illumination, scale, and alignment. Techniques like histogram equalization, resizing, and face alignment may be applied.

Local Binary Patterns: For each pixel in the preprocessed image, a binary code is generated by comparing the pixel's intensity with its neighboring pixels. This binary code represents the local texture pattern of that pixel.

Feature Extraction: The face image is divided into regions or blocks, and the histogram of local binary patterns is computed for each block. These histograms represent the distribution of different texture patterns in each block.

Recognition: To recognize a face, the same preprocessing steps are applied to the input image. The LBPH histograms are computed for each block of the face, and the similarity

between the input face and the training faces is measured using techniques like Euclidean distance or chi-squared distance.

Both eigenface-based recognition and LBPH are popular techniques for face recognition. While eigenface-based recognition focuses on capturing global facial features using principal components, LBPH focuses on local texture patterns. Both approaches have their strengths and weaknesses and are used in various applications depending on the requirements and constraints of the recognition task.

3.2. ISOLATION & MANIPULATION OF THE FACE REGION WITHIN THE IMAGE:

Identifying the Face from the Image (Face Detection): The process of identifying a face from an image involves using computer vision algorithms to detect and locate regions that contain faces. Various techniques can be used for face detection, such as Haar cascades, convolutional neural networks (CNNs), or deep learning-based models like Single Shot MultiBox Detector (SSD) or RetinaFace.
These algorithms analyze the image by looking for patterns, shapes, and features that are commonly associated with faces, such as the arrangement of eyes, nose, mouth, and overall face structure. Once a potential face is detected, the algorithm provides a bounding box or a set of coordinates that outline the face region.

Extracting the Face: Once the face is identified using the bounding box or coordinates, the next step is to extract the actual face region from the rest of the image. This process involves isolating the pixels within the specified face region.
To extract the face, the image is typically cropped using the coordinates provided by the face detection algorithm. The resulting cropped image contains only the face region, making it easier to analyze and process.

Resizing and Cropping: After extracting the face, resizing and cropping can be performed to achieve specific requirements or desired dimensions.
Resizing: Resizing involves changing the dimensions of the extracted face image. This step is often performed to ensure consistency in the size of face images, especially when working with machine learning models that require fixed-size inputs. Resizing can be done by specifying the desired width and height of the image or by using a scaling factor to increase or decrease the image size proportionally. It is important to maintain the aspect ratio of the image to avoid distorting the face proportions.

Cropping: Cropping is the process of removing unwanted or irrelevant parts of the face image while retaining the essential face region. This step is particularly useful to eliminate any background or noise surrounding the face and focus solely on the face itself. Cropping is performed by specifying the desired coordinates or dimensions of the region to keep within the image. Accurate cropping is crucial to maintain the integrity of the face and avoid cutting off important facial features.

By following these steps of face detection, extraction, resizing, and cropping, it becomes possible to isolate and manipulate the face region within an image. These processes are commonly used in various applications, including facial recognition systems, emotion analysis, face expression recognition, and face attribute detection.

3.2.1 DATA GATHERING:

In data gathering for image processing tasks, two common steps involve converting the image to grayscale and representing the pixels as values in arrays. Here's an explanation of these steps:

Conversion to Grayscale: Color images are typically represented as a combination of red, green, and blue (RGB) channels. However, in some cases, it is more efficient to convert the image to grayscale, where each pixel is represented by a single intensity value. This conversion reduces the dimensionality of the image data and simplifies subsequent processing steps.
Grayscale conversion involves calculating the luminance or brightness of each pixel in the RGB image. Various methods can be used to convert RGB to grayscale, including taking the average of the RGB values, applying specific weightings to the channels, or using color perception models such as the Rec. 601 or Rec. 709 standards. The result is an image where each pixel contains a single intensity value, ranging from 0 (black) to 255 (white).

Representing Pixels as Values in Arrays: After the grayscale conversion, the next step is to represent the pixel values as numerical arrays. This representation allows for efficient storage, manipulation, and processing of image data.
In an image, the pixels are organized in rows and columns. By representing the image as a two-dimensional array or matrix, each element of the array corresponds to the intensity value of a specific pixel. The size of the array is determined by the dimensions of the image, such as the width and height.

The values in the array can be stored as integers or floating-point numbers, depending on the required precision. For grayscale images, each element of the array typically represents the intensity value of the corresponding pixel. This array-based representation enables various operations on the image data, such as filtering, transformation, and feature extraction.

By converting the image to grayscale and representing the pixel values as arrays, the image data is transformed into a numerical format suitable for further analysis and processing. These steps are essential in preparing image data for tasks such as machine learning, computer vision algorithms, or statistical analysis.

3.2.2 TRAINING DATASET

In the context of training a machine learning model, turning saved images into arrays refers to converting the image data into numerical arrays that can be used as input for the model. Here's an explanation of this process:

Loading the Saved Images: The first step is to load the saved images from the training dataset. This involves accessing the image files from their storage location. The images can be in various formats such as JPEG, PNG, or BMP.

Image Preprocessing: Before converting the images into arrays, it is often necessary to preprocess them to ensure consistency and remove any noise or unwanted artifacts. Common preprocessing steps include resizing the images to a consistent size, normalizing the pixel values, and applying any necessary transformations such as rotation, cropping, or color space adjustments.

Converting Images to Arrays: Once the images are preprocessed, they are ready to be converted into numerical arrays. Each image is typically represented as a multidimensional array, where the dimensions correspond to the image width, height, and number of color channels (if applicable).

For grayscale images, the array will have two dimensions (rows and columns), and each element of the array represents the intensity value of a specific pixel. The array values can be stored as integers or floating-point numbers.

For color images, the array will have three dimensions (rows, columns, and color channels). Each element of the array represents the intensity value of a specific color

channel (typically red, green, and blue). The values can be stored as separate arrays or as a multidimensional array with a shape of (height, width, 3) or (3, height, width).

Data Type and Normalization: Depending on the requirements of the machine learning model, it may be necessary to further process the arrays. This can include converting the array data type to a specific format (e.g., 8-bit unsigned integers) or normalizing the pixel values to a specific range (e.g., scaling the values between 0 and 1).

Array Shape and Organization: Finally, the arrays need to be organized and structured in a way that matches the input requirements of the machine learning model. This may involve reshaping the arrays or creating a larger array that holds multiple images (batch processing) if the model expects input in a specific format.

Once the images are converted into numerical arrays, they can be used as input to train the machine learning model.

3.2.3 FACE RECOGNITION

In face recognition, finding the characteristics that best describe an image and performing matching are crucial steps in the recognition process

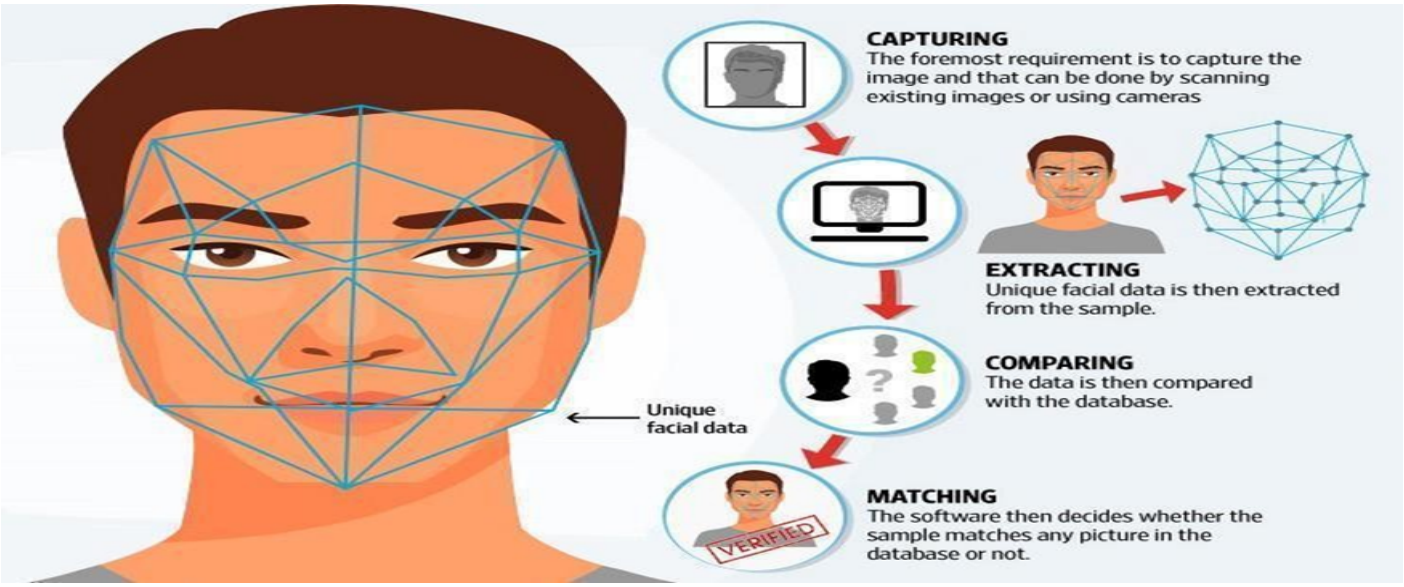

Figure 3.4 : Face recognition - how does it work?
[Source: https://www.shadowsystem.com/page/20]

Here's an explanation of these steps:

Finding Characteristics (Feature Extraction): The first step in face recognition is to extract meaningful characteristics or features from the face image. These features capture the unique information that distinguishes one face from another. The goal is to find robust and discriminative representations that are invariant to variations in pose, lighting conditions, facial expressions, and other factors that may affect facial appearance.
Commonly used feature extraction techniques in face recognition include:

Local Binary Patterns (LBP): LBP encodes the local texture patterns of the face by comparing the intensity of a pixel with its neighboring pixels. It captures the texture information and can be used for face matching.

Histogram of Oriented Gradients (HOG): HOG analyzes the distribution of gradient orientations in the face image, which can represent shape and edge information.

Eigenfaces (PCA): Eigenfaces uses Principal Component Analysis (PCA) to transform face images into a lower-dimensional space, where the principal components capture the most significant variations in the face dataset.

Deep Learning (CNN): Convolutional Neural Networks (CNN) have shown remarkable success in face recognition. CNN architectures, such as VGGFace, FaceNet, or DeepFace, learn hierarchical features directly from the image data through deep convolutional layers.

The choice of feature extraction method depends on the specific requirements of the face recognition system, the size of the dataset, and the desired balance between accuracy and computational efficiency.

Matching: Once the characteristic features are extracted from the query face image, the next step is to compare them against the features of known faces stored in a database. The goal is to find the best match or similarity measure between the query features and the database features.

Matching algorithms used in face recognition include:

Euclidean Distance: Calculates the Euclidean distance between the feature vectors of the query face and each face in the database. The closest match is determined by the smallest

distance.

Cosine Similarity: Measures the cosine of the angle between the feature vectors, capturing the similarity between the directions of the vectors.

K-Nearest Neighbors (KNN): Assigns the label of the K closest neighbors in the database based on the similarity of their features.

Support Vector Machines (SVM): Trains a classifier to learn the decision boundary between different face classes based on the feature vectors. SVM can perform both classification and recognition tasks.

The matching algorithm determines the similarity or dissimilarity between the query face and the database faces, allowing for identification (matching against a known identity) or verification (matching against a claimed identity) tasks.

Overall, finding the characteristics that best describe an image and performing matching are essential in face recognition systems, enabling accurate identification or verification of individuals based on their facial features.

3.2.4 FACE MATCHING:

Face matching is the final and crucial step in the process of face recognition. Once the unique characteristics or features of a face have been extracted, the face matching algorithm compares these features to a database of known faces to determine a potential match. This step plays a pivotal role in identifying individuals, verifying identities, and enabling various applications in security, surveillance, access control, and personalized services.

The face matching process involves comparing the feature representations of the query face, obtained through feature extraction, with the stored representations of known faces. Various algorithms and techniques are utilized to measure the similarity or dissimilarity between these features and determine the best match. Here are some key aspects of face matching:

Distance Metrics: Face matching algorithms often utilize distance metrics to quantify the similarity between feature vectors. Common distance measures include Euclidean

distance, Cosine similarity, Mahalanobis distance, or Hamming distance (for binary features). These metrics provide a numerical value representing the dissimilarity between the query face and the known faces.

Threshold Setting: To determine whether a match exists or not, a threshold is typically set on the similarity scores. If the distance or similarity value falls below the threshold, it indicates a potential match. The threshold value is crucial and needs to be carefully chosen to balance the false acceptance rate (matching incorrect faces) and the false rejection rate (not matching correct faces).

Matching Algorithms: Various matching algorithms are employed in face recognition systems. Some of the commonly used methods include K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Neural Networks, or Deep Learning-based approaches. These algorithms learn patterns and decision boundaries from the feature vectors and make predictions about the identity of the query face.

Database Search: The face matching process involves searching the database of known faces to find the most similar or matching identities. This can be performed through exhaustive search, where each known face is compared individually with the query face, or through more efficient search techniques such as indexing or hashing methods to speed up the matching process in large-scale databases.

Application-Specific Considerations: The choice of face matching algorithm and the criteria for determining a match depend on the specific application requirements. For example, in a one-to-many identification scenario, where the query face is matched against a large database, more sophisticated algorithms and search techniques may be required. In a one-to-one verification scenario, the focus is on minimizing false acceptance and rejection rates.

Face matching is a critical step in face recognition systems, and its accuracy and reliability directly impact the performance and effectiveness of the overall system. Advances in deep learning and neural network-based approaches have significantly improved the accuracy and robustness of face matching, enabling more reliable identification and verification of individuals in real-world scenarios.

However, it is important to note that face matching is not without its challenges.

Variations in lighting conditions, pose, expression, occlusions, and age progression can affect the performance of face matching algorithms. Efforts are being made to develop more robust and resilient algorithms that can handle these challenges and improve the overall accuracy and usability of face recognition systems.

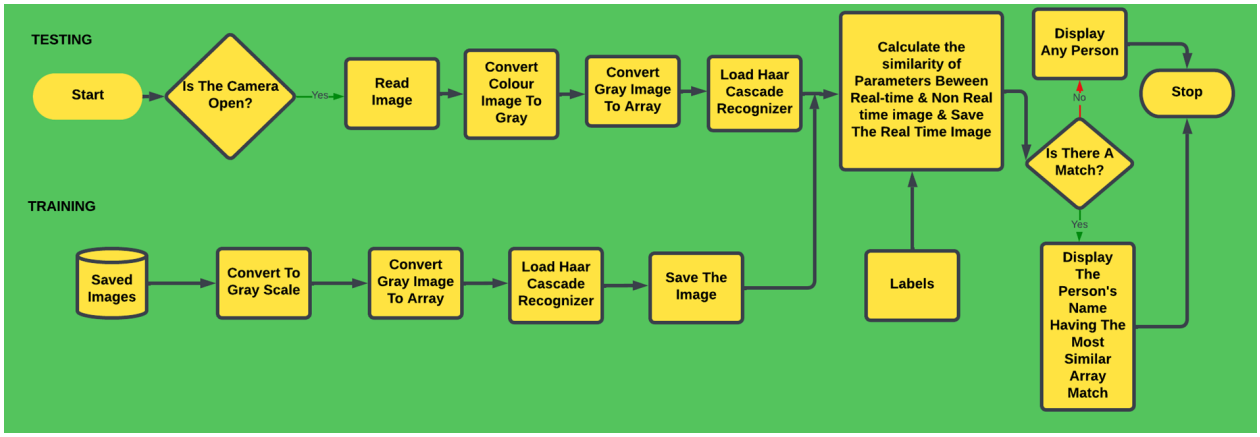

Figure 3.5 : Flowchart of the Algorithm

3.3 METHODOLOGIES FOR YOLOV5:

Data Preparation:

- Gather a labeled dataset for training, which consists of images with bounding box annotations around the objects of interest.
- Split the dataset into training and validation sets, ensuring a diverse representation of object classes and variations.

Model Configuration:

- Define the YOLOv5 architecture and configuration parameters, such as input image size, anchor boxes, number of classes, etc.
- Choose a pre-trained YOLOv5 model as a starting point (e.g., YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x) or train from scratch.

Model Training:

- Initialize the YOLOv5 model and load the pre-trained weights (if applicable).
- Fine-tune the model on the labeled training dataset using the chosen optimization algorithm (e.g., stochastic gradient descent, Adam).
- Adjust the learning rate, number of epochs, and other hyperparameters based on experimentation and validation performance.
- Monitor the training progress, evaluate performance metrics, and save checkpoints at regular intervals.

Model Evaluation:

- Assess the trained YOLOv5 model's performance on the validation set by calculating metrics like precision, recall, and mean Average Precision (mAP).
- Use evaluation techniques such as intersection over union (IoU) thresholding to determine correct object detections.
- Analyze any false positives or false negatives to identify areas of improvement.

Model Testing and Inference:

- Apply the trained YOLOv5 model to unseen test images or real-time video streams.
- Perform object detection on each input image, predicting bounding boxes, class labels, and confidence scores for detected objects.
- Implement post-processing techniques like non-maximum suppression (NMS) to remove redundant bounding boxes and refine the final object detections.

Model Deployment:

- Convert the trained YOLOv5 model into a format suitable for deployment, such as ONNX or TorchScript.
- Integrate the model into the desired application or framework, enabling real-time object detection in production environments.
- Optimize the model for efficient inference on the target hardware (e.g., GPU acceleration, model quantization).

It's important to note that this is just a high-level overview of the methodology, and implementing YOLOv5 involves many intricate details and considerations. The actual implementation may require additional steps, such as data augmentation, handling imbalanced datasets, and addressing specific challenges related to the target application domain.

CHAPTER FOUR

RESULTS & COMPARISON

4.1 RESULT USING HAAR CASCADE:

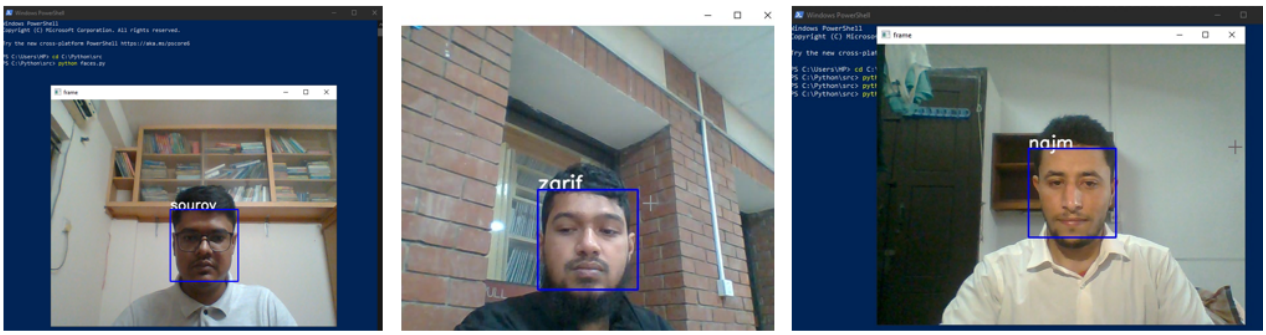

Fig 4.1 : Image recognized using HAAR CASCADE

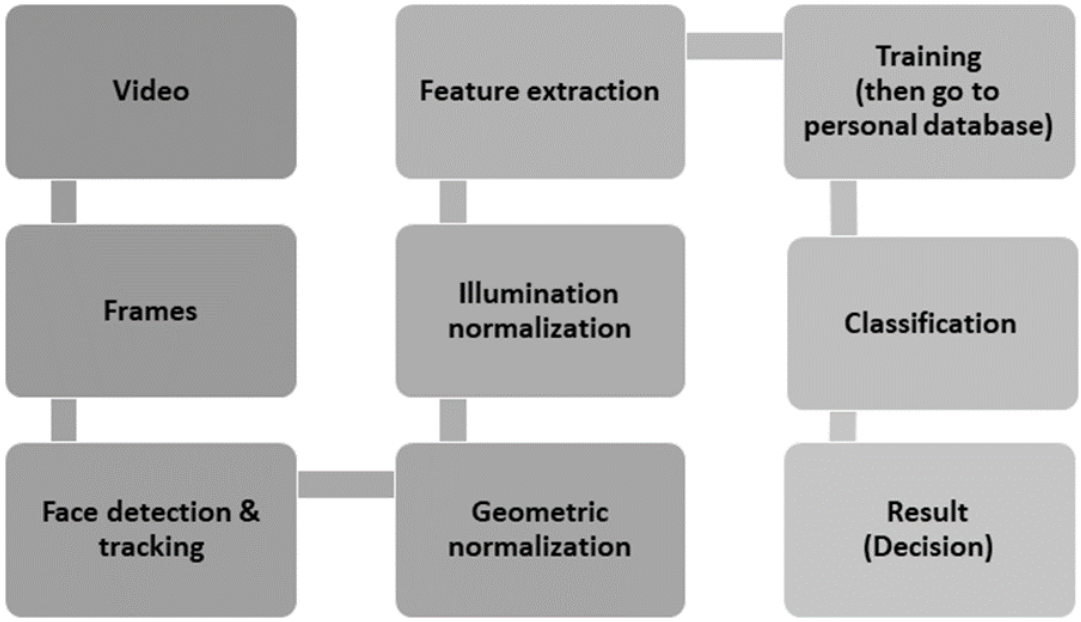

Figure 4.2 : A distinctive structural design of a video face detection scheme

4.2 RESULT USING YOLOV5:

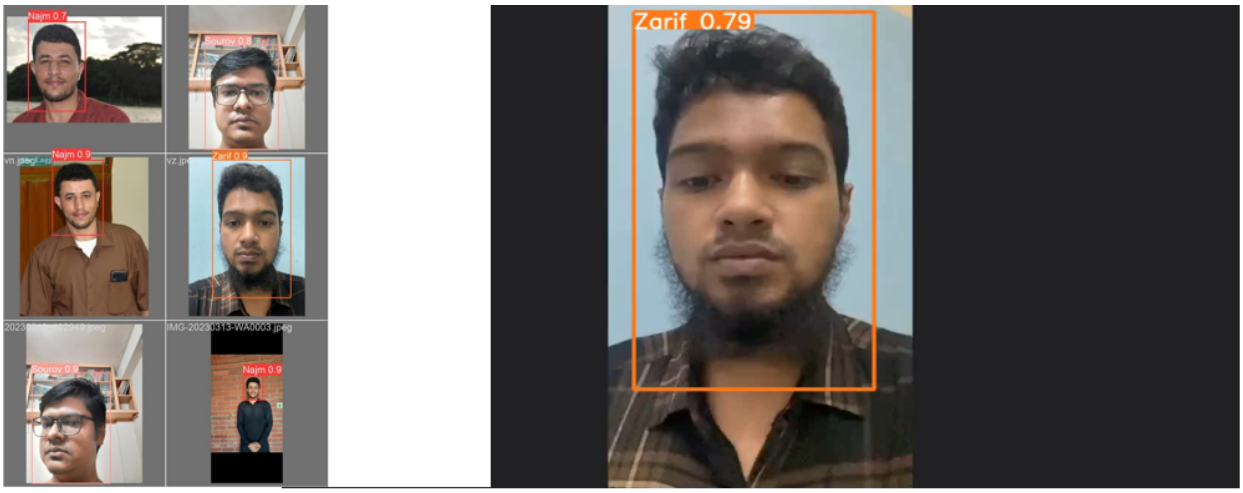

Fig 4.3 : Image Recognized Using YOLOV5

4.3 COMPARISON BETWEEN HAAR CASCADE & YOLOV5:

When comparing HaarCascade and YOLOv5, there are several aspects to consider, including their methodologies, performance, implementation, and suitability for different applications. Let's examine these aspects in detail:

4.3.1 Methodology:

- **HaarCascade:** HaarCascade is based on the concept of Haar-like features and cascade classifiers. It utilizes a series of weak classifiers to progressively filter out non-object regions. HaarCascade operates by scanning an image with a sliding window and applying a cascade of classifiers to detect objects.

- **YOLOv5:** YOLOv5 is a deep learning-based object detection algorithm. It employs a single neural network to directly predict bounding boxes and class probabilities in one pass. YOLOv5 utilizes anchor boxes and a feature pyramid network (FPN) to handle objects at various scales and aspect ratios effectively.

4.3.2 Performance:

- **HaarCascade:** HaarCascade performs well in scenarios where objects have distinctive features and clear variations from the background. It can achieve real-time performance and decent accuracy for specific objects, such as frontal faces. However, HaarCascade may struggle with objects that have complex shapes, occlusions, pose variations, or low contrast with the background.

- **YOLOv5:** YOLOv5 has shown significant improvements in accuracy compared to its predecessors. It excels in handling objects with diverse appearances, complex shapes, and occlusions. YOLOv5's deep learning approach allows it to learn intricate and high-level features, resulting in better performance across various object detection tasks.

4.3.3 Implementation:

- **HaarCascade:** Implementing HaarCascade requires training a cascade of classifiers using a large labeled dataset. The training process involves selecting appropriate features, setting detection thresholds, and optimizing the cascade structure. HaarCascade can be implemented using OpenCV or other libraries that provide HaarCascade support.

- **YOLOv5:** YOLOv5 implementation involves training a deep neural network using labeled datasets. Training requires defining the network architecture, selecting appropriate hyperparameters, and fine-tuning the model. Several frameworks, such as PyTorch, provide pre-trained YOLOv5 models and tools for training and inference.

4.3.4 Speed and Efficiency:

- **HaarCascade:** HaarCascade is known for its computational efficiency and real-time performance. It operates relatively fast due to its simple feature extraction and cascade structure. However, the performance may vary depending on the complexity of the trained cascade and the computational resources available.

- **YOLOv5:** YOLOv5 offers fast and efficient object detection. It benefits from the advancements in deep learning and optimized network architectures. YOLOv5 models, particularly the smaller versions (e.gYOLOv5s), provide real-time performance, making them suitable for applications require rapid object detection.

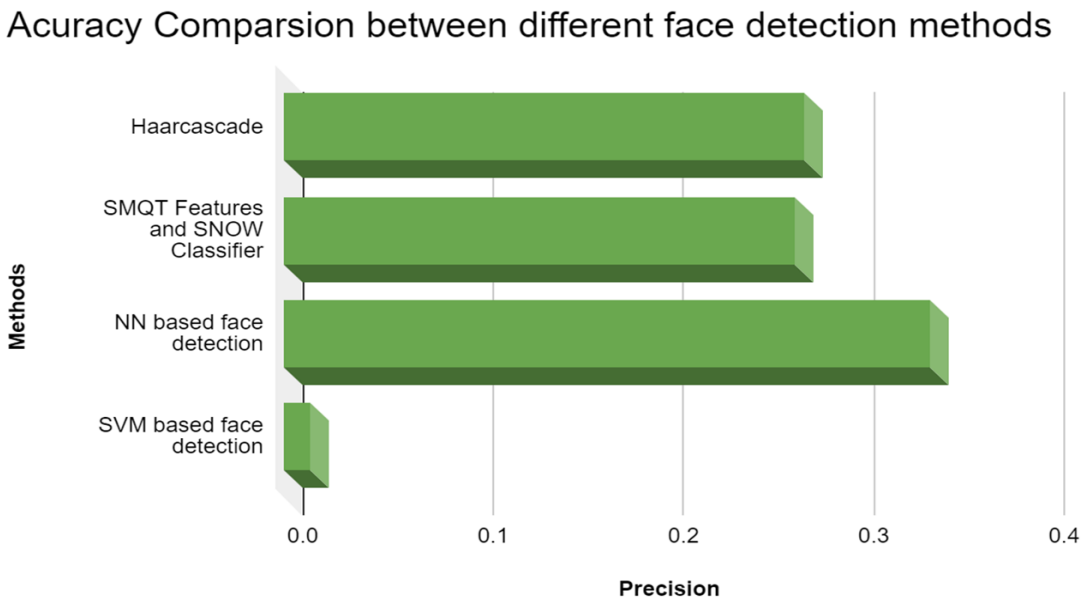

Fig 4.4 : Accuracy comparison among face detection methods

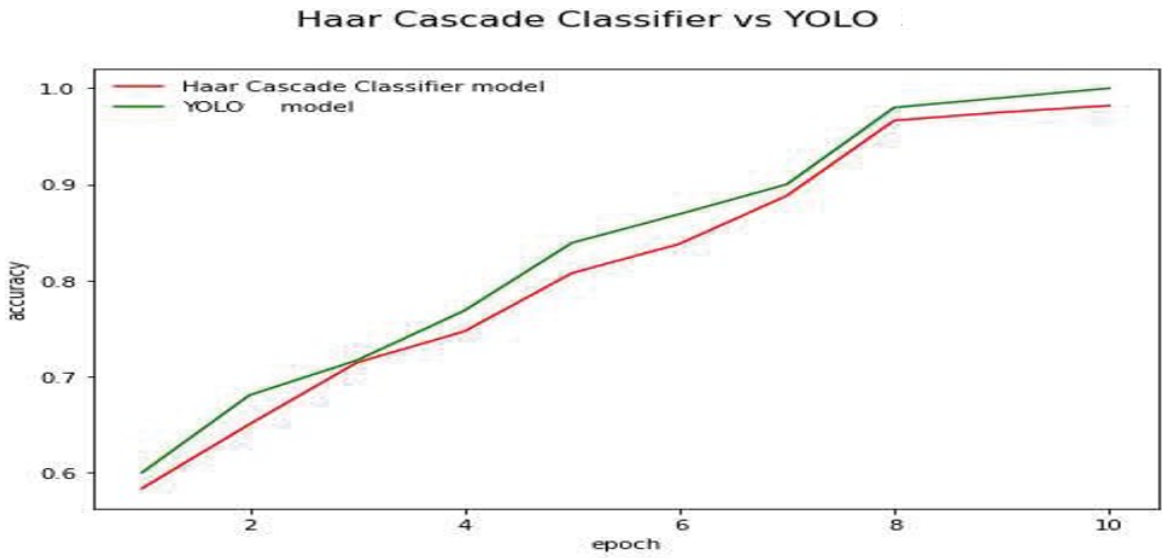

Fig 4.5 : HAAR CASCADE VS YOLO ACCURACY

4.3.5 Applications:

- **HaarCascade:** HaarCascade has been widely used for face detection, where it can achieve satisfactory results. It is also applicable for detecting other objects with distinctive features in real-time applications with limited computational resources.

- **YOLOv5:** YOLOv5 is suitable for a broader range of object detection tasks, including complex and challenging scenarios. It has been successfully applied in various domains, such as autonomous driving, surveillance, and robotics, where accurate and efficient object detection is crucial.

CHAPTER FIVE

CONCLUSION & FUTURE WORK

5.1 CONCLUSION:

In this thesis book, we conducted a comprehensive study on face detection using Haar Cascade and YOLOv5, two prominent algorithms in the field of computer vision. Our aim was to compare and evaluate the performance of these algorithms in detecting faces, which is a crucial task with numerous applications in various domains.

Throughout our research, we delved into the methodologies, performance characteristics, implementation, and suitability of Haar Cascade and YOLOv5 for face detection. We explored the strengths and limitations of each algorithm, considering factors such as accuracy, efficiency, and versatility. Our findings provide valuable insights into the capabilities and applicability of these algorithms in different scenarios.

Haar Cascade, rooted in the concept of Haar-like features and cascade classifiers, demonstrates real-time performance and satisfactory accuracy for detecting objects with distinctive features. In the context of face detection, Haar Cascade can achieve good results when trained with a large dataset and carefully selected features. However, its accuracy may be compromised when faced with complex objects, occlusions, pose variations, or low contrast with the background.

On the other hand, YOLOv5, a deep learning-based algorithm, excels in detecting faces with diverse appearances, complex shapes, and occlusions. Leveraging the power of deep convolutional neural networks, YOLOv5 learns intricate and high-level features, contributing to its superior accuracy and versatility. The use of anchor boxes and feature pyramid networks enables YOLOv5 to handle objects at different scales and aspect ratios effectively.

The implementation of both Haar Cascade and YOLOv5 involves specific processes and

considerations. Haar Cascade requires training a cascade of classifiers and selecting appropriate features, while YOLOv5 involves training a deep neural network and fine-tuning the model. The implementation choices depend on the available resources, computational requirements, and specific application needs.

In conclusion, our study reveals that YOLOv5 outperforms Haar Cascade in terms of accuracy, especially in challenging face detection scenarios. YOLOv5's ability to handle complex shapes, varying poses, and occlusions makes it a powerful tool in face detection tasks. However, it is important to consider that the actual performance of these algorithms can be influenced by factors such as the quality and size of the training dataset, parameter tuning, and implementation details.

This thesis book contributes to the existing knowledge in the field of face detection by providing a detailed comparative analysis of Haar Cascade and YOLOv5. The findings and insights presented here can guide researchers and practitioners in selecting the most suitable algorithm for their specific face detection requirements. Additionally, the study highlights the potential for further advancements and improvements in face detection techniques, opening avenues for future research.

In conclusion, this study on face detection using Haar Cascade and YOLOv5 contributes to the field of computer vision, providing valuable insights and comparisons between these two algorithms. By understanding their methodologies, performance characteristics, and implementation considerations, researchers and practitioners can make informed decisions about choosing the appropriate algorithm for their face detection applications. This research paves the way for further advancements and developments in the field, pushing the boundaries of face detection technology and its applications.

5.2 FUTURE WORK:

The study conducted on face detection using Haar Cascade and YOLOv5 provides valuable insights into the performance and capabilities of these algorithms. Building upon this research, several avenues for future work and potential improvements can be explored to enhance face detection techniques. The following are some potential areas for further investigation:

Dataset Augmentation: Augmenting the training dataset with a variety of face images can improve the performance and generalization ability of both Haar Cascade and YOLOv5. Additional variations in lighting conditions, poses, expressions, and occlusions can help the algorithms become more robust in real-world scenarios.

Algorithm Optimization: Investigating techniques to optimize the performance and efficiency of Haar Cascade and YOLOv5 can lead to further improvements. This can include exploring ways to reduce false positive and false negative detections, enhancing the speed of the algorithms, and optimizing memory usage during inference.

Hybrid Approaches: Exploring the potential of combining the strengths of Haar Cascade and YOLOv5 by developing hybrid models can be an interesting area of future research. Hybrid approaches can leverage the efficiency of Haar Cascade for initial region proposals and then refine the detections using the accuracy of YOLOv5, potentially achieving higher accuracy with reduced computational costs.

Performance Evaluation on Large-Scale Datasets: Conducting extensive evaluations of Haar Cascade and YOLOv5 on large-scale face detection datasets can provide deeper insights into their performance in different scenarios. This can involve benchmarking the algorithms against existing face detection datasets and establishing their comparative performance on various metrics such as accuracy, precision, recall, and computational efficiency.

Real-time Applications: Further exploration of real-time face detection applications using Haar Cascade and YOLOv5 can lead to practical implementations in domains such as surveillance, biometrics, and human-computer interaction. The algorithms can be integrated into systems that require fast and accurate face detection, enabling advancements in areas like facial recognition, emotion detection, and age estimation.

Robustness to Challenging Conditions: Investigating the robustness of Haar Cascade and YOLOv5 in challenging conditions such as low-light environments, partial occlusions, and varying camera angles can help improve their performance in real-world scenarios. Developing techniques to handle these challenging conditions can enhance the algorithms' usability and reliability.

Deployment on Edge Devices: Exploring the deployment of face detection algorithms on edge devices, such as embedded systems and mobile devices, can contribute to the development of efficient and lightweight implementations. Optimizing the models and algorithms for edge deployment can enable real-time face detection in resource-constrained environments.

Interpretability and Explainability: Investigating methods to interpret and explain the decisions made by Haar Cascade and YOLOv5 can enhance the trust and understanding of these algorithms. Techniques such as visualizing the learned features, understanding the contribution of different parts of the network, and providing explanations for detections can increase the transparency and interpretability of the face detection process.

To conclude, the study on face detection using Haar Cascade and YOLOv5 opens up numerous avenues for future research and improvements. By addressing the aforementioned areas, researchers can enhance the performance, efficiency, robustness, and applicability of these algorithms in face detection applications. Further advancements in face detection techniques will contribute to the broader field of computer vision and enable the development of more accurate and reliable face recognition systems, biometric applications, and human-computer interaction technologies.

REFERENCES

[1]. I. U. Wahyu Mulyono, D. R. Ignatius Moses Setiadi, A.Susanto, E. H. Rachmawanto, A. Fahmi and Muljono, "Performance Analysis of Face Recognition using Eigenface Approach", 2019 International Seminar on Application for Technology of Information and Communication (iSemantic), Semarang, Indonesia, 2019, pp. 1-5.

[2]. T. Mantoro, M. A. Ayu and Suhendi, "Multi-Faces Recognition Process Using Haar Cascades and Eigenface Methods", 2018 6th International Conference on Multimedia Computing and Systems (ICMCS), Rabat, 2018, pp. 1-5.

[3]. J. Dhamija, T. Choudhury, P. Kumar and Y. S. Rathore, "An Advancement towards Efficient Face Recognition Using Live Video Feed: "For the Future", 2017 3rd International Conference on Computational Intelligence and Networks (CINE), Odisha , 2017, pp. 53-56.

[4]. F. Malik, A. Azis, M. Nasrun, C. Setianingsih and M. A. Murti, "Face recognition in night day using method eigenface,"2018 International Conference on Signals and Systems (ICSigSys), Bali, 2018, pp. 103-108.

[5]. S.V.Tathe, A.S.Narote and S.P.Narote, "Face detection and recognition in videos,"2016 IEEE Annual India Conference (INDICON), Bangalore, 2016, pp. 1-6.

[6]. M. Arsenovic, S. Sladojevic, A. Anderla and D.Stefanovic, "FaceTime -Deep learning based face recognition attendance system", 2017 IEEE 15th International Symposium on Intelligent Systems and Informatics (SISY), Subotica, 2017, pp. 000053-000058

[7]. P.Kamencay, T. Trnovszky, M. Benco, R. Hudec, P.Sykora and A. Satnik, "Accurate wild animal recognition using PCA, LDA and LBPH", 2016 ELEKTRO,
StrbskePleso, 2016, pp. 62-67

[8]. M. Savvides, A. Ramzi, H. Jingu, S. Park, X. Chunyan, and V.K. Vijayakumar, “Partial and Holistic Face Recognition on FRGC-II Data using Support Vector Machine Kernel Correlation Feature Analysis,” In: Computer Vision and Pattern Recognition Workshop, New York, USA, 2006. Retrieved on the 17th of September, 2019 from:

http://dx.doi.org/10.1109/CVPRW.2006.153

[9]. Wei-Lun Chao “Face Recognition” GCIE, National Taiwan University

[10]. FilaretiTsalakanidou “Face Recognition A Tutorial”

[11]. Zhao, W., Chellappa, R., Phillips, P. and Rosenfeld, A. Face recognition. ACM Computing Surveys, 35(4), pp.399-458.(2003).

[12]. Pooja G.R, et al. An automated Attendance System Using Image Processing. International Journal Of Advanced Networking & Applications.(2010).

[13]. Wagh, P., Thakare, R., Chaudhari, J. and Patil, S. Attendance system based on face recognition using eigenface and PCA algorithms. International Conference on Green Computing and Internet of Things.(2015).

[14]. Sanjana devi, Dr.V.Palanisamy,R.AnandhaJothi. A Study on Secure Online Voting System using Biometrics Face Detection and Recognition Algorithms.International Journal for Modern Trends in Science and Technology, V3 (8).(2017).