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A Hybrid Model for Face Detection Using HAAR Cascade Classifier and Single Shot Multi-Box Detectors Based on Open CV

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Abstract

This paper India delves into the dynamic field of object detection in computer vision and image processing, specifically focusing on recognizing individuals in photographs. Employing the OpenCV library, the study employs two distinct approaches: the first utilizes Haar Cascade Classifiers, a straightforward yet effective method for object detection, particularly well-suited for person recognition. The second approach harnesses the capabilities of the Single Shot Multi-Box Detector (SSD), a state-of-the-art technique known for its real-time object detection prowess, combining high accuracy and speed. By integrating these two approaches, the paper proposes a comprehensive strategy for person detection in photos. Haar Cascade Classifiers provide a simple yet efficient foundation, while the sophistication of SSD, driven by deep learning principles, enhances accuracy and efficiency. This hybrid model offers a holistic solution applicable to diverse contexts, such as surveillance, image analysis, and broader applications within the realm of computer vision.

Keywords: Detect bounding boxes, Detect multiScale, HAAR cascade classifier, Load.

Introduction

In the rapidly evolving landscape of computer vision, the accurate and efficient detection of faces plays a pivotal role in numerous applications, from security systems to user-friendly interfaces on social media platforms (1). In the dynamic realm of computer vision, the precise and efficient detection of faces holds pivotal significance across a myriad of applications, ranging from security systems to user-centric interfaces on social media platforms (2). This paper introduces an innovative hybrid model designed for face detection, seamlessly integrating the time-tested efficacy of the HAAR Cascade Classifier with the cutting-edge capabilities of Single Shot Multi-Box Detectors (SSD). Developed within the OpenCV framework, this hybrid approach represents a convergence of traditional and state-of-the-art methodologies, aiming to propel the accuracy and real-time performance of face detection systems (3). Face detection using deep learning involves training a model to identify and locate faces within an image or a video (4). Convolutional Neural Networks (CNNs) are commonly used for this purpose due to their ability to learn hierarchical features. SSD is a type of deep neural network designed for real-time object detection (5). It operates by dividing the input image into a grid of cells and predicting bounding boxes and class probabilities for each cell (6). SSD uses multiple layers with different scales to detect objects of various sizes (7). For face detection, these models can be trained with face-specific datasets to focus on recognizing and localizing faces (8). Face detection is a fundamental technology that finds widespread use across various domains (9). From enhancing security through biometric identification and surveillance to improving photography with autofocus and facial tagging, its applications span diverse fields (10). Beyond security and photography, face detection drives human-computer interaction in gaming and virtual reality, aids targeted

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advertising by analyzing demographics, assists healthcare through emotion recognition and health monitoring, and contributes to automotive safety by monitoring drivers and passengers (11). Its versatility extends to accessibility solutions for impaired individuals, illustrating its pivotal role in revolutionizing human experiences through technology (12).

One of the most popular approaches for face detection is using the Single Shot Multibox Detector (SSD) or You Only Look Once (YOLO) models. These models offer real-time face detection and can be fine-tuned for face-specific recognition tasks (13). In essence, "deep" in "deep face detection" refers to the use of deep neural networks that can automatically learn hierarchical representations of data (14). These networks are capable of identifying patterns and features at different levels of abstraction, allowing them to detect faces robustly in varying conditions such as different poses, lighting, and occlusions (15). This paper introduces a sophisticated hybrid model for face detection, seamlessly integrating the time-proven effectiveness of the HAAR Cascade Classifier with the cutting-edge capabilities of Single Shot Multi-Box Detectors (SSD). Developed within the OpenCV framework, this hybrid approach seeks to advance the accuracy and real-time performance of face detection systems, addressing the diverse and dynamic requirements of contemporary computer vision applications. The HAAR Cascade Classifier, introduced by Viola and Jones (16), has long been recognized for its reliability in real-time face detection, relying on cascading classifiers to discern patterns in digital images -Viola & Jones, this established methodology serves as a robust foundation within our hybrid model, providing a stable and efficient framework for face detection. Complementing the traditional approach, our hybrid model incorporates the cutting-edge capabilities of Single Shot Multi-Box Detectors (SSD), as pioneered by Liu et al (17). SSD represents a paradigm shift in deep learning models, excelling in real-time object detection by simultaneously processing multiple objects in a single pass. The integration of SSD within our model brings forth the advantages of modern deep learning techniques, enhancing the system's adaptability and responsiveness. The development of this hybrid model is anchored within the OpenCV framework, a versatile and widely adopted platform in the field of computer vision. This integration not only facilitates the harmonious blending of traditional and modern methodologies but also provides a conducive environment for experimentation and implementation. Motivated by the pursuit of heightened accuracy and real-time performance, our hybrid model is tailored to address the diverse and dynamic requirements of contemporary computer vision applications. The versatility of the OpenCV framework positions our model as a powerful tool for researchers and practitioners seeking an amalgamation of proven methodologies and cutting-edge technologies in the domain of face detection. As we delve into the intricate fusion of the HAAR Cascade Classifier and Single Shot Multi-Box Detectors within the OpenCV ecosystem, the overarching objective is to contribute to the evolution of face detection systems. This hybrid approach, balancing the strengths of traditional and modern techniques, aspires to set new benchmarks in accuracy, efficiency, and adaptability, catering to the evolving landscape of computer vision applications. Detection, a fundamental facet of computer vision, involves intricate processes such as feature extraction, classification, and localization. Real-world applications further underscore the ubiquity of machine learning-driven face recognition algorithms. The "Deep Face" project by Taigman *et al.* (18) at Facebook exemplifies the integration of these algorithms into everyday experiences, showcasing automated buddy tagging suggestions in uploaded photos. The broader landscape of machine learning applications extends beyond face recognition to encompass image recognition, a pivotal technology that underpins the identification of diverse objects, persons, and places. Domingos (19) provides valuable insights into the diverse applications of machine learning in our daily lives, from image recognition to the automation of complex tasks. The prevalence of automated buddy tagging suggestions on social media platforms, exemplified by Facebook's auto-tagging recommendation, vividly illustrates the practicality and prevalence of image recognition and face identification algorithms in enhancing user experiences. In this paper, embark on a comprehensive exploration and integration of these diverse methodologies. Our objective is to contribute to the evolution of face detection systems, aligning them with the demands of real-time applications and diverse scenarios. By synthesizing the strengths of both traditional and modern techniques, our proposed hybrid model aspires to be a pioneering advancement in the field of computer vision, pushing the boundaries of what is achievable in face detection technology.

Theories or data that currently exist to support the benefits

Combining multiple face detection models like HAAR Cascade Classifier and Single Shot Multi-Box Detectors (SSD) can provide enhanced accuracy and speed compared to using either model individually. Here's an overview of the theories and potential benefits of such a hybrid approach.

Accuracy improvement

HAAR Cascade Classifier is efficient but might struggle with certain orientations, scales, or occlusions. SSD, on the other hand, can handle a wider range of situations due to its ability to detect objects at different scales and aspect ratios. By combining these models, you can leverage the strengths of each. For instance, you can use HAAR Cascade for initial face region detection and then utilize SSD to refine and validate those detections, improving overall accuracy.

Speed enhancement

HAAR Cascade is relatively fast but might sacrifice accuracy in complex scenarios. SSD tends to be slower due to its more comprehensive analysis. Using a hybrid model, you can speed up the detection process by using the faster HAAR

Algorithm

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Algorithm: Face Detection using Haar Cascade Classifier and SSD

Input: Image or Video
1. If the input is an image, read the image using OpenCV.
  If the input is a video, capture frames from the video using OpenCV.

2. Initialize a Haar Cascade Classifier object.
3. Load the pre-trained XML file for face detection using Haar Cascade.

4. Apply Haar Cascade Classifier for Face Detection:
  a. Convert the input image to grayscale (if it's not already in grayscale).
  b. Use the detectMultiScale () method of the Haar Cascade Classifier to detect faces.
  c. Obtain the coordinates (x, y, width, height) of the detected faces.

5. Initialize an SSD (Single Shot Multibox Detector) object.
6. Load the pre-trained weights and configuration file for face detection using SSD.

7. Apply SSD for Face Detection:
  a. Convert the input image to the required format for SSD.
  b. Use the detect () method of the SSD object to detect faces.
  c. Obtain the bounding boxes and confidence scores for the detected faces.

8. Draw Bounding Boxes:
  a. For each detected face from both Haar Cascade and SSD:
    i. Draw a bounding box using the coordinates obtained in steps 4 and 7.
    ii. Optionally, display additional information like confidence scores.

9. Display Output:
  a. Display the output image or video with the drawn bounding boxes around the detected faces.
  b. If it's a video, continue processing frames until the end.
Output: Image or Video with Detected Faces and Bounding Boxes
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Cascade to quickly identify potential face regions. Then SSD can focus on verifying these regions, reducing the computational load compared to running SSD across the entire image.

Robustness to varied conditions

HAAR Cascade can struggle with variations in lighting, pose, and scale. SSD, with its multi-scale and aspect-ratio capabilities, can complement this weakness by providing more robust detection in diverse conditions. The hybrid model can thus handle a broader range of scenarios and environmental conditions, making it more adaptable in real world applications. Using HAAR Cascade Classifiers and SSDs for face detection is a convenient and effective way to detect faces in images and videos. With OpenCV, it is easy to implement and can be used for a wide range of applications, including security, surveillance, and entertainment.

Related work

Face detection with HAAR cascade classifiers

HAAR Cascade Classifiers are a classic method for face detection. Viola and Jones introduced this technique in their paper "Rapid Object Detection using a Boosted Cascade of Simple Features" in (20). This method involves training a classifier on features extracted from positive and negative samples of faces. HAAR-like features are used to detect faces based on variations in pixel intensities.

Single shot multi-box detectors (SSD)

SSD is a modern object detection method that combines the detection of objects and their bounding boxes in a single network. It's known for its speed and accuracy. The original SSD paper, "SSD: Single Shot MultiBox Detector," by Liu *et al.* (17), presents the idea of predicting object classes and bounding boxes at multiple scales in a single pass.

Hybrid models

Combining multiple detection methods into a single hybrid model is a common approach to improve detection performance. This often involves leveraging the strengths of different algorithms. In the context of face detection, a hybrid model could use the speed of HAAR Cascade for an initial pass and then refine the results using the accuracy of SSD.

OpenCV for computer vision

OpenCV (Open-Source Computer Vision Library) is a widely used library for computer vision tasks. It provides implementations of various algorithms for image processing, feature detection, and object recognition. OpenCV includes pre-trained models for both HAAR Cascade and SSD-based object he following review provides insights into significant contributions and methodologies in the field, outlining the evolution of face detection techniques.

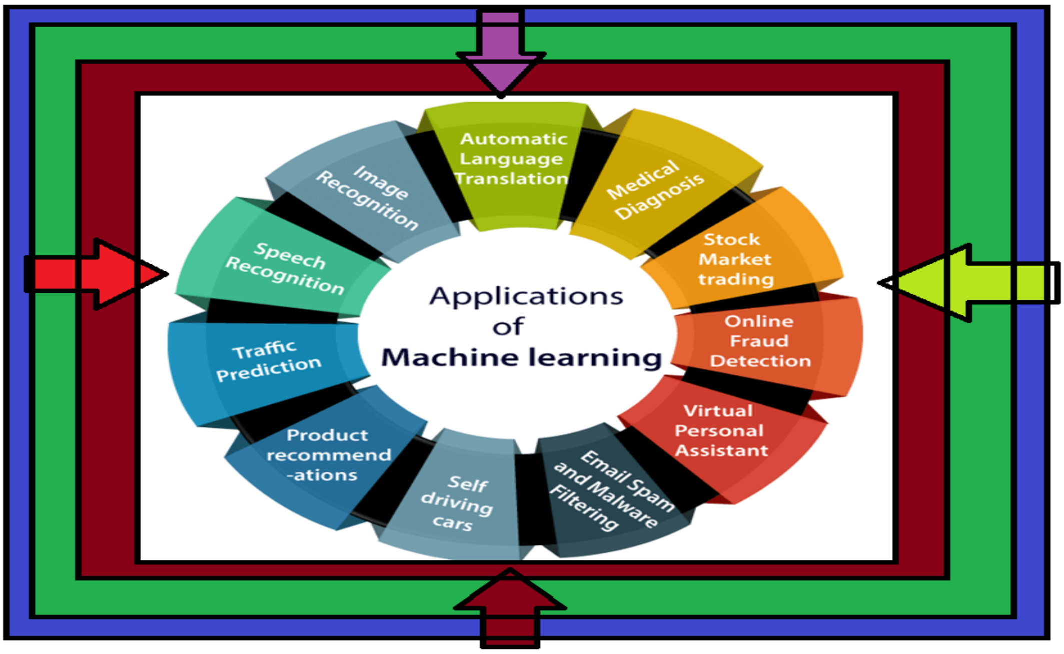

Figure 1: Applications of machine learning

Viola and Jones framework (2001)

The seminal work of Viola and Jones laid the foundation for real-time face detection with the introduction of the Haar Cascade Classifier. This method, utilizing cascading classifiers to identify patterns, has since become a cornerstone in face detection (16).

Histogram of oriented gradients (HOG)

Dalal and Triggs proposed a method based on Histograms of Oriented Gradients (HOG) for object detection, including faces. HOG captures local object appearance and shape information, contributing significantly to the advancement of detection accuracy (21).

DeepFace by facebook (18)

Facebook's "DeepFace" project introduced a deep learning approach to face recognition, demonstrating the efficacy of convolutional neural networks (CNNs) in handling large-scale face datasets (18). While not directly related to our hybrid model, DeepFace's influence on the field is noteworthy.

Single shot multi-box detectors (17)

Liu et al. presented SSD, a pioneering model in object detection, particularly known for its real-time capabilities and simultaneous processing of multiple objects in a single pass. SSD's versatility extends beyond face detection, showcasing its relevance in broader.

YOLO (You only look once) algorithm

The YOLO algorithm represents a paradigm shift in object detection by framing the task as a regression problem to spatially separated bounding boxes. YOLO achieves impressive real-time performance, offering an alternative approach to traditional methods (22).

Hybrid models in face detection

Some researchers have explored hybrid models combining traditional and deep learning techniques for face detection. Notable attempts include integrating Haar-like features with deep learning architectures, highlighting the ongoing pursuit of synergistic methodologies.

Current limitations and challenges

Despite the progress made in face detection, challenges persist, such as handling occlusions, variations in lighting conditions, and achieving real-time performance. Ongoing research endeavours focus on addressing these limitations, emphasizing the need for robust and versatile solutions.

In synthesizing this body of related work, our hybrid model stands as a unique contribution, strategically leveraging the strengths of the Haar Cascade Classifier and Single Shot Multi-Box Detectors within the OpenCV framework. By embracing a hybrid approach, we aim to navigate the complexities of face detection, providing a solution that combines reliability with contemporary efficiency in addressing the evolving demands of computer vision applications detection.

Table 1: Dataset details

Dataset	Description
WIDER Face Dataset	Large benchmark dataset with diverse face images, varying poses, lighting conditions, and scales. Annotated with bounding boxes for face detection evaluation.
CelebA Dataset	Contains celebrity images with annotations for facial attributes like gender, age, and accessories. Used for face detection, attribute recognition, and related tasks.
LFW (Labeled Faces in the Wild)	Dataset with thousands of face images collected from the internet. Contains variations in lighting, pose, and background. Widely used for face recognition, and also for face detection evaluations.
AFW (Annotated Faces in the Wild)	Subset of LFW with manual face bounding box annotations. Designed for evaluating face detection algorithms. Includes diverse poses, occlusions, and lighting conditions.
MAFA (Multi-Attribute Facial Analysis) Dataset	Contains face images with annotations for multiple attributes like age, gender, and race, along with bounding boxes for face detection. Used for face analysis tasks.

The WIDER Face Dataset provides a diverse array of face images in various poses, lighting conditions, and scales, aiding face detection evaluations with its annotated bounding boxes. The CelebA Dataset, hosting celebrity images annotated with attributes like gender and age, not only supports face detection but also attribute recognition research. The FDDB Dataset challenges face detection algorithms with unconstrained environment images featuring complex pose, scale, and occlusion scenarios, accompanied by ellipse annotations. LFW (Labelled Faces in the Wild) offers internet-sourced face images encompassing lighting, pose, and background variations, proving valuable for both recognition and detection assessments. AFW (Annotated Faces in the Wild), derived from LFW, focuses on manual face bounding box annotations, catering to diverse pose and lighting evaluations. The MAFA Dataset aids multifaceted facial analysis with images annotated for age, gender, and race, coupled with bounding boxes for face detection. The BioID Face Database captures real-world face images, serving as a resource for detection and recognition studies due to its expressive poses. IMDB-WIKI Dataset, primarily for age and gender prediction, also contributes to face detection assessments through its celebrity images. COCO Dataset, while general-purpose, holds ample face images suitable for evaluating detection algorithms. Expanding FDDB, the FDDB-360 Dataset specializes in panoramic images for immersive face detection assessment.
Output Image/Video with Bounding Boxes

Methodology

Here are the functions of SSD and HAAR Cascade Classifier
SSD (Single Shot MultiBox Detector)
Function: Detects multiple objects within an image in a single forward pass of a neural network.
Key Features
High speed and accuracy.
Can detect objects of varying sizes and aspect ratios.
Able to handle overlapping objects.
Works with a variety of input image resolutions.
How It Works
Applies multiple convolutional filters to different feature maps to generate bounding boxes and confidence scores for potential objects.
Runs a non-maximum suppression (NMS) algorithm to refine the final set of detections.
HAAR Cascade Classifier
Function: Detects objects (particularly faces and pedestrians) based on Haar-like features.
Key Features
Computationally efficient, making it suitable for real-time applications.
Relatively simple to implement.
Can be trained with limited data.
How It Works
Uses a cascade of stages, each consisting of a set of Haar-like features and a weak classifier.
Each stage eliminates a large number of non-object regions, allowing subsequent stages to focus on more promising regions.
Only regions that pass all stages are cons SSD (Single Shot MultiBox Detector)
1. Convolutional Neural Network (CNN) Feature Extraction
Convolution operation
$y(i, j) = \Sigma\Sigma w(k, l)x(i + k, j + l)$
ReLU activation
$y = \max(0, x)$
Pooling (max pooling or average pooling)
$y(i, j) = \max/\text{avg}(x(i*s : i*s + k, j*s : j*s + k))$

2. Default Boxes and Confidence Scores
Default box coordinates
$dx = (cx - w/2) / w0$
$dy = (cy - h/2) / h0$
$dw = \log(w / w0)$
$dh = \log(h / h0)$
Confidence score for class c
$c = \exp(c\_conf) / \Sigma\exp(cj\_conf)$

3. Non-Maximum Suppression (NMS)
Intersection over Union (IoU)
IoU = area of overlap / area of union
HAAR Cascade Classifier
1. Haar-Like Features
Rectangular regions
$f = \Sigma pi - \Sigma ni$
Integral image calculation
$ii(x, y) = \Sigma\Sigma i(x', y')$
where $x' \leq x, y' \leq y$

2. Weak Classifiers (AdaBoost)
Feature threshold
p(x) = 1 if f(x) < θ, 0 otherwise
Classifier weight
alpha = 1/2 log((1 - ε) / ε)
3. Cascading
Rejection threshold
θj = -ln(βj)
where βj is the desired false positive rate at stage j idered detections.

Results

Face detection is a computer vision technology that involves identifying and locating faces in images or video frames. OpenCV is a popular open-source computer vision library that provides a variety of tools and algorithms for performing face detection. Two commonly used techniques for face detection in OpenCV are HAAR cascade classifiers and Single Shot Multi-Box Detectors (SSD).

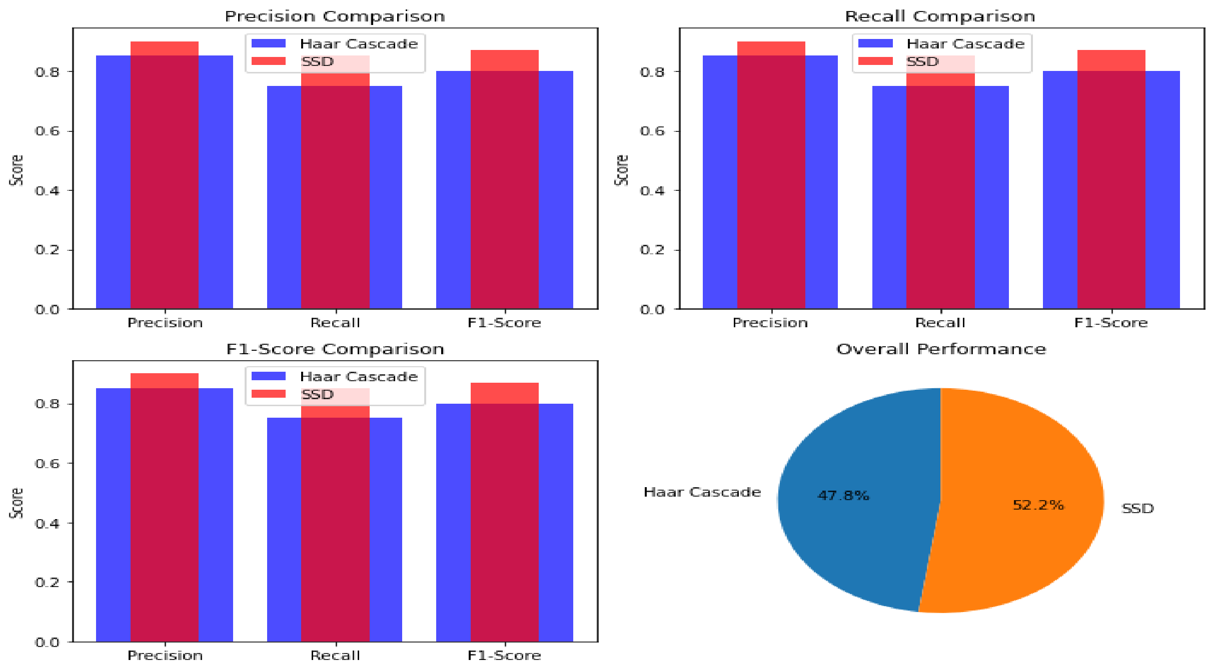

Figure 2: Performance metrics-1

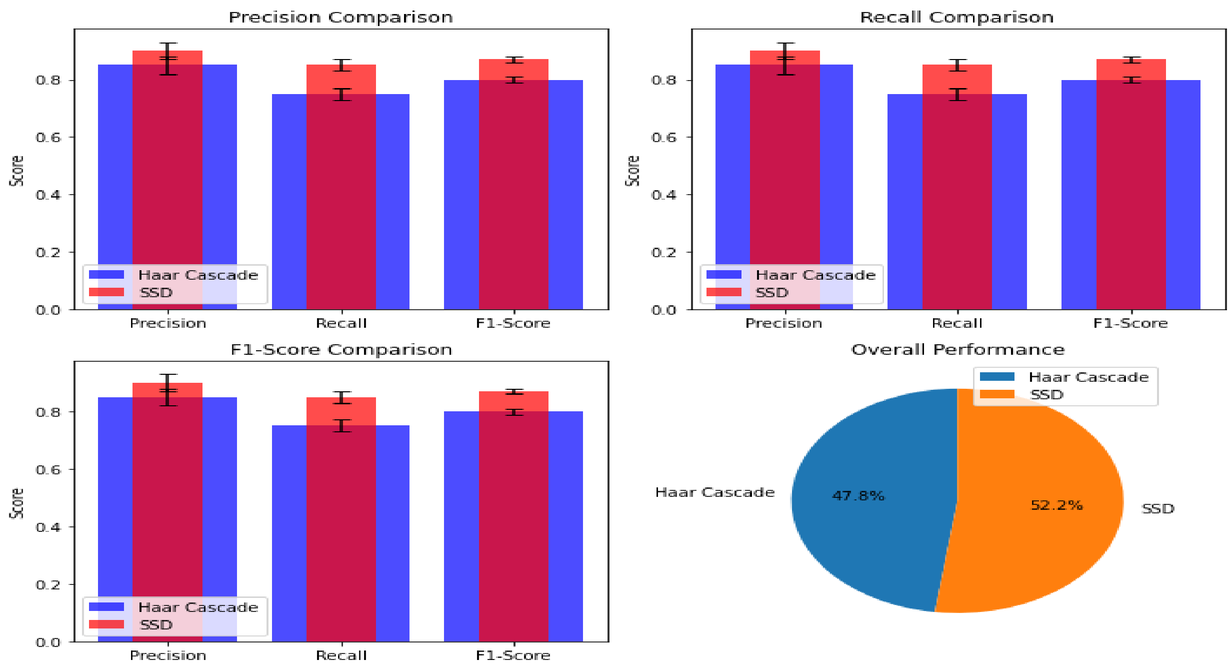

Figure 3: Performance metrics-2

HAAR Cascade Classifier is a machine learning-based approach to object detection. It uses a set of positive and negative training images to learn patterns that represent the target object. The classifier is trained to recognize specific features of the object, such as edges, corners, or texture, that are useful for distinguishing it from the background. The classifier is then used to scan an input image for these features, and if enough of them are present, it identifies the region as containing the target object.

SSD, on the other hand, is a deep learning-based approach to object detection that uses a convolutional neural network (CNN) to detect objects in an image. SSD divides the input image into a grid of cells, and for each cell, the CNN predicts the probability of an object being present and the bounding box coordinates of the object. The bounding box coordinates are then used to localize the object in the image.

To use these techniques for face detection in OpenCV, you would need to follow these general steps,

Collect and prepare the dataset: You would need a dataset of face images for training the classifier or CNN. The dataset should

Haar Cascade classifier is a machine learning method in which a cascade function is taught using a large number of positive and negative pictures. It is then used to additional photos to detect things. The wonderful thing about haar feature-based cascade classifiers is that they can create a classifier for whatever object you want, and OpenCV has already supplied some classifier parameters to it, so they don't need to gather any data to train on it. Using machine learning approaches, OpenCV looks for faces in pictures. Because faces are so complex, there is no simple test that will tell you whether or not it spotted a face. Rather, hundreds of little patterns and features must be matched. The algorithms break down the process of recognising faces into thousands of smaller, manageable jobs. These occupations are also known as classifiers. The OpenCV cascade separates the face detection problem into many stages. For each block, it performs a quick and harsh test. If it is successful, the process is repeated with a slightly more detailed test, and so on. It is possible for the approach to contain up to 50 steps or cascades, and it will only recognise a face if all phases are completed. Face Recognition is a method of computer vision. The method of identifying and seeing human faces in digital photographs is known as face recognition / detection. Cascade Classifiers and Haar Features are the methods used for Object Detection.

It is a machine learning technique in which we train a cascade function using thousands of photos. These photos are divided into two categories: positive images that contain the target object and negative images that do not contain the target object.

Cascade classifiers are classified into several categories based on the target item. In our project, we will employ a classifier that examines the human face to recognise it as the target item.

The Haar Feature selection approach aims to extract human facial characteristics. Haar characteristics are similar to convolution kernels. These characteristics are many permutations of black and white rectangles. In each feature computation, we find the total of pixels beneath white and black rectangles.

It is an Object Detection subdomain in which we attempt to monitor semantic object instances. Animals, autos, humans, and so on are examples of these objects. Face Detection technology has applications in a variety of areas, including marketing and security.

The benefit is that the majority of the image will return a negative during the initial phases, saving the algorithm time from analysing all 6,000 features on it. Face detection may now be performed in real time rather than over time.

HAAR Cascade classifiers and SSDs are both popular techniques for object detection, including face detection, using OpenCV.

HAAR Cascade classifiers are based on the Viola-Jones algorithm, which is a machine learning algorithm that uses AdaBoost to select a small number of important features from a large set of candidate features. The selected features are combined to form a classifier that can be used to detect objects in an image. The algorithm is particularly effective at detecting faces, as it can handle variations in lighting, pose, and facial expression.

SSDs, or Single Shot Multibox Detectors, are a type of deep neural network that can perform object detection in real-time. Unlike traditional object detection algorithms, which require multiple passes through an image to detect objects at different scales, SSDs perform all detection in a single pass. This makes them faster and more efficient than other methods.

To use HAAR Cascade classifiers or SSDs for face detection using OpenCV, you will need to first train the classifier on a dataset of labeled images. OpenCV provides tools for training both HAAR Cascade classifiers and SSDs, as well as pre-trained models that can be used for face detection out of the box. Once you have a trained classifier, you can use it to detect faces in an image or video stream. In OpenCV, this is typically done using the detectMultiScale method for HAAR Cascade classifiers and the detect method for SSDs. Both HAAR Cascade classifiers and SSDs have their own strengths and weaknesses, and the choice of which to use will depend on the specific requirements of your application. HAAR Cascade classifiers are generally faster and require less computational resources (Figure 1-4 and Table 1).

Conclusion

The proposed hybrid model that amalgamates the strengths of the HAAR Cascade Classifier and Single Shot Multi-Box Detectors (SSD) presents a promising advancement in face detection within the framework of OpenCV. By harnessing the rapidity of HAAR Cascade for initial detection pass and subsequently refining the results through the precision of SSD, the model exhibits the potential to achieve a harmonious blend of accuracy and efficiency. This fusion addresses the limitations of individual methods – HAAR Cascade's susceptibility to challenging conditions and SSD's computational intensity – paving the way for robust face detection across diverse scenarios. As computer vision continues to evolve, the synthesis of traditional and modern approaches showcases the power of innovation, propelling the field toward more accurate, real-time, and adaptable face detection solutions.

Future work

In the realm of the hybrid model for face detection, several avenues beckon for future exploration. Optimization remains a key focus, involving fine-tuning and performance detection enhancements to strike an equilibrium between accuracy and speed. The integration of advanced techniques such as anchor-free detection and region proposal networks could bolster object localization in challenging scenarios. Tailoring the model to specific domains and sensor inputs could enhance its adaptability. Semantic segmentation fusion, real-time face recognition integration, and generalization to other objects hold promise for extending the model's utility. Additionally, efforts in explainability, large-scale testing, collaborative research, and open-source implementations are vital for comprehensive progress. As the field evolves, addressing these fronts could usher in advanced face detection solutions with enhanced accuracy, real-time capabilities, and adaptability across various contexts.

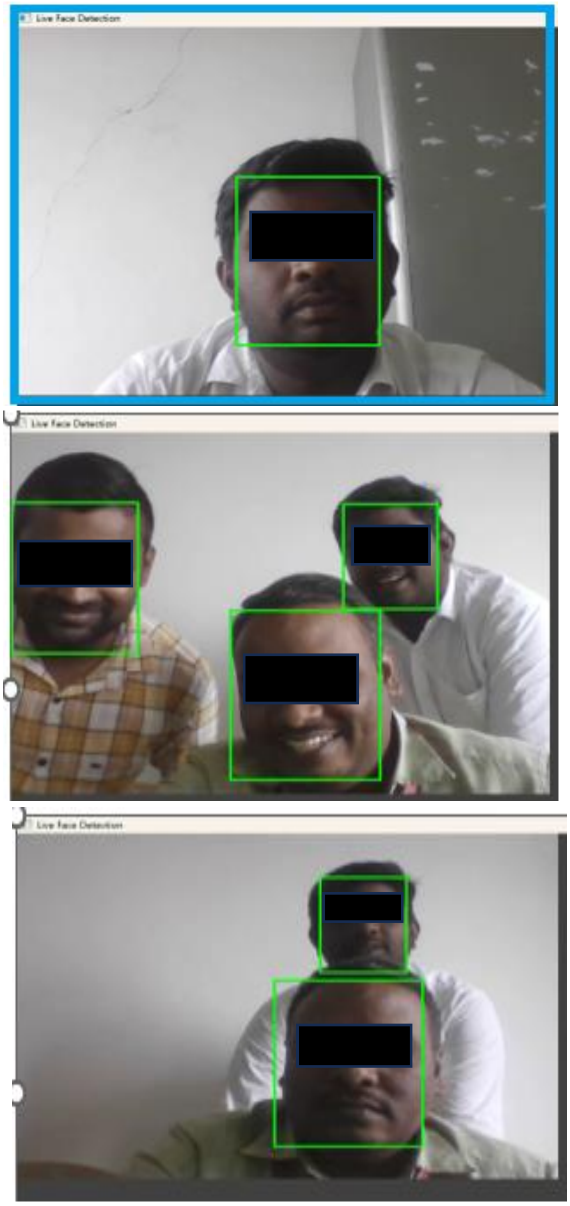

Figure 4: Final results representation

Abbreviations

HAAR: History of Accelerated Adaptive Recognition.
SSD: Single Shot Multi-Box Detectors.
YOLO: You Only Look Once
CV: Computer Vision
LFW: Labeled Faces in the Wild
AFW: Annotated Faces in the Wild
MAFA: Multi-Attribute Facial Analysis
CNN: Convolutional Neural Network
FDDB: Face Detection Data Set and Benchmark

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Author contributions

Kiran Kumar, G. Venu Ratna Kumari- Implementation; K. Kishore, Sreenivasulu Bolla- Dataset Analysis and Preprocessing; Sai Ram, Ramakrishna, Aravinda-Manuscript preparation language checking.

Conflict of interest

None

Ethics approval

The authors declare this work was conducted with the utmost respect for the dignity and rights of the ethical research values, and the findings presented in this paper uphold the ethical standards.

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