AI-Based Image Enhancement Techniques for Detect Face Using Haar Cascade and RetinaFace

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Abstract:
Face detection is a process that identifies human faces in any digital photo or video. Face detection is used in various fields like security, biometrics, authentication, social media, etc. For detection, various algorithms are introduced in the traditional method to train deep learning models. Using an AI technique, a comparative study was conducted to evaluate the performance of face detection algorithms. This contrastive analysis of two distinct face detection algorithms, the traditional Haar Cascades and the deep learning-based RetinaFace, evaluates their performance in terms of both method accuracy and detection processing time under controlled, varying image conditions. Using a single image captured via webcam, it quantitatively compared the overlap of detections using Intersection over Union (IoU), qualitatively assessed the number and accuracy of bounding boxes and measured the processing time for each algorithm. This research describes downstream tasks, including face recognition and emotion detection, emphasising their dependency on accurate initial face detection. Additionally, a system was developed to capture images with a precise time stamp and apply an AI technique to enhance image quality, facilitating future dataset expansion.

Introduction:

Face detection is a crucial component of computer vision, essential for various applications such as biometric authentication, video surveillance, and facial recognition. The primary goal is to identify and outline faces in pictures or videos, allowing for further analysis.

Although face detection has improved significantly, it's still challenging to apply in the real world. That's because of issues such as poor lighting, varying facial expressions, people's heads being turned, parts of faces being obscured, and low-quality images. All of these factors can make it harder for detection systems to work accurately.

To handle these issues, researchers have developed different methods. Older methods, such as Haar Cascades, are simple and fast, but they don't perform well with variations in image quality or environment. Newer methods, such as RetinaFace, employ advanced deep learning techniques to perform significantly better in challenging situations. However, even these advanced systems are affected by image quality problems, which highlights the importance of studying how image enhancement can improve face detection reliability. This paper aims to provide a comparative analysis of these face detection algorithms under controlled variations in image quality and the application of a basic enhancement technique.

Literature Review

This study investigates that early face detection methods, Haar Cascade, enabled real-time applications but were limited by variations in lighting, pose, and occlusion. Later, like

HOG-SVM and LBP offered incremental improvements but lacked robustness. Deep learning models, particularly RetinaFace, have since achieved superior accuracy and resilience by leveraging feature pyramids and landmark localisation. However, studies show that image quality issues like noise and blur still degrade performance, highlighting the trade-off between the efficiency of traditional methods and the robustness of deep learning-based approaches.[1]

This study compares Haar Cascade and Convolutional Neural Network (CNN) approaches for face detection. Their research highlighted that while Haar Cascade offers faster detection suitable for real-time applications, CNN-based methods provide higher accuracy and robustness under varying image conditions, including changes in illumination, pose, and partial occlusion. The study emphasises the trade-off between computational efficiency and detection performance, suggesting that hybrid or optimised approaches could enhance real-world face detection systems.[2]

This author's work focuses on AI-based image enhancement techniques for in-vehicle vision systems operating under adverse weather conditions. This focuses on the image preprocessing in improving detection and recognition accuracy, particularly in conditions affected by rain, fog, and low light. Various AI-driven methods, including deep learning-based denoising and super-resolution, were analysed for their effectiveness in enhancing image quality and robustness of vision systems. The findings emphasise the importance of adaptive enhancement techniques to maintain reliable performance in real-world applications.[3]

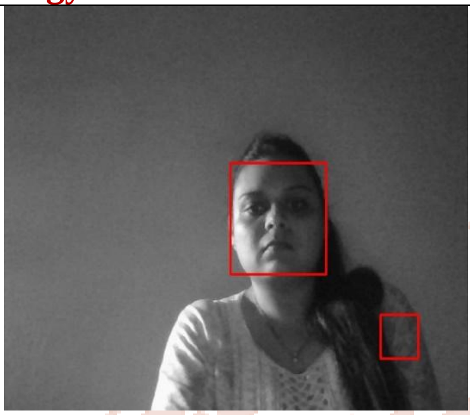
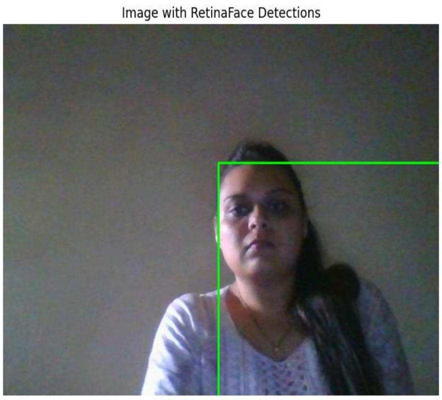
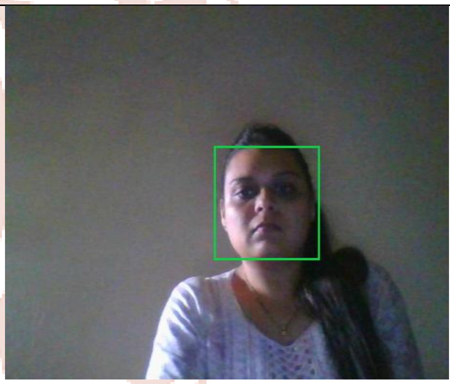
RetinaFace is a single-stage face detection algorithm that performs pixel-wise face localisation. The method uses multi-task learning with supervised and self-supervised signals to predict face scores, bounding boxes, landmarks, and dense 3D vertices. RetinaFace achieves accurate detection across scales and challenging conditions, performs well on the WIDER FACE dataset, detects small and occluded faces, and runs efficiently in real-time with lightweight backbones like MobileNet and ResNet. Its robust design supports high-precision applications such as facial recognition and demographic analysis.[4]

Detecting faces in difficult conditions, like different poses, lighting, and partial occlusions, is challenging. Haar Cascades work fast but perform poorly in such situations. Deep learning methods, like RetinaFace, give better results and can detect even partially hidden faces reliably, showing their strength in real-world conditions.[5]

Face detection and recognition using 3D Local Binary Patterns (3D-LBP), which capture both depth and texture information to improve recognition accuracy. This approach demonstrated robust performance under varying lighting and facial conditions, making it suitable for applications such as automated attendance and security systems.[6]

Face detection and recognition techniques for blurred and noisy images. The study highlighted methods to improve detection accuracy under challenging conditions, emphasising the need for robust preprocessing and feature extraction to handle image degradation effectively.[7]

Methodology

 **1.1 Before Applying AI Technique**	 **1.2 After applying AI Technique on the Haar Cascade**
 **1.3 Before Applying AI Technique**	 **1.4 After applying AI Technique on RetinaFace**

This study adopted a comparative experimental approach to assess the performance of two face detection algorithms: the classical Haar Cascade and the deep learning-based RetinaFace. The experiments were designed to evaluate their robustness under different image conditions and resolution enhancement through a super-resolution placeholder.

Dataset

The dataset for this study was very small and consisted of just one picture, photo.jpg, taken with a regular webcam. This picture was treated as the original reference. To test how face detection works on lower-quality images, I created a second version of the picture by adding

Gaussian noise, which slightly distorts the image in a controlled way. This version is referred to as noisy_image. I also made another version called super_resolved_image by using a basic upscaling method (interpolation) to improve its resolution. Even though using only one image limits the scope of the results, it helped in making a fair comparison of both algorithms under the same conditions.

Face Detection Algorithms

The two face detection algorithms evaluated were:

Haar Cascades: A widely-used object detection framework based on Haar-like features and a cascade of boosted classifiers.

RetinaFace: RetinaFace is a deep learning approach that works in a single stage using dense predictions combined with a feature pyramid network. It applies multi-task learning to handle tasks such as identifying faces, locating landmarks, and performing 3D regression. In this study, the pre-trained RetinaFace model available through the RetinaFace Python library was used.

Both algorithms were applied to the original, noisy, and super-resolved images to obtain the bounding box coordinates of the detected faces.

Experimental Procedure

- Load the original image ("photo.jpg").
- Apply the Haar Cascades face detection algorithm to the original image.
- Apply the RetinaFace face detection algorithm to the original image.
- Record the number of faces detected by each algorithm on the original image.
- Apply Super Resolution.
- Apply the Haar Cascades face detection algorithm to the Super Resolution image.
- Apply the RetinaFace face detection algorithm to the Super Resolution image.
- Record the number of faces detected by each algorithm on the image.

Visualise the bounding boxes from both algorithms on the original image as well as on the Super Resolution image for comparison and calculate the IoU between corresponding detections and Processing time.

Evaluation Metrics

Number of Detections: The total count of bounding boxes identified as faces by each algorithm.

Intersection over Union (IoU): Measures the overlap between the predicted bounding box and the ground truth bounding box.

Processing Time: The time taken by each algorithm to perform face detection on the input image, providing an indication of their computational efficiency.

Results

Figures 1.1 and 1.3 show the detection results before applying AI-based image enhancement. Haar Cascades detect multiple bounding boxes, including false positions, while RetinaFace provides a more focused detection, but still lacks precision due to poor image quality. After applying AI-based enhancement, as shown in Figures 1.2 and 1.4, both algorithms improved. Haar Cascades reduced false position, and RetinaFace produced a more accurate and tightly fitted bounding box, showing the impact of image enhancement on detection performance."

Comparing RetinaFace and Haar Cascade using Face Detection and Processing Time

Method	Face Detection	Processing Time
Haar Cascade	2	0.1426 sec
RetinaFace	1	4.4662 sec

Comparing RetinaFace and Haar Cascade detections using IoU:

IoU Scores:

RetinaFace Face 1 vs Haar Cascade Face 1: IoU = 0.8436

Conclusion

This study highlights the critical role of image quality in the impact of face detection systems. Haar Cascades are computationally efficient and quick, but they show notable limitations under difficult conditions. In contrast, RetinaFace offers greater robustness and accuracy thanks to its deep learning framework. Image enhancement techniques can further improve detection outcomes, highlighting the importance of preprocessing in practical applications. This study has several limitations, primarily the use of a single image, a specific type and level of noise, and a placeholder for super-resolution. To obtain a more comprehensive understanding of the comparative performance and robustness of face detection algorithms, future research should evaluate algorithms on larger datasets encompassing a wide range of facial variations and environmental conditions. Investigate the effectiveness of different AI-based image enhancement techniques (e.g., real super-resolution models, advanced.

References

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