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Review on Face Detection Technology

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Abstract:- With the marvellous increase in video and image database there is an incredible need of automatic understanding and examination of information by the intelligent systems as manually it is getting to be plainly distant. Face plays a major role in social intercourse for conveying identity and feelings of a person. Human beings have not tremendous ability to identify different faces than machines. So, automatic face detection system plays an important role in face recognition, facial expression recognition, head-pose estimation, human– computer interaction etc. Face detection is a computer technology that determines the location and size of a human face in a digital image. Face detection has been a standout amongst topics in the computer vision literature.

Furthermore, the research paper explores the key components of face detection systems, including feature extraction, classification, and localization techniques. It delves into the technical aspects of popular algorithms such as Viola-Jones, Histogram of Oriented Gradients (HOG), and Convolutional Neural Networks (CNN), providing insights into their strengths and limitations.

Overall, this research paper provides a comprehensive exploration of face detection technology, its underlying algorithms, challenges, applications, and future prospects. It serves as a valuable resource for researchers, practitioners, and enthusiasts interested in understanding the advancements and potential of this rapidly evolving field.

keywords: Working Face Detection, Process Of Face Detection, , Techniques Of Face Detection.

I. INTRODUCTION

Face recognition and face prediction are important for face recognition. For example, when using security cameras for personal identification, a face of unknown size, position and shape must be detected. Face estimation after face detection is important for accurate face recognition because we can select the face image with the best orientation from the face images captured by multiple cameras. Many methods have been proposed for face recognition. One of them matches as face template image. However, the size and appearance of the face is limited due to the limited cost of specifying all dimensions of the image template. On the other hand, the tan technique can detect faces of any size and pose. Since it is difficult to detect a human face from skin colour, information such as head shape or hair colour is also used in this method. In addition, it should be ensured that the real face is in the detection area with the false rejection method. Methods of removing facial features such as pupils, nose, and mouth are considered to determine whether a human face is real.

A method based on facial geometric pattern is proposed for facial feature extraction.

II. LITERATURE SURVEY

Face detection is the process of detecting human faces in photos or videos. There are many applications in this project such as face recognition, video surveillance and social media. In recent years, face detection has received a lot of attention from computer scientists and many algorithms have been proposed to solve this problem.

Here is a brief description of some important functions in face detection:

1. Viola-Jones face detection algorithm: Viola-Jones algorithm is one of the most famous and widely used face detection algorithms.

It uses Haar-like descriptors and a set of classifiers to detect faces in images. The algorithm is fast and efficient and has been used in many applications.

2. Convolutional Neural Networks (CNN): CNNs have shown great potential in face detection. Researchers have developed CNN models such as R-CNN, Fast R-CNN and Faster R-CNN that can detect faces with high accuracy.

This model uses a combination of convolutional and full layers to extract features and make predictions.

3. Histogram of Directed Gradints (HOG): The HOG algorithm is another popular face detection method. It works by calculating the gradient direction and size of the image pixels and then creating a histogram of those results. The agent is then trained to identify faces based on histograms.

4. Deep learning: Recently, researchers developed deep learning-based face detection. These methods, such as YOLO (You Look Alone) and SSD (One Shot Detector), use deep neural networks to detect faces in real time. This model can identify faces with high accuracy and shows great potential in practical applications.

5. Cascading Classifier: The cascading classifier algorithm is another popular face detection method. The algorithm works using several levels of classifiers, each of which filters out non-face areas of the image. The algorithm calculates the results and has been shown to achieve high results.

In summary, face recognition is an important and frequently researched area in computer vision. Many algorithms have been proposed, each with its own advantages and limitations.

With the advent of deep learning, we can expect to see further progress in this area with new techniques that will improve the accuracy and performance of face detection.

History of Facial Recognition

The dawn of Facial Recognition – 1960s

The early pioneers of facial recognition were Woody Bledsoe, Helen Chen Wolfe, and Charles Beeson. In 1964 and 1965, Bledsoe, along with Wolf and Bisson, began using computers to recognize faces. Because funding for Project came from an anonymous intelligence agency, much of his work has not been published. But later it turned out that his early work involved marking various "regions" of the face, such as the eyes, mouth and other things. These are numbers translated by a computer to compensate for the change. The distance between critical areas was also determined and compared between images to determine identity.

Bledsoe, Wolf, and Bisson's first steps towards facial recognition were heavily influenced by the technology of the time but were nevertheless an important first step in proving that facial recognition was biometrically valid.

Advancing the accuracy of Facial Recognition – 1970s

From Bledsoe's original work, the razor was taken by Goldstein, Harmon, and Lesk in the 1970s and expanded their work to include 21 unique characters for automatic recognition, including hair colour and thick lips. While accuracy has improved, the

requires manual calculation of metrics and functions, which has proven to be less powerful but still represents an advance on Bledsoe's RAND tablet machine.

Using linear algebra for Facial Recognition – 1980s/90s.

It wasn't until the 1980s that we saw further progress in the development of facial recognition software based on business biometric technology. In 1988, Sirovich and Kirby began applying linear algebra to the face recognition problem. A later system called.

Eigenface showed that the analysis of facial images could be easily improved. They were also able to show that less than a hundred values are required to correctly encode a static face. In 1991, Turk and Pentland discovered faces in images following the work of Sirovich and Kirby, which led to the earliest examples of facial recognition.

This major breakthrough was hindered by business and the environment but paved the way for future advances in facial recognition.

FERET Programme – 1990s/2000s

The US Defence Advanced Research Projects Agency (DARPA) and the National Institute of Standards and Technology (NIST) established the Facial Recognition Technology (FRET) program in the early 1990s to support the commercialization of the facial recognition technology business. This project involves creating a database of facial images. The test set included 2,413 static faces representing 856 people. It is hoped that the big data of image analysis for face recognition will lead to new changes and possibly make the face recognition system more powerful.

Face Recognition Vendor Tests – 2000s

The National Institute of Standards and Technology (NIST) launched the Face Seller Test (FRVT) in the early 2000s. FRVT, home of FERET, aims to provide the government with an independent assessment of the facial recognition business as well as technological standards. These measures are intended to provide law enforcement and the US government with the necessary information to determine the best way to use facial recognition technology.

Face Recognition Grand Challenge – 2006

The Facial Recognition Grand Challenge (FRGC) was launched in 2006 to support and develop facial recognition technology designed to complement the US government's existing facial recognition system. The FRGC measures the accuracy of existing face recognition algorithms. High resolution face images, 3D face scans and iris images were used in the experiment.

The results show that the new algorithm is 10 times more accurate than the 2002 facial recognition algorithm and 100 times more accurate than the 1995 facial recognition algorithm, demonstrating the advancement in face selling technology over the past decade.

Social Media – 2010-Current

In 2010, Facebook started using facial recognition to help identify potential faces in photos that Facebook users update daily. The show immediately sparked media controversy and sparked a spate of privacy-related comments. However, Facebook users in general don't seem to care about it. More than 350 million photos uploaded and tagged every day using facial recognition do not have any negative impact on the user's location or location.

iPhone X – 2017

Facial recognition has developed rapidly since 2010 and September 12-2017, marked another milestone in the integration of facial recognition into our daily lives. That day, Apple announced the iPhone X—the first iPhone owners could unlock with FaceID, Apple's commercial breakthrough in facial recognition.

III. WORKING OF FACE DETECTION USING ALGORITHMS

Face detection uses machine learning and techniques to extract faces from larger images; such images often contain many non-face objects such as buildings, landscapes, and many other objects.

Face detection algorithms usually start with finding one of the easiest facial features to detect, the eyes. Next, the algorithm will try to find the mouth, nose, eyebrows, and irises. After identifying facial features, the algorithm concludes that it subtracts the face, and then runs further tests to confirm that it's a real face. For algorithms to be as accurate as possible, they must learn to use large datasets containing hundreds of thousands of images.

Some of these images have faces, while others do not. The training process helps the algorithm determine which images contain faces and where the faces are located.

Major Algorithm Types - Machine Learning, Artificial Intelligence and Deep Learning.

Machine Learning (ML):

ML algorithms use statistics to find patterns in large amounts of data. This information can be text, numbers, images, clicks, etc. may contain.

Machine learning is the process behind many services today - voice assistants (Siri and Alexa), search engines (Google and Baidu) and recommendations (Spotify and Netflix).

Also, here are some machine learning algorithms that can be used for face detection:

3.1 Random Forest:

The Random Forest algorithm is a machine learning technique that can be used for many tasks, including face detection. Here's an explanation of how it works in terms of facial recognition:

Data Preparation: To train a random forest model for face detection, you need a dataset containing images with faces and descriptions that indicate the presence or absence of faces.

Feature Extraction: The first step is to extract the relevant features from the input image. These properties may include pixel values, texture information, image descriptions, or other properties that help distinguish faces from faces.

Building the Forest: A random forest consists of decision trees. Each decision tree is generated independently using a random subset of the training data and a random subset of the features. Randomness helps incorporate variation into the tree, reduces overfitting, and improves generalization.

Training Decision Trees: At each point of the decision tree, a feature is selected to classify data based on its ability to distinguish face and non-face patterns. The goal is to find the most distinctive features that can distinguish human faces from non-human faces. The separation process continues to repeat until a limit is reached (ie, the maximum depth or minimum number of samples at a point is reached).

Voting and Aggregation: During testing, the input image is passed through all the trees identified in the forest. Each tree independently votes as a separate decision whether it is a face or not. The final estimate is determined by counting the votes of all decision trees, usually by majority vote. If most of the voting trees are yes, detect the face.

Post-processing: After the face detection step, post processing techniques can be used to optimize the results. These techniques may include removing overlapping or misperceptions, adjusting bounding boxes, or applying additional filters based on size, shape, or other constraints.

Evaluation and Optimization: The performance of random forest models can be evaluated using metrics such as precision, recall, and F1 score. Additionally, you can optimize the model's hyperparameters, such as tree, maximum depth, or the number of features required in each bin, with methods such as competition or search grid. The

Random Forest algorithm can capture faces in high quality images by combining multiple decision trees and using their collective decisions. It is known for its robustness, scalability, and ability to manage high-dimensional feature space.

3.2Cascade Classifier:

The cascade classifier is a machine learning algorithm that uses the Haar cascade classifier method for face detection. It has several levels and each level has poor training to measure the face. Once detected, an advanced algorithm scans the image and uses all levels of classifiers. An image is defined as having a face if its area crosses all levels of individual objects.

The digit classifier algorithm popularized by Viola and Jones is a machine learning based on face detection. It is known for its efficiency and speed. Here's an explanation of how the Cascade Classifier algorithm works:

Haar-like Features: The cascading classifier algorithm relies on Haar-like features, which are simple filters applied to images. This feature captures differences in different regions of images, such as edges, corners, and textures.

Integral Image: A full image is calculated from the input image to speed up the calculations. Integral images allow a quick calculation of the sum of the pixel intensities in certain areas of the image.

AdaBoost Training: The cascading classifier algorithm uses the AdaBoost (Adaptive Boosting) algorithm to train robust classifiers. The training process involves selecting a set of positive (face) and negative (non-face) images from the field.

Feature Selection and Weak Classifiers: The algorithm looks for the most distinctive Haar-like feature that can distinguish faces from non-human faces during training. As a starting point for the computed feature area, a weak classifier is constructed for each selected feature, which classifies the image area as face or non-face.

Boosting: AdaBoost assigns weight to the training model and repeats the weak training model. At each iteration, the algorithm focuses on misclassified samples and adjusts weights to highlight unclassified samples. This iterative process is meant to improve the overall efficiency of the deployment.

Cascade Structure: Cascading classifiers use a cascading model with multiple levels. Each level has several weak classifiers. When detected, it is used as a cascade and evaluates a set of features at each stage and quickly rejects areas that are unlikely to be faces. This reduces calculations by allowing non-directional fields to be rejected.

Stage-wise Classification: Each stage of the cascade gradually increases the difficulty and lowers the quality. Fields that pass one classifier level move on to the next level for further evaluation. While non-face regions are discarded early in the process, potential face regions continue to be analysed in later stages.

False Positive Filtering: After the cascading model, post-processing steps can be used to reduce the error. This may include techniques such as maximum restraint to eliminate overlap or additional analysis to increase the potential of the face. The Cascading Classifier algorithm provides fast face detection using a set of classifiers to speed up non-face regions. It focuses on the effectiveness and speed of the work of sites that are likely to have a face.

3.3 The Viola-Jones algorithm:

Viola-Jones algorithm is one of the most widely used face detection algorithms. It is a machine learning-based algorithm introduced in 2001 by Paul Viola and Michael Jones. The Viola-Jones algorithm is a machine learning-based method that uses a simple set of Haar features and the AdaBoost classifier to recognize faces.

Here's a high-level overview of the process:

1. **Training Stage:**
   - **Positive Samples:** A set of positive samples, which are images containing faces, is used for training. These images are labelled to indicate the presence of a face.
   - **Negative Samples:** A set of negative samples, which are images without faces, is also required. These images should be representative of the background or non-face regions.
   - **Haar-like Features:** Haar-like features are rectangular filters that are applied at various locations and scales on the image. These features capture the contrast differences between different regions of the face.

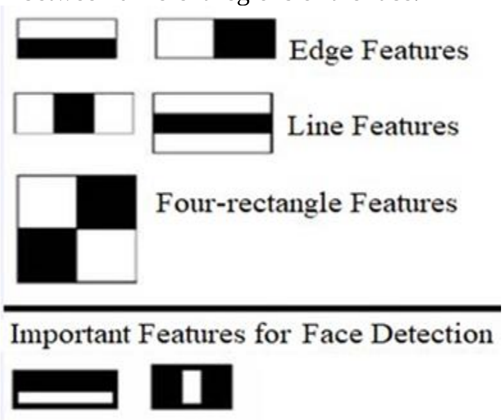

Fig 3.1 Haar like feature

   - **AdaBoost Training:** AdaBoost is a boosting algorithm that combines many weak classifiers (Haar-like features) into one strong classifier. During training, AdaBoost places more weight on unclassified patterns, allowing poor post-processing to pay more attention to these patterns.
   - **Cascade Training:** The Viola-Jones algorithm uses a set of classifiers for efficiency. The cascade consists of several stages, each of which has several weak classifiers. The levels are taught in order, with each level more difficult than the previous one. The purpose of the step is to quickly reject the free space at the

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first stage and reduce the cost of the necessary calculations at the next stage.

2. **Detection Stage:**
   - **Image Pyramid:** To detect faces at different scales, the input image is often scaled down into multiple image pyramids or layers.
   - **Sliding Window:** A sliding window is used to scan each image pyramid at different positions and scales. At each position, the Haar-like features are applied to the window to compute the feature values.
   - **Cascade** Classification**:** The cascade of classifiers is applied to each window. At each stage, if the window is rejected, it is immediately discarded. Only windows that pass the classifier at a certain stage move on to the next stage. This helps in quickly rejecting non-face regions.
   - **Non-Maximum Suppression:** After passing through all stages of the cascade, the remaining windows are potential face detections. However, there might be multiple detections for the same face. To remove duplicates, non-maximum suppression is applied, which keeps only the most confident face detection and suppresses overlapping detections.

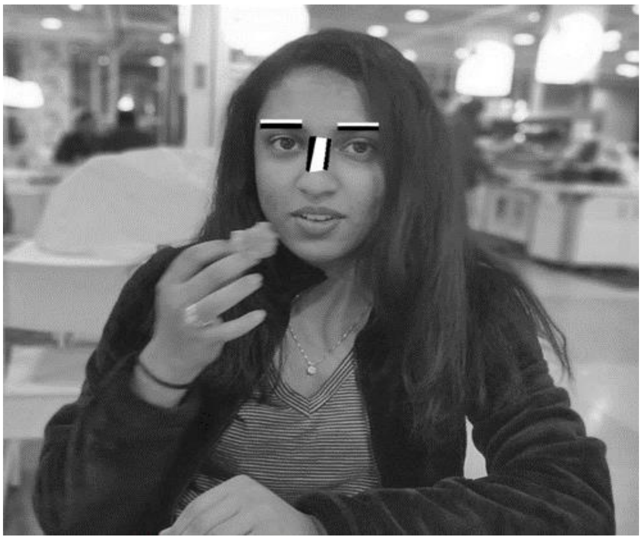

Fig 3.2 Detecting face using Viola-Jones algorithm example.

The Viola-Jones algorithm is known for its efficiency and has been widely used in real-time face detection applications. It offers a good balance between accuracy and speed, making it suitable for a range of face detection scenarios. Viola-Jones is designed for forward-facing use, so it's best to check the face looking straight ahead, not sideways, up or down. Before face detection, images are converted to grayscale as it is easier to process and requires less data to process.

3.4 Histogram of Oriented Gradients (HOG) :

The Histogram of Oriented Gradients (HOG) algorithm is a popular feature-based approach used for face detection.

Here's a step-by-step explanation of how HOG is used in face detection:

1. **Image Pre-processing:**
   - Grayscale Conversion: The input image is typically converted to grayscale to simplify further processing.
   - Image Normalization: The grayscale image is often normalized to enhance contrast and handle variations in lighting conditions.
2. **Gradient Calculation:**
   - Gradient Computation: The gradients (strength and direction) of image pixels are computed using methods like Sobel or Scharr operators. Gradients capture the local intensity variations in the image.
3. **Cell Formation:**
   - Image Division: The gradient image is divided into small rectangular cells. Each cell usually has a size of, for example, 8x8 pixels. The purpose of cell division is to capture local information about edge orientations and intensities.
4. **Histogram Calculation:**
   - Gradient Orientation Binning: Within each cell, the orientations of gradients are binned into orientation histograms. Typically, 9 or 12 orientation bins are used. The gradients are weighted by their magnitudes while filling the histograms.
5. **Block Normalization:**
   - Block Formation: Overlapping cells are grouped to form larger blocks, usually consisting of multiple cells. The blocks can be, for example, 2x2 or 3x3 cells in size.
   - Block Normalization: Within each block, the histograms of neighbouring cells are concatenated. Then, the histogram values are normalized to account for lighting variations and contrast differences in the image.
6. **Feature Extraction:**
   - Concatenation: The normalized histograms from all the blocks are concatenated to form a feature vector representation for the entire image.
   - Dimensionality Reduction: Techniques like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) can be applied to reduce the dimensionality of the feature vector.
7. **Training and Classification:**
   - Supervised Learning: The HOG features are typically used as input to a classifier, such as a Support Vector Machine (SVM) or a neural network. The classifier is trained using a

labelled dataset containing positive samples (faces) and negative samples (non-faces).

- Classification: During the testing phase, the trained classifier is applied to new images. The HOG features are extracted, and the classifier determines whether each region of the image contains a face or not.

The HOG algorithm effectively captures local edge and gradient information, making it robust to variations in face appearances. It is particularly suitable for face detection tasks due to its ability to handle complex backgrounds and lighting conditions.

For the time being, though, the technology's inadequacies and people's reliance on it means facial recognition still has much room to grow and improve.

IV. METHODS AND TECHNIQUES

4.1 Methods: Methods that are commonly used in facial detection:

I. Feature-based method

This method finds faces by extracting features. First, train the algorithm as a classifier.

It is then used to determine the face area from the non-face area. The general idea is to go beyond people's curiosity about faces. When the process is based on the processing of images of many faces, it achieves 94 percent success.

Summary: Features such as a person's nose or eyes are used to detect a face.

II. Knowledge-based methods

Knowledge-based algorithms are based on methods based on human experience. For example, "right" might include the relative position of the eyes, nose, and mouth of the face. However, this approach poses a major challenge: it is difficult to establish the necessary rules. If the rules are too broad, there may be more flaws - on the contrary, if the rules are too strict, the system will create more flaws.

Summary: A face is determined by whether it conforms to the rules drawn by hand.

III. Template matching method

Parametric or predefined templates are used to find or capture the face using template matching algorithms - the system measures the correlation between the input image and the template. For example, the model can show the human face divided into nose, mouth, eyes, and facial features. In addition, the face model can only have edges and use the edge detection method - this method is easy to use, but not sufficient for face detection.

Summary: Comparing images with previously stored canonical face models.

IV. Appearance-Based Methods

Bell-based algorithms use a set of training images to "learn" faces. Generally, this approach relies on machine learning and statistical analysis to identify facial expressions. The resulting process is generally considered more powerful than the aforementioned process.

Summary: The provides statistical analysis and machine learning for face image recognition.

4.2 Techniques:

Here are some more **specific face detection techniques**:

1. **Scale-Invariant Feature Transform (SIFT)**: SIFT is a feature-based approach that extracts distinctive features from an image and matches them to a database of features. It is invariant to scale, rotation, and illumination changes, making it effective for face detection.

2. **Speeded Up Robust Features (SURF):** SURF is similar to SIFT but is faster and more robust to changes in lighting and perspective. It can be used for real-time face detection in video streams.

3. **Local Binary Patterns (LBP):** LBP is a texture-based approach that encodes the local structure of an image using binary patterns. It is commonly used for face recognition but can also be used for face detection.

4. **Deep Convolutional Activation Features (DeCAF):** DeCAF is a deep learning approach that uses pre-trained convolutional neural networks to extract features from an image. It has been shown to outperform other state-of-the-art face detection methods.

5. **Joint Cascade Face Detection and Alignment (JDA):** JDA is a multi-task learning approach that jointly optimizes face detection and alignment. It is designed to handle variations in pose, lighting, and expression, making it effective for real-world face detection applications.

V. PROCESS OF FACE DETECTION

Face detection is a computational technique used to detect and recognize human faces in images or videos. This process includes several steps, including image acquisition, pre-processing, extraction, classification, and postprocessing. The first step in the process is to take a photo or video of the face to be seen. Images are then processed to improve quality and improve detection aids. Extract features from images that help distinguish human faces from other objects.

A classification algorithm is used to determine whether the image contains a face. Finally, post-processing techniques can be used to improve results and eliminate imperfections or imperfections. Facial recognition in general, security, entertainment, human-computer interaction, etc. It is an important technology with many applications in fields.

Here is a more detailed explanation of the face detection process:

5.1 Capturing: In the capture step, a photo or video frame is transmitted using the camera or by uploading a pre-existing image to the system. The captured image must have sufficient resolution and illumination to accurately identify the face. It is important to ensure that the face is well positioned and visible in the captured image.

1. **Pre-processing:** Pre-processing is applied to the captured image before face detection is performed. These techniques aim to improve image quality and eliminate noise, thus increasing the accuracy of the next step. Pre-processing steps include converting the image to a standard size, converting it to grayscale, and applying filters such as Gaussian blur or histogram equalization to improve contrast and reduce image distortion.
2. **Face Detection:** Face detection algorithms first analyse images to identify areas that may contain human faces. Haar digits are popular techniques that use simple learned techniques to describe facial features such as eyes, nose, and mouth. These classifiers are combined to form a cascade that gradually increases the area of the face. Areas that pass through each stage of the stage are considered face detection. Deep learning-based face detection uses convolutional neural networks (CNNs) to learn facial expressions directly from images, providing accurate and powerful changes in pose, lighting, and occlusion.

5.2 Extracting: When the face detection algorithm identifies the region of the face, the visible faces are removed from the image. This includes cropping the image from the face detection algorithm based on coordinates or bounding box. The subtracted regions of the face are used as input for further processing or analysis to separate regions of the face from the rest of the image.

1. **Feature Extraction:** Feature extraction aims to capture distinctive characteristics of the face that can be used for further comparison or recognition tasks. Geometric features involve extracting information about the face shape and spatial relationships between facial landmarks such as eyes, nose, and mouth. Methods like Active Shape Models (ASM) or Active Appearance Models (AAM) can be used to extract these geometric features. Local texture features focus on capturing fine-grained details in the facial texture, describing local texture patterns using techniques like Local Binary Patterns (LBP). Deep learning-based methods utilize deep CNN architectures like FaceNet or VGGFace to extract high-level features that are highly discriminative for face matching. These features capture both low-level texture patterns and high-level semantic information from the face regions.

5.3 Comparing: After extracting features from the detected face, the next step is to compare them with the features of known faces stored in a reference set or database. There are different methods for face comparison:

1. **Similarity scores:** Features of the detected face can be compared with the reference faces using similarity metrics such as Euclidean distance or cosine similarity. A threshold can be set to determine if the similarity score is above a certain threshold to consider it a match.
2. **Classification algorithms:** Face recognition can also be formulated as a classification problem. Classification algorithms like Support Vector Machines (SVM), k-Nearest Neighbour's (k-NN), or Neural Networks can be trained on labelled data to classify the detected face into known individuals.

5.4 Matching: Based on the comparison results, a decision is made on whether the detected face matches any known faces or if it is an unknown face. If the similarity score exceeds the threshold or the classification algorithm identifies the detected face as belonging to a known individual, a match is considered. Additional information or actions can be associated with the recognized person, such as retrieving their identity from a database or triggering specific functionalities in an application.

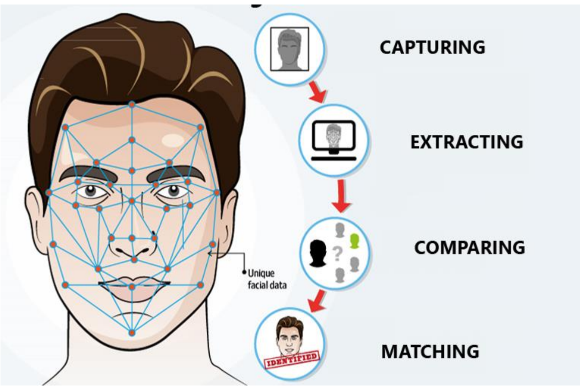

Fig.5.1 Process of Face Detection

VI. ADVANTAGES

As a key element in facial imaging applications, such as facial recognition and face analysis, face detection creates various advantages for users, including:

a. Improved security-

Face detection improves surveillance efforts and helps track down criminals and terrorists. Personal security is also enhanced since there is nothing for hackers to steal or change, such as passwords.

b. Easy to integrate-

Face detection and facial recognition technology is easy to integrate, and most solutions are compatible with the majority of security software.

c. Automated identification-

In the past, identification was manually performed by a person; this was inefficient and frequently inaccurate. Face detection allows the identification process to be automated, thus saving time and increasing accuracy.

VII. CONCLUSION

In recent years face detection has achieved considerable attention from researchers in biometrics, pattern recognition, and computer vision groups. There is countless security, and forensic applications requiring the use of face recognition technologies. As you can see, face detection system is very important in our day-to-day life. Among the entire sorts of biometric, face detection and recognition system is the most accurate. It is exciting to see face detection techniques be increasingly used in real-world applications and products. The most straightforward future direction is to further improve the face detection in presence of some problems like face occlusion and non-uniform illumination.

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