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PERFORMANCE ANALYSIS OF HAAR CASCADE-BASED FACE DETECTION IN MULTI-FACE IMAGES UNDER DIGITALLY SIMULATED LIGHTING CONDITIONS

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Abstract
In this study, the performance of the Haar Cascade Classifier was evaluated in images containing varying numbers of faces captured from both frontal and non-frontal perspectives. The images extracted from the Face Detection Dataset (FDD) were digitally manipulated to achieve different lighting conditions by adjusting brightness, contrast, and gamma parameter values using a Python program. The Haar Cascade Classifier, implemented in a separate Python program, was used to carry out the face detection process. Two objective metrics were employed to estimate detection accuracy: the F-measure, derived from GroundTruth data of the reference images, and Det.F, representing the total number of detected faces. The findings indicate that variations in brightness, contrast, and gamma parameters slightly affect detection outcomes, while changes in the angle of perspective have a far more significant impact. The Haar Cascade Classifier achieved the best results in images showing frontal faces, especially when there is a small number of faces represented in an image, regardless of the lighting conditions; images containing a large number of non-frontal faces confirmed the classifier's limited robustness under such complex conditions.
Keywords: Face Detection, Haar Cascade Classifier, Brightness, Contrast, Gamma.

INTRODUCTION

The rapid advancement of intelligent computer systems has extensively shaped technological development and expanded how humans interact with machines. One clear example of this progress is face detection, which represents a specific type of object detection. In essence, object detection involves identifying and locating elements within digital images or video sequences, such as detecting faces or vehicles. These characteristics have enabled the technique to find its use in many areas, including facial recognition, monitoring pedestrians, and security systems [1].

Face detection serves as the essential initial step that allows the following processes, like face recognition and verification, to take place. During this stage, human faces are identified and located within digital images, laying the foundation for subsequent image analysis. The detection process involves analyzing the input image using pattern differentiation, separating facial features from the surrounding background, and extracting the spatial coordinates for each detected face [2].

Digital images have become prevalent due to the swift advancements in imaging devices and computer vision technologies. Typically, we encounter images of low

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quality that exhibit low contrast and inadequate lighting resulting from different capture conditions. Such low-quality visual images create difficulties for human perception and complicate tasks in image processing and computer vision applications. Based on evaluations in earlier research, inadequate contrast and insufficient lighting are common obstacles in image processing, computer vision, and various fields, including medical technology, military applications, satellite imaging, video surveillance, traffic systems, industrial manufacturing, and underwater image enhancement [3].

Image enhancement is crucial for improving visual perception in areas such as computer vision, pattern recognition, and the processing of digital images [4]. It refers to the process of modifying the intensity of pixels in the original image, intending to make the resulting image appear more visually appealing. The intention behind image enhancement is to enhance the clarity or perception of the information present in the image for human viewers, or to deliver a "superior" input for other automated systems involved in image processing [5].

Face detection represents an important area of research, having been explored for over three decades, yet still exhibiting certain shortcomings in various areas [6].

The authors in [1] examined the effect of JPEG, JPEG2000, and SPIHT compression techniques on face detection using the Haar Cascade Classifier, considering both frontal and non-frontal images from a specific dataset. The authors in [7] evaluated the Haar Cascade Classifier for face detection under different lighting conditions, specifically sunlight and lamp illumination, using a webcam to capture images and analyzing its performance across three lighting levels: dim light, medium light, and bright light. This paper aims to examine how different, digitally generated lighting levels, achieved by separately adjusting brightness, contrast, and gamma parameters, affect face detection using the Haar Cascade Classifier, considering both frontal and non-frontal images from a specific dataset.

The rest of this paper is organized as follows: Section 2 provides an overview of the system model that establishes the foundational framework for a detailed examination of the face detection process. Section 3 presents the outcomes of the face detection process using the Haar Cascade Classifier on both frontal and non-frontal images. The results are displayed in tables, which include F - the numerical accuracy values (F-measure/F-score), Det.F - the total number of detected faces (including true and false detections), and, in parentheses, the number of correctly detected faces when additional false detections are present. Finally, Section 4 summarizes the conclusions and suggests potential directions for future research.

SYSTEM MODEL

This paper presents the analysis of the impact of applying different brightness, contrast, and gamma values to images, prior to performing face detection using the Haar Cascade Classifier.

A general image processing operator can be defined as a function that receives one or more input images and generates an output image. In the continuous domain, this relationship can be expressed as

$$g(x) = h(f(x)) \qquad (1)$$

or

$$g(x) = h(f_0(x), \dots, f_n(x)), \qquad (2)$$

where x lies within a D-dimensional domain (typically D = 2 for images) of the input and output functions f and g. These functions operate over a certain range, which may be either scalar or vector-valued; for instance, in the case of color images or two-dimensional motion fields. For discrete (sampled) images, the domain is composed of a finite set of pixel coordinates, $x = (i, j)$, leading to the discrete representation [8]:

$$g(i,j) = h(f(i,j)). \quad (3)$$

Among the simplest and most widely applied point operations are those that involve either multiplying or adding a constant to the image intensity values [8]:

$$g(x) = \alpha f(x) + \beta. \quad (4)$$

The parameters $\alpha > 0$ and β are commonly referred to as the gain and bias parameters; in some contexts, they are associated with the control of image contrast and brightness, respectively. Both bias and gain parameters can exhibit spatial variation

$$g(x) = \alpha(x)f(x) + \beta(x) \quad (5)$$

such as when emulating a photographer's graduated density filter, which darkens the sky selectively, or when reproducing vignetting phenomena in optical systems [8]. One of the most frequently applied non-linear transformations in image processing is gamma correction. This technique is used to counteract the non-linear mapping that exists between the actual light intensity captured by a sensor and the corresponding quantized pixel values. To reverse the gamma mapping introduced by the sensor, one can apply

$$g(x) = [f(x)]^{\frac{1}{\gamma}} \quad (6)$$

where a gamma value of $\gamma \approx 2.2$ generally provides an appropriate fit for the response characteristics of most digital cameras [8].

The images were obtained from the FDD database [9], accompanied by the corresponding GroundTruth data, which specifies the actual position of each facial component [10]. All three mentioned parameter changes were performed separately for each image. The parameter values used for brightness (beta) were: -60, -40, -20, 0, 40, 80, 160. The parameter values used for contrast (alpha) are: 0.25, 0.5, 0.75, 1.0, 1.5, 2.0, 3.0. The parameter values used for gamma are: 0.3, 0.5, 0.7, 1.0, 1.5, 3.0, 5.0. Images were selected to match those in [1], ensuring they met the specifications for face count (1, 3, 5, and 10) as well as perspective, covering both frontal and non-frontal views. Each image depicted a different number of faces from multiple angles.

The entire process proceeded as follows: The first step involved selecting images from the Kaggle FDD database that met the previously specified requirements. Then, the images extracted from the FDD database were manipulated in order to change their lighting by applying the brightness, contrast, and gamma parameter values described earlier, using a code written and run in Python. Finally, the Haar Cascade Classifier from OpenCV, implemented in a separate, independent Python program, was used for face detection in the obtained images.

A repository [11], set up by the authors of this paper, contains all images used in the study, the obtained datasets, and the related code.

The following objective measures were considered for the analysis:

1. F - which corresponds to the evenly balanced F-measure, obtained through the equation provided below [12,13]:

$$F = \frac{2PR}{P+R} \quad (7)$$

where P represents Precision, also known as positive predictive value (PPV), and R represents Recall or Sensitivity [10].

Under ideal conditions, F is equal to 1, though, in general, it varies within the interval $0 \leq F \leq 1$ [14].

The calculation of Precision is performed according to the equation below [13]:

$$P = \frac{TP}{TP+FP} \quad . \quad (8)$$

The calculation of Recall is performed according to the equation below [13]:

$$R = \frac{TP}{TP+FN} \quad . \quad (9)$$

Here, TP refers to True Positive pixels, which are accurately segmented as foreground; FP refers to False Positive pixels, which are mistakenly segmented as foreground; *TN* refers to True Negative pixels, correctly identified as background; and *FN* refers to False Negative pixels, which are incorrectly detected as background [14].

2. Det.F - which represents the total number of detected faces, including both true and false detections, with the count of correctly identified faces shown in parentheses when false detections occur [1]. Ideally, Det.F matches the number of rectangles in the GroundTruth data, but theoretically ranges from 0 to +∞ [1].

RESULTS AND DISCUSSIONS

From Table 1, it can be clearly observed that, when dealing with frontal images containing a small number of faces (one and three), the Haar Cascade Classifier performs exceptionally well, regardless of the selected brightness parameter values. For images with a larger number of faces (five and ten), the results are largely similar. Perfect detection results are achieved at extremely high brightness values, while in other cases, face detection remains excellent. However, alongside all correctly detected faces, there are occasionally one or, less frequently, two false detections.

The results presented in Table 2 show an almost identical situation when varying the contrast parameters for images with a small number of faces (one and three), as previously observed with brightness adjustments. The only exception occurs when the contrast value is set to 0.25. For images with a larger number of frontal faces (five and ten), a specific pattern emerges where extreme contrast values (the lowest and highest) yield the most promising detection performance, resulting in perfect detection. In all other cases, similarly to the earlier observations, detection remains accurate - all faces are detected - but there are one or two additional false detections, without a clear pattern regarding the parameter values.

Table 1. *Accuracy and detected faces using Haar cascade frontal face detection on images with different brightness.*

Brightness		**-60**	**-40**	**-20**	**0**	**40**	**80**	**160**
1 face	F	1	1	1	1	1	1	1
	Det.F.	1	1	1	1	1	1	1
3 faces	F	1	1	1	1	1	1	1
	Det.F.	3	3	3	3	3	3	3
5 faces	F	0.91	0.91	0.91	0.91	0.91	0.91	1
	Det.F.	6(5)	6(5)	6(5)	6(5)	6(5)	6(5)	5
10 faces	F	0.91	0.95	0.95	0.95	0.95	0.91	1
	Det.F.	12(10)	11(10)	11(10)	11(10)	11(10)	12(10)	10

Table 2. *Accuracy and detected faces using Haar cascade frontal face detection on images with different contrast.*

Contrast		**0.25**	**0.5**	**0.75**	**1.0**	**1.5**	**2.0**	**3.0**
1 face	F	1	1	1	1	1	1	1
	Det.F.	1	1	1	1	1	1	1
3 faces	F	0	1	1	1	1	1	1
	Det.F.	1	3	3	3	3	3	3
5 faces	F	1	0.83	0.91	0.91	0.91	0.83	1
	Det.F.	5	7(5)	6(5)	6(5)	6(5)	7(5)	5
10 faces	F	1	0.95	0.91	0.95	0.91	0.91	1
	Det.F.	10	11(10)	12(10)	11(10)	12(10)	12(10)	10

***Table 3**. Accuracy and detected faces using Haar cascade frontal face detection on images with different gamma values.*

Gamma		0.3	0.5	0.7	1.0	1.5	3.0	5.0
1 face	F	1	1	1	1	1	1	1
	Det.F.	1	1	1	1	1	1	1
3 faces	F	1	1	1	1	1	1	1
	Det.F.	3	3	3	3	3	3	3
5 faces	F	0.91	0.83	0.83	0.91	0.91	0.91	0.91
	Det.F.	6(5)	7(5)	7(5)	6(5)	6(5)	6(5)	6(5)
10 faces	F	0.91	1	1	0.95	0.95	0.95	0.95
	Det.F.	12(10)	10	10	11(10)	11(10)	11(10)	11(10)

Table 3 presents the results for face detection on frontal images under varying gamma values. As with the previous two parameters (brightness and contrast), it is evident that changing the gamma parameter does not affect detection quality in images with a small number of faces (one or three); perfect detection is achieved in these cases. For images containing a larger number of frontal faces, the trend closely matches the earlier results, where, in addition to correctly detected faces, one or two false detections appear. A positive exception occurs in images containing ten frontal faces, with gamma values of 0.5 and 0.7, where perfect detection was recorded. Thus, a moderate reduction in the gamma parameter appears to have a favorable effect on face detection performance in images with a large number of frontal faces.

Observing Table 4, it can be concluded that, for images with a single non-frontal face where brightness values vary, the Haar Cascade Classifier performs almost perfectly, except at extremely high brightness levels, where no true positive cases occur. For images containing three non-frontal faces, detection results improve as the brightness parameter increases; however, not all the detections are true positives. For the images with five non-frontal faces, the situation is mostly similar - partial detection with three correctly identified faces - except when the brightness parameter equals 80, where one additional false detection occurs.

Table 5 shows that face detection results for images containing a single non-frontal face are best when contrast values fall within the range of 0.5 to 1.0. Moving the contrast parameter toward its extreme values (either lower or higher) results in poorer performance, producing additional false detections or failing to detect any faces at all. In the case of five non-frontal faces, the results are identical to those obtained by adjusting brightness - partial detection with one exception. Images displaying ten non-frontal faces again prove to be the most challenging task for the Haar Cascade Classifier; still, higher contrast values tend to yield slightly better detection outcomes, with minor deviations.

***Table 4.** Accuracy and detected faces using Haar cascade non-frontal face detection on images with different brightness.*

Brightness		-60	-40	-20	0	40	80	160
1 face	F	1	1	1	1	1	1	0
	Det.F.	1	1	1	1	1	1	0
3 faces	F	0	0.33	0.40	0.67	0.67	0.67	0.80
	Det.F.	1(0)	3(1)	2(1)	3(2)	3(2)	3(2)	2(2)
5 faces	F	0.75	0.75	0.75	0.75	0.75	0.67	0.75
	Det.F.	3(3)	3(3)	3(3)	3(3)	3(3)	4(3)	3(3)
10 faces	F	0.18	0.18	0.29	0.29	0.43	0.40	0.43
	Det.F.	1(1)	1(1)	4(2)	4(2)	4(3)	5(3)	4(3)

Table 5. *Accuracy and detected faces using Haar cascade non-frontal face detection on images with different contrast.*

Contrast		0.25	0.5	0.75	1.0	1.5	2.0	3.0
1 face	F	0	1	1	1	0.67	0	0
	Det.F.	0	1	1	1	2(1)	1(0)	0
3 faces	F	0.50	0.67	0.67	0.67	0.67	0.33	0.80
	Det.F.	1(1)	3(2)	3(2)	3(2)	3(2)	3(1)	2(2)
5 faces	F	0.75	0.75	0.75	0.75	0.75	0.67	0.75
	Det.F.	3(3)	3(3)	3(3)	3(3)	3(3)	4(3)	3(3)
10 faces	F	0.15	0.15	0.14	0.29	0.43	0.40	0.43
	Det.F.	3(1)	3(1)	4(1)	4(2)	4(3)	5(3)	4(3)

Table 6. *Accuracy and detected faces using Haar cascade non-frontal face detection on images with different gamma values.*

Gamma		0.3	0.5	0.7	1.0	1.5	3.0	5.0
1 face	F	1	1	1	1	1	1	1
	Det.F.	1	1	1	1	1	1	1
3 faces	F	0.40	0.40	0.40	0.67	0.40	0.50	0.50
	Det.F.	2(1)	2(1)	2(1)	3(2)	2(1)	1(1)	1(1)
5 faces	F	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	Det.F.	3(3)	3(3)	3(3)	3(3)	3(3)	3(3)	3(3)
10 faces	F	0.18	0.18	0.18	0.29	0.37	0.37	0.40
	Det.F.	1(1)	1(1)	1(1)	4(2)	6(3)	6(3)	5(3)

Table 6 indicates that varying the gamma parameter in images with a single non-frontal face does not affect detection quality when using the Haar Cascade Classifier - perfect detection is achieved. For images containing three non-frontal faces, there is no clear correlation between gamma value changes and detection results; the outcomes are relatively poor, except at the gamma value of 1.0, where three faces were detected, including two true positives and one false positive. For images with five non-frontal faces, the previously noted pattern of partial detection is repeated, this time without exceptions. Images with ten non-frontal faces once again yield the weakest detection performance, and, as before, higher gamma values produce somewhat improved results.

CONCLUSION

Based on the obtained results, the Haar Cascade Classifier is significantly more effective at detecting faces in images captured from a frontal perspective. When there is a small number of frontal faces represented in an image (one or three), the detection results demonstrate almost perfect accuracy, regardless of changes in lighting. For images representing a larger number of frontal faces (five or ten), detection performance remains great, with cases of perfect detection occurring at extremely high brightness values, at both very low and very high contrast values, and at gamma values of 0.5 and 0.7. In all other cases, face detection remains highly reliable; however, one or two additional false detections occasionally appear alongside correctly detected faces, without a clear pattern. It is important to note that, across all frontal image cases, there were no instances of missed true faces.

When it comes to images showing non-frontal faces, the results indicate that the Haar Cascade Classifier is not the optimal choice for face detection, particularly when dealing with images that contain a large number of faces. Generally, as the number of non-frontal faces in an image increases, the likelihood of achieving accurate detection decreases. In many cases, higher brightness, contrast, and gamma values appear to improve detection performance; however, due to frequent inconsistencies, it cannot be concluded that increasing these parameters consistently provides better detection outcomes.

The results of this study indicate that the Haar Cascade Classifier performs best when applied to images containing frontal faces, with a smaller number of faces guaranteeing excellent detection results, regardless of lighting variation. However, certain combinations of brightness, contrast, and gamma parameters may further enhance detection accuracy in images with a larger number of frontal faces, which represents a potential direction for future research.

Images containing non-frontal faces present a significant challenge for the Haar Cascade Classifier. As the number of faces and the degree of facial rotation increase, the accuracy of face detection gradually decreases, highlighting the need for further improvements and optimization to efficiently manage these difficult situations.

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REFERENCE

[1] I. Šarkoćević, V. Maksimović, B. Jakšić, P. Spalević, Đ. Banđur, "Performance Analysis of Haar Cascade-Based Face Detection in Multi-Face Images under Diverse Compression Algorithms," *Proceedings of the Sinteza 2025*, Belgrade, Serbia, 2025, pp. 164-171.

[2] K. Dang, S. Sharma, "Review and comparison of face detection algorithms," in *Proceedings of the 7th International Conference Confluence on Cloud Computing, Data Science & Engineering*, Noida, India, 2017, pp. 629-633.

[3] B. Bataineh, "Brightness and contrast enhancement method for color images via pairing adaptive gamma correction and histogram equalization," in *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 3, 2023.

[4] M. Veluchamy, B. Subramani, "Image contrast and color enhancement using adaptive gamma correction and histogram equalization," in *Optik*, vol. 183, 2019, pp. 329-337.

[5] I. Haidi, N. S. P. Kong. "Brightness preserving dynamic histogram equalization for image contrast enhancement." in *IEEE Transactions on Consumer Electronics*, vol. 53, no. 4, 2007, pp. 1752-1758.

[6] H. W. Lee, F. F. Peng, X. Y. Lee, H. N. Dai, Y. Zhu, "Research on face detection under different lighting," in *IEEE International Conference on Applied System Invention (ICASI)*, 2018, pp. 1145-1148.

[7] D. T. P. Hapsari, G. B. C. G. Berliana, P. Winda, M. A. Soeleman, "Face detection using haar cascade in difference illumination," in *2018 International Seminar on Application for Technology of Information and Communication*, 2018, pp. 555-559.

[8] R. Szeliski, "*Computer Vision: Algorithms and Applications* (2nd ed.)", Springer, 2022, ISBN-13: 978-3030343729.

[9] F. Elmenshawii, "Kaggle". [Online]. Available:https://www.kaggle.com/datasets/fareselmenshawii/face-detection-dataset. [Accessed 10.10.2025].

[10] R. Queiroz, M. Cohen, J. L. Moreira, A. Braun, J. C. J. Júnior and S. R. Musse, "Generating facial ground truth with synthetic faces," in *23rd SIBGRAPI - Conference on Graphics, Patterns and Images*, Gramado, Brazil, 2010.

[11] I. Šarkoćević, "Google Drive: Dataset Repository - Haar Cascade-Based Face Detection," [Online]. Available: https://drive.google.com/drive/folders/1Yt-x6uNf8INYEmJsuMlMyX6dRLRH0XKC?usp=sharing. [Accessed 10.10.2025].

[12] Y. Sasaki, "The truth of the F-measure," in *Teach tutor mater,* vol.1, no.5, 2007, pp. 1-5.

[13] M. Sokolova, N. Japkowicz, S. Szpakowicz, "Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation," in *Proceedings of the 19th Australian Joint Conference on Artificial Intelligence,* Hobart, Australia, December 4-8, 2006.

[14] V. Maksimović, B. Jakšić, M. Petrović, P. Spalević and M. Milošević, "Analysis of Edge Detection on Compressed Images with Different Complexities," in *Acta Polytechnica Hungarica,* vol. 2, no. 2, 2020. pp. 77-81.