# PERFORMANCE ANALYSIS OF HAAR CASCADE-BASED FACE DETECTION IN MULTI-FACE IMAGES UNDER DIVERSE COMPRESSION ALGORITHMS

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Abstract:

With the tremendous development of face detection systems, there is a growing need to achieve highly accurate detection results in images compressed using different compression algorithms. This manuscript provides face detection analysis in images representing different numbers of faces (1, 3, 5, and 10 faces) from both frontal and non-frontal perspectives. The images extracted from the FDD (Face Detection Dataset) database were compressed using three different compression algorithms - JPEG, JPEG2000, and SPIHT, for different bits-per-pixel values.

The analysis was performed by using the Haar Cascade Classifier, implemented in Python. The quality of face detections was determined using the objective measures: F-measure (based on reference values from the GroundTruth images) and Det.F (number of detected faces). Based on the results presented in the tables, it can be concluded that face detection behaves slightly differently depending on the value of bits-per-pixel and the applied compression algorithm, but vastly differently depending on the angle of perspective.

The Haar Cascade Classifier has proven to be the best solution when it is necessary to perform face detection in compressed, frontal face images, especially for a small number of faces; non-frontal images with a large number of faces have proven to be the most challenging assignment for the Haar Cascade Classifier.

Keywords:

Face Detection, Compression, Image Processing, Haar Cascade Classifier, F-measure.

## INTRODUCTION

Regarding modern-day multimedia systems, it is nearly impossible to find a system that doesn't utilize image, video, or audio compression. The advancements in technology have led to a growing need for image processing - from everyday applications to critical professional fields, such as medical image analysis, sensor networks, security systems, and television [1].

Cameras capture images in analog format; the images are then converted into digital formats for efficient processing, transmission, and storage [2]. Uncompressed images demand substantial storage capacity and computational resources for processing, in addition to greater bandwidth for transmission across communication networks.





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As a result of the presence of these challenges, image processing and compression techniques have become a substantial focus of research in digital signal processing [1].

The aim of developing image compression techniques is to remove redundant or unnecessary data. The techniques are categorized based on their ability to recreate the original image from the compressed data. There are two types of digital image compression: lossy compression and lossless compression. Lossy compression allows for greater compression ratios by selectively discarding redundant data. Lossless compression keeps all the original image data intact, thereby allowing for perfect reconstruction without any loss of information [2] [3]. The choice of compression methods, techniques, and algorithms is based on the requirements of the application. A variety of techniques have gained prominence in digital image processing. JPEG (Joint Photographic Experts Group), JPEG2000, and SPIHT (Set Partitioning in Hierarchical Trees) have appeared to be three of the most prevalent standards, each offering distinct advantages [1].

The JPEG compression standard has become well-known and widely used in multiple areas of application, including digital photography, web content, and medical diagnostics. The JPEG uses the Discrete Cosine Transform (DCT), so that it can divide an image into different frequency components. This process separates important visual details from less noticeable ones. The image becomes easier to compress effectively [4] [5].

The JPEG2000 compression standard was developed as a successor to the original JPEG standard to address the demands of emerging applications. It delivers advanced functionality while achieving superior compression performance [6] [7]. Unlike traditional JPEG standard, which uses DCT, as mentioned above, the newer JPEG2000 compression standard uses the Discrete Wavelet Transform (DWT) as its mathematical framework [1].

While JPEG is a lossy compression method [8], and JPEG2000 offers both lossy and lossless compression [7], the SPIHT algorithm is entirely lossless [8]. SPIHT represents a wavelet-based compression method that is very efficient and highly effective. It outperforms the majority of traditional techniques by achieving superior image quality at equivalent compression ratios. The quality is measured by the Peak Signal-To-Noise Ratio - PSNR. The Embedded Zerotree Wavelet (EZW) algorithm represents the mathematical framework for the SPIHT coder [8].

The growing intelligence of computer systems has had a tremendous impact on the ongoing advancement of technology, starting a new era of human-computer interaction. An important example of this interaction is face detection - a special case of object detection. Object detection is used to identify objects in digital images and videos, such as human faces or vehicles. This characteristic of object detection leads to an extensive application of the technique, including face recognition, pedestrian detection, and surveillance systems [9].

Face detection is the critical first step that enables subsequent stages of face analysis, such as face recognition and verification. This stage identifies and locates human faces in a digital image so that further analysis can be performed. The detection process consists of analyzing input images through pattern differentiation, isolating facial features from background elements and outputting spatial coordinates for each detected face [9].

The authors in [10] examined the effect of compression on face detection using Haar-like features, while the authors in [11] examined frontal and non-frontal face detection using deep neural networks. The aim of this paper is to examine how JPEG, JPEG200, and SPIHT compression techniques affect face detection using the Haar Cascade Classifier, considering both frontal and non-frontal images.

The remainder of the paper is structured as follows: Section 2 outlines the system model which provides the fundamental setting for a detailed analysis of the face detection process. It includes several images used for the analysis, along with tabulated PSNR values, obtained during compression using various algorithms. Section 3 presents the results of the face detection process using the Haar Cascade Classifier for frontal and non-frontal compressed images. The results are represented in tabular form. The tables contain F - the numerical values for accuracy (F-measure/F-score) and Det.F - the total count of detected faces (true and false), as well as the number of correctly detected faces, written in parenthesis (when there are additional false detections). Finally, Section 4 provides the conclusion and key insights, along with potential directions for future research.

## 2. SYSTEM MODEL

This paper analyzes the impact of the JPEG, JPEG2000, and SPIHT algorithms on face detection using the Haar Cascade Classifier. The images were extracted from the FDD database [12], along with the corresponding GroundTruth, which defines the exact position of every facial component [13]. All three compression techniques were applied to each image using the following bits-per-pixel (BPP) values: 0.1, 0.2, 0.4, 0.5, 1, and 1.5. The selected images met the criteria for the number of faces represented, specifically 1, 3, 5, and 10, along with the perspective criteria of frontal and non-frontal. Each image represented a different number of faces captured from various perspectives.

The images extracted from the FDD database were converted to BMP (bitmap) format using Python code, allowing the image compression to be performed using VcDemo software [14]. Face detection was performed utilizing OpenCV's Haar Cascade Classifier, serving as an essential element of the Python code.

The images used for the analysis, the obtained images, and the codes were all stored in a repository [15] created by the authors of this paper.

The following objective measures were used:

F - the evenly balanced F-measure that is calculated using the following equation [16] [17]:

$$F = \frac{2PR}{P + R}$$

**Equation 1.** Calculation of F-measure

Where P represents Precision, and R represents Recall or Sensitivity [16].

In an ideal situation, F is equal to 1, but, generally, F lies within the limits of $0 \leq F \leq 1$ [1].

The Precision is calculated using the following equation [17]:

$$P = \frac{TP}{TP + FP}$$

**Equation 2.** Calculation of Precision

The Recall is calculated using the following equation [17]:

$$R = \frac{TP}{TP + FN}$$

**Equation 3.** Calculation of Recall

Where: TP represents True Positive - the pixels correctly segmented as foreground; FP represents False Positive - the pixels falsely segmented as foreground; TN represents True Negative - the pixels correctly detected as background, and FN represents False Negative - the pixels falsely detected as background [1].

Det.F - the total count of detected faces (true and false), with the number of correctly detected faces written in parenthesis (when there are additional false detections).

Peak signal-to-noise ratio (PSNR) values for the three compression algorithms used in multi-face images are represented in the following tables. Table 1 presents the PSNR values obtained from compressing images containing either one face or three faces; Table 2 presents the PSNR values obtained from compressing images containing either five faces or ten faces.

It's readily observed how bits-per-pixel (BPP) values influence image compression. Higher value of BPP results in a better image quality, especially with JPEG compression. JPEG2000 and SPIHT achieve similar results, but JPEG2000 achieves slightly better PSNR values at lower BPP and SPIHT at higher BPP values.

**Table 1.** PSNR values for the three compression algorithms at different BPP values for frontal and non-frontal images containing one face and three faces

| Perspective | Compression Algorithm | One Face | | | | | | Three Faces | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | BPP value | | | | | | | | | | | |
| | | **0.1** | **0.2** | **0.4** | **0.5** | **1** | **1.5** | **0.1** | **0.2** | **0.4** | **0.5** | **1** | **1.5** |
| **Frontal** | **JPEG** | 24.6 | 40.7 | 44.6 | 48 | 55.3 | 56 | 23.6 | 33.5 | 38.3 | 39.3 | 42.4 | 52 |
| | **JPEG2000** | 42.3 | 45.1 | 48.4 | 49.5 | 51.1 | 51.1 | 35.1 | 38.4 | 41.3 | 42.1 | 45.5 | 48.5 |
| | **SPIHT** | 42.7 | 45.5 | 48.9 | 50.1 | 54.2 | 57.3 | 35 | 38.4 | 41.3 | 42.3 | 45.8 | 49 |
| **Non-frontal** | **JPEG** | 23.5 | 31.2 | 35 | 36.2 | 39.6 | 50.5 | 24.9 | 35.7 | 39.8 | 40 | 54.3 | 56.8 |
| | **JPEG2000** | 32.5 | 35.2 | 38.3 | 39.7 | 45.4 | 49.4 | 36.6 | 39.1 | 42.4 | 43.7 | 48.8 | 51.1 |
| | **SPIHT** | 32.1 | 35 | 38.3 | 39.7 | 45.6 | 50 | 36.9 | 39.5 | 42.7 | 44 | 49.4 | 53.7 |

**Table 2.** PSNR values for the three compression algorithms at different BPP values for frontal and non-frontal images containing five faces and ten faces

| Perspective | Compression Algorithm | Five Faces | | | | | | Ten Faces | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | BPP value | | | | | | | | | | | |
| | | 0.1 | 0.2 | 0.4 | 0.5 | 1 | 1.5 | 0.1 | 0.2 | 0.4 | 0.5 | 1 | 1.5 |
| Frontal | JPEG | 21.9 | 26.9 | 33.3 | 34.8 | 39.7 | 42.4 | 21.2 | 25.1 | 29.3 | 31 | 34.4 | 44.1 |
| | JPEG2000 | 28.5 | 32.2 | 36.4 | 37.9 | 43.2 | 46.6 | 25.8 | 28.6 | 32.3 | 33.8 | 39.3 | 43.4 |
| | SPIHT | 28.1 | 32 | 36.3 | 37.7 | 43.1 | 46.7 | 25.4 | 28 | 31.9 | 33.4 | 39.1 | 43.3 |
| Non-frontal | JPEG | 22.9 | 30.1 | 37 | 38.6 | 42.9 | 45.7 | 21.5 | 26.1 | 31.9 | 33.5 | 38.4 | 42.1 |
| | JPEG2000 | 32 | 36 | 40.4 | 41.7 | 45.8 | 48.5 | 27.3 | 31 | 35.6 | 37.2 | 43.1 | 46.9 |
| | SPIHT | 31.6 | 35.2 | 40 | 41.4 | 45.8 | 48.7 | 26.3 | 30.1 | 35.1 | 36.9 | 42.9 | 47.1 |

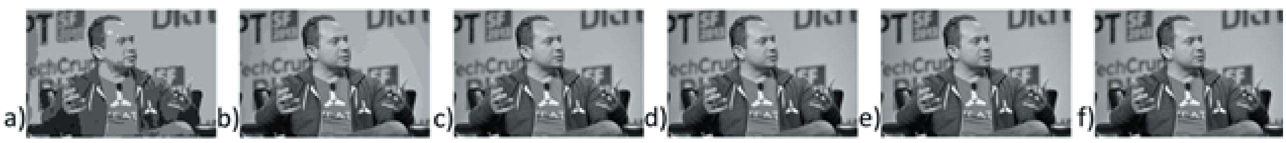


**Figure 1.** Non-frontal images representing one face with JPEG compression at the BPP value of: *a) 0.1, b) 0.2, c) 0.4, d) 0.5, e) 1, f) 1.5*


**Figure 2.** Frontal images representing three faces with JPEG2000 compression at the BPP value of: *a) 0.1, b) 0.2, c) 0.4, d) 0.5, e) 1, f) 1.5*

Several images resulting from the compression processes are shown below.

Figure 1 shows compressed, non-frontal images for different values of BPP, representing one face when using JPEG compression. Figure 2 shows compressed, frontal images for different values of BPP, representing three faces when using JPEG2000 compression. The rest of the compressed images used in this work are available in the dataset repository [15].

Figure 1 and Figure 2 show that image quality remains acceptable across various compression methods, but lower BPP values and certain compression algorithms significantly affect image quality. The most noticeable loss in quality occurs at low BPP values when using the JPEG compression. This is confirmed by the data in Table 1.

In 2001, Paul Viola and Michael Jones introduced the Viola-Jones object detection framework [9]. This framework is the first to achieve competitive real-time detection performance. Due to its accuracy and efficiency, it has been used in face detection ever since. It is important to note that the primary goal of this framework is face detection, not recognition. This detection phase serves as an elemental processing step that comes before any subsequent face recognition processes [9].

The Viola-Jones face detection algorithm represents the core foundation of the Haar Cascade Classifier. Training this classifier requires a sufficient number of both positive and negative images. It uses Haar-like features. A specific object in an image can be detected using Haar-like features. The eyes, nose, and mouth, as the integral parts of a human face, represent features that can be used for classification. By comparing calculated and trained feature values (the reference values), the Haar Cascade Classifier gains the ability to detect human faces [18] [19].

The following section presents the results obtained during the face detection process.

## 3. RESULTS

This section presents the results of the face detection processes. These results were gathered using the mathematical models and software tools outlined in Section 2. Table 3, Table 4, Table 5, and Table 6 display the F and Det.F values for frontal and non-frontal images, based on the number of represented faces. These values were obtained by running a Python code with the Haar Cascade Classifier as its fundamental part, changing digital image inputs based on the number of faces, perspective, and applied compression algorithms.

As shown in Table 3, it is evident that for images containing a single frontal face, the F-score consistently equals 1, indicating perfect face detection, regardless of the BPP value or the applied compression algorithm; the results are almost identical for a single non-frontal face, with only one exception: in the image compressed using the JPEG algorithm at the BPP value of 0.1, where no faces were detected.

Table 4 presents data indicating perfect face detection in compressed images representing three frontal faces, using JPEG2000 compression standard, regardless of the BPP value. The situation is slightly different for the remaining two compression algorithms, with the F-score falling below 1 for the BPP value of 1.5 applying JPEG and for the BPP values of 1 and 1.5 applying the SPIHT algorithm, showing subtle inverse proportionality characteristics. In the case of non-frontal images representing three faces, the results suggest that, for most of the BPP value cases, face detection using the Haar Cascade Classifier achieves the same results - the F-score of 0.67, with two true detections and a false one. There are a few exceptions, with the worst case for the BPP

**Table 3.** Accuracy and number of detected faces using the Haar Cascade Classifier for face detection in frontal and non-frontal images representing one face, compressed by various methods at different BPP values

| Frontal images | | | | | | | | | | | | Non-frontal images | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| JPEG | | | | | | | | | | | | JPEG | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| JPEG2000 | | | | | | | | | | | | JPEG2000 | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| SPIHT | | | | | | | | | | | | SPIHT | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

**Table 4.** Accuracy and number of detected faces using the Haar Cascade Classifier for face detection in frontal and non-frontal images representing three faces, compressed by various methods at different BPP values

| Frontal images | | | | | | | | | | | | Non-frontal images | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| JPEG | | | | | | | | | | | | JPEG | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 0.86 | 4(3) | 0.57 | 4(2) | 0.8 | 2(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) |
| JPEG2000 | | | | | | | | | | | | JPEG2000 | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) |
| SPIHT | | | | | | | | | | | | SPIHT | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 0.86 | 4(3) | 0.86 | 4(3) | 0.33 | 3(1) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) | 0.67 | 3(2) |

value of 0.1 with SPIHT, the second worst for with BPP value of 0.1 with JPEG, and the best for the BPP value of 0.2 with JPEG.

Referring to images representing five frontal faces, Table 5 shows that the JPEG compression algorithm achieves both the best and worst results, with an F-score of 1 for the BPP value of 0.1 and an F-score of 0.83 for the BPP value of 0.2 (2 additional false detections). For the remaining cases of BPP values, JPEG achieves an identical F-score to all the BPP cases with both JPEG2000 and SPIHT algorithms, where the F-score has the same value of 0.91 (1 additional false detection). Therefore, it is observed that JPEG2000 and SPIHT achieve identical, consistent F-scores regardless of the BPP value, while there are slight deviations in accuracy when using JPEG. The results for non-frontal images representing five faces showed an F-score of 0.75 (3 correct detections) for almost all the BPP values and using all three compression methods, except with SPIHT at the BPP value of 0.1, which represents the worst scenario of Haar Cascade-based face detection in non-frontal images representing five faces, achieving the F-score of 0.67 (4 detections, 3 correct).

Observing data represented in Table 6, the first situation of unclear conclusion and absence of BPP to F-score relation occurs. Regarding compressed images representing ten frontal faces, from the results obtained, it is seemingly impossible to find a causal-consequential relationship between BPP values and the F-score. All three algorithms provide a case of perfect face detection, JPEG for the BPP value of 0.1, and both JPEG2000 and SPIHT for the BPP value of 0.4, and a case of worst F-score of 0.87 (3 additional false detections) for the BPP value of 0.2. The rest of the F-scores, for all the remaining BPP

**Table 5.** Accuracy and number of detected faces using the Haar cascade classifier for face detection in frontal and non-frontal images representing five faces, compressed by various methods at different BPP values

| Frontal images | | | | | | | | | | | | Non-frontal images | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| JPEG | | | | | | | | | | | | JPEG | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 5 | 0.83 | 7(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) |
| JPEG2000 | | | | | | | | | | | | JPEG2000 | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) |
| SPIHT | | | | | | | | | | | | SPIHT | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.91 | 6(5) | 0.67 | 4(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) | 0.75 | 3(3) |

**Table 6.** Accuracy and number of detected faces using the Haar Cascade Classifier for face detection in frontal and non-frontal images representing three faces, compressed by various methods at different BPP values

| Frontal images | | | | | | | | | | | | Non-frontal images | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| JPEG | | | | | | | | | | | | JPEG | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 1 | 10 | 0.87 | 13(10) | 0.95 | 11(10) | 0.91 | 12(10) | 0.95 | 11(10) | 0.91 | 12(10) | 0.18 | 1(1) | 0.29 | 4(2) | 0.4 | 5(3) | 0.15 | 3(1) | 0.29 | 4(2) | 0.27 | 5(2) |
| JPEG2000 | | | | | | | | | | | | JPEG2000 | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 0.91 | 12(10) | 0.87 | 13(10) | 1 | 10 | 0.95 | 11(10) | 0.95 | 11(10) | 0.91 | 12(10) | 0.15 | 3(1) | 0.29 | 4(2) | 0.37 | 6(3) | 0.4 | 5(3) | 0.37 | 6(3) | 0.29 | 4(2) |
| SPIHT | | | | | | | | | | | | SPIHT | | | | | | | | | | | |
| 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | | 0.1 | | 0.2 | | 0.4 | | 0.5 | | 1 | | 1.5 | |
| F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F | F | Det.F |
| 0.95 | 11(10) | 0.87 | 13(10) | 1 | 10 | 0.95 | 11(10) | 0.95 | 11(10) | 0.91 | 12(10) | 0.17 | 2(1) | 0.29 | 4(2) | 0.4 | 5(3) | 0.4 | 5(3) | 0.37 | 6(3) | 0.29 | 4(2) |

value cases in all the applied compression algorithms, switch between 0.91 (2 additional false detections) and 0.95 (1 additional false detection) without discernible causality. A large number of non-frontal faces in a compressed image leads to poor face detection results when using the Haar Cascade Classifier, with the highest F-score being as low as 0.4.

Examining the obtained results, it is noticeable that there are several characteristic cases of Haar Cascade-based face detection in images representing faces from the frontal perspective, as well as in images representing faces from the non-frontal perspective. The following figures show the above-mentioned characteristic cases. Figure 3 displays JPEG images with faces captured from the frontal perspective and compressed at the BPP value of 0.1, showing perfect face detection regardless of the number of faces represented. Figure 4 displays images with ten faces captured from both frontal and non-frontal perspectives and compressed using JPEG, JPEG2000, and SPIHT algorithms at various BPP values, showing the worst face detection results.

The remaining face detection images generated in this study are available in the dataset repository [15].

By gathering all the results from the processes detailed in Section 2 and Section 3, the following conclusions were drawn.

## 4. CONCLUSION

This paper presents an analysis of face detection using the Haar Cascade Classifier in frontal and non-frontal images representing different numbers of faces and compressed using JPEG, JPEG2000, and SPIHT algorithms at different bits-per-pixel values.

The obtained results indicate that the Haar Cascade Classifier does a significantly better job performing face detection in images showing frontal faces, regardless of the applied compression algorithm. Given the collected data, the described face detection method achieves the perfect F-score of 1 in frontal JPEG images for the BPP value of 0.1. There aren't cases of undetected faces in frontal face images, regardless of the compression algorithm. Single-face images have the best chance of getting the perfect F-score; as the number of faces in an image increases, the F-score remains high but becomes more unpredictable, with no distinct connection to the BPP value.

The data collected for the non-frontal face images confirms that the Haar Cascade Classifier is less effective when face detection is needed in non-frontal images, with better results being achieved in images representing smaller numbers of faces and the F-score dropping in an inverse proportionality manner to the rising number of represented faces. Additionally, there's an observed relationship between the angle of rotation of the face and the face detection accuracy, with a smaller angle of rotation increasing the chance of a correct face detection.

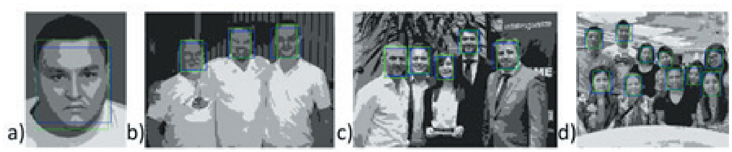


**Figure 3.** Frontal JPEG images compressed at the BPP value of 0.1, showing perfect face detection regardless of the number of faces represented

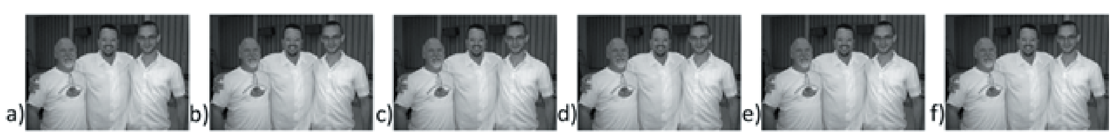


**Figure 4.** Frontal a) JPEG, b) JPEG2000, and c) SPIHT images compressed at the BPP value of 0.2, and non-frontal d) JPEG, e) JPEG2000, and f) SPIHT images compressed at the highest BPP value of 1.5, representing ten faces, showing the worst results of face detection

The findings contribute to the further development of image compression algorithms to make them more suitable for use in face detection systems and, also, to the necessity of additional improvements in the Haar Cascade Classifier, especially in cases with a larger number of faces and greater angles of perspective. Finding an approach for solving these problems indicates a possible direction for future research.

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