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An Experiment using the Haar-Cascade and LBPH Algorithms for Real-Time Recognition of Multiple Faces in a Single Frame

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Abstract

Face recognition is an important field in digital image processing and artificial intelligence that is widely applied in security systems, automatic attendance, and human-computer interaction. This research aims to develop and test a real-time multiple face recognition system using a combination of the Haar Cascade algorithm for face detection and the Local Binary Pattern Histogram (LBPH) for face recognition. The system is implemented using the Python programming language and the OpenCV library, and tested under various conditions, such as variations in lighting, face viewing angles, and the number of faces in one frame. Test results show that the system is able to recognize multiple faces with approximately 90% accuracy under normal lighting conditions with varying distances and maintains performance above 80% under low lighting conditions or side-facing face angles. The average detection and recognition time per face ranges from 40–60 milliseconds, which still supports real-time performance. Compared with deep learning-based approaches, this system has advantages in terms of efficiency and ease of implementation, especially on devices with limited specifications. This study shows that the combination of Haar Cascade and LBPH is still relevant and effective for light- to medium-scale multiple face recognition applications.

Keywords: Multiple faces, Haar Cascade, Face recognition, LBPH

I. INTRODUCTION

Advances in artificial intelligence and computer vision have opened up vast opportunities for practical applications in various aspects of life, including security, presence, authentication, and human-computer interaction. One crucial technology within this field is facial recognition, which enables systems to detect and recognize an individual's identity based on facial images. The success of such systems is heavily influenced by accurate facial detection and robust facial recognition capabilities against confounding factors such as lighting, viewing angle, resolution, facial expressions, and occlusion.

Two classic methods frequently used in facial recognition systems are the Haar Cascade algorithm for face detection and the Local Binary Pattern Histogram (LBPH) for face recognition. Haar Cascade is a relatively fast object (facial) detection method because it uses a cascade of Haar-like features, while LBPH extracts local texture patterns in facial images, which are then converted into a histogram as a feature representation. This method has proven to be quite efficient and tolerant of several variations, particularly lighting and facial expressions.

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Although many modern systems use deep learning methods (e.g., CNN) that offer high accuracy, the use of Haar Cascade and Local Binary Pattern Histogram (LBPH) remains attractive, especially in situations with limited resources (light computing), real-time settings, or simple hardware such as a webcam or Raspberry Pi. However, several challenges remain in using these methods, including the accuracy of face recognition within a single frame when multiple faces must be recognized simultaneously using the Haar Cascade and LBPH algorithms, and the extent to which lighting conditions, facial angle, and distance to the camera affect system performance.

Several studies in the last 5 years that have been successfully summarized regarding face detection and facial recognition include those researches. Research conducted by Denny aims to detect the correct use of face masks by detecting the presence of a visible nose and mouth [1]. Then Yilmazer did the research to identify someone who is wearing a mask using cloud computing [2]. Suherwin implements Viola-Jones, Local Binary Pattern Histogram, and Euclidean Distance for real-time face recognition and calculates the face detection time [3]. The integration of Local Binary Pattern and Histogram of Oriented Gradient feature extraction with multiclass Support Vector Machine classification demonstrates an effective and robust approach to improving face recognition accuracy under varying imaging conditions [4] and then, face mask detection using CNN [5]. From these studies, there is a research gap, namely that no one has recognized several faces simultaneously in one frame. Therefore, in this study, a combination of the Haar Cascade and Local Binary Pattern Histogram (LBPH) algorithms was applied for face recognition in one frame containing several faces simultaneously, using Python and OpenCV programming. System performance testing was also carried out including: (accuracy, precision, recall, and recognition time) in different lighting conditions (normal and dim) and variations in the distance of the face to the camera.

The expected benefits of this research include adding theoretical contributions to literature in the domain of classic face recognition using non-deep learning methods, particularly in multiple face recognition scenarios within a single frame and varying real-world environmental conditions. Furthermore, it offers practical contributions, as this system can serve as the basis for applications such as automated attendance, access control, security systems, or identity verification, particularly in educational institutions or organizations. With optimization, the system is expected to operate at adequate speed while maintaining accuracy, thus aiding system development.

II. LITERATURE REVIEW

One of the most popular facial recognition algorithms, the Local Binary Pattern Histogram (LBPH), is the primary technique used in this study. This method is known to be highly robust against light glare in images, which can disrupt model performance, in addition to its easy-to-understand concept. This is because this algorithm converts the value of each pixel to a value comparable to the surrounding pixels. Furthermore, the reason this model is robust is because the conversion is performed in small units (3 x 3 pixels). For example, given a pixel in the image has values as in the following 3 x 3 matrix. The pixel in the center, which has a value of 4, will be used as the threshold for converting the pixel value to binary type. So, if the pixel value ≥ 4, the conversion result is 1 and if the pixel value < 4, the conversion result is 0 [6]. Figure 1 illustrates the conversion of pixel values in a matrix.

$$\begin{array}{|c|c|c|} \hline 5 & 9 & 1 \\ \hline 4 & 4 & 6 \\ \hline 7 & 2 & 3 \\ \hline \end{array} \longrightarrow \begin{array}{|c|c|c|} \hline 1 & 1 & 0 \\ \hline 1 & & 1 \\ \hline 1 & 0 & 0 \\ \hline \end{array}$$

Fig. 1. Matrix Illustration [6]

Mathematically, the LBPH algorithm can be formulated in equation (1).

$$LBP(x_c, y_c = \sum_{p=0}^{p-1} 2^p s(i_p - i_c) \tag{1}$$

Color conversion into binary numbers can not only be done on neighboring 3x3 pixels, but can be set with 4 parameters that will form a circular LBP shown in Figure 2. The first parameter is the radius. This parameter determines the radius distance from the center pixel to the outermost pixel; the default radius is 1 pixel. The second parameter is the number of neighbors. Usually the number used is 8, which means samples are taken from 8 neighboring points. The third parameter is the X grid. This sets the division of the image area on the X axis. By default, it is 8. The third parameter is the Y grid which sets the division of the image area on the Y axis. By default, it is also 8. If the point taken as a sample fall within the border between several pixels, then a point estimation method called bilinear interpolation is used [6].

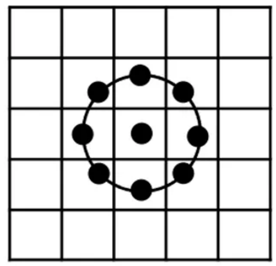

Fig. 2. Round LBP Illustration [6]

In this section, we summarize several relevant studies in the last 5 years, using a combination of the Haar Cascade and LBPH algorithms, especially for the purpose of face detection and recognition, in real conditions, many faces, lighting variations, and presence or security applications. Research conducted by Salman et al. [7], conducted a study of the combination of LBPH and Haar Cascade, with pre-processing histogram equalization for dim lighting conditions resulting in high accuracy of around 88% for face detection and recognition in low light conditions. However, variations in pose and facial accessories can degrade performance. Then research by Pahlevi et al. showed decreased performance in night conditions (low lighting) and large rotation angles (rotation). Then research conducted by Beri et al. [8], on a real-time face recognition-based attendance system by combining Haar Cascade for detection & LBPH. The system showed high accuracy and reliability in various conditions, suitable for educational institutions/offices. Research conducted by Hutama Hadi et al. on face identification tests based on light intensity (bright, normal, dark). The results show that the highest accuracy in bright conditions is 62%, lower in normal and dark conditions [9]. Then, research conducted by Dwi Cahyo et al. [10] the system successfully recognized faces in various conditions with satisfactory performance despite variations in angles and facial expressions. In the same year, Deva et al. [11] also conducted almost the same research. The system was able to detect & recognize faces in real time, but the level of confidence / accuracy was sometimes unstable in difficult conditions (poor lighting, half-obstructed face).

III. RESEARCH METHOD

This research aims to implement the Haar-Cascade algorithm for face detection and the Local Binary Pattern Histogram (LBPH) algorithm for face recognition. This research was conducted to determine the performance of these algorithms in recognizing multiple faces simultaneously within a single frame. The methods used in this research are explained in the following steps:

A. Research Design

This study uses a quantitative experimental approach, with the aim of testing the performance of a multiple face detection and recognition system (multiple faces in one frame) using the Haar Cascade and Local Binary Pattern Histogram (LBPH) algorithms. All implementations were carried out using the Python programming language and OpenCV libraries, with testing in various situations (lighting, face angle, and distance to the camera).

B. Hardware and Software

The hardware used is a standard webcam (minimum resolution of 720 or as high as possible), a computer/laptop with minimum specifications (a processor equivalent to Intel i5 / NVIDIA GeForce 820M, 8 GB of RAM, and storage for the dataset).

The software used includes Python (version 3.6 or higher), OpenCV (latest version), NumPy (a library required for image processing), and other necessary modules (OS, time, etc.). The operating system is Windows 10.

C. Datasets

The dataset used in this study includes several parameters, namely:

1) Number of Subjects: 1 person to more than 3 people, with different variations in facial conditions including: (expressions, use of accessories such as glasses to the use of headscarves/hijabs for women). Figure 3 are image samples of dataset.
2) Number of Images: There is training data and testing data. 100 individual training images. Testing data using a real-time application with 25 tests/image frame.
3) Variation: images were taken in normal light and low light conditions, different facial angles (frontal and sideways), different distances to the camera (30 cm, 50 cm, 100 cm).
4) Data Preprocessing: Includes conversion of training images to grayscale, normalization of facial image size (resize), cropping of faces based on bounding box from Haar Cascade detection, and application of Local Binary Pattern Histogram (LBPH) algorithm for facial recognition.

Fig. 3. Image samples of Dataset

D. System stages

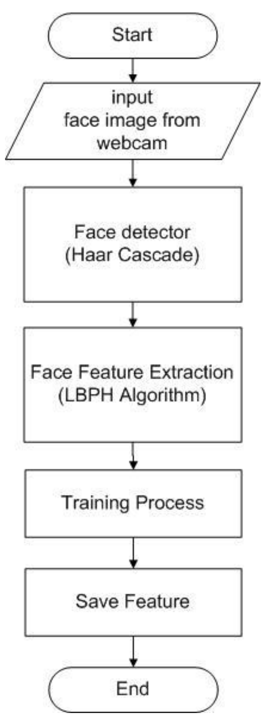

Fig 4. Training Process

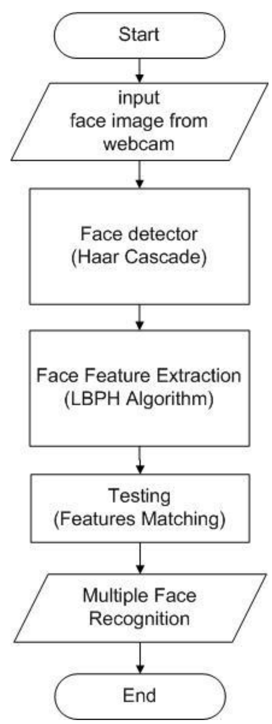

Fig 5. Testing Process

1) Face Detection
The algorithm used in this stage is the Haar-Cascade (a pre-trained classifier, using haarcascade_frontalface_default.xml) to detect faces in the frame. Parameters such as scale Factor, minimum Neighbors, and minimum face size (min-Size) will be adjusted and their effects tested.

2) Features Extraction
After face detection, the facial image is processed and resized to achieve the same dimensions. Feature extraction uses the LBPH algorithm, with parameter settings such as radius, neighbors, and grid size varied for testing.

All training and testing process explained in diagram at Figure 4 and Figure 5.

E. Model Training and Testing

The training data is used to train the LBPH facial recognition model and save the model (supporting files) for use in the testing phase. From a video or stream from a camera, the system detects and crops faces, then performs the recognition function by comparing the trained facial data to produce labels and confidence values. If multiple faces are present in a single frame, each face is processed separately.

The system will be tested under several conditions to determine the reliability of the designed system, including:

1) Lighting: normal and low light,
2) Facial angles: frontal and 30-degree tilted face,
3) Distance to camera (30 cm, 50 cm, 100 cm),
4) Multiple faces in one frame: for example, 1 face, 2 faces, 3–5 faces at once, to test how performance decreases when there are many faces.

F. Performance Evaluation and Measurement

The parameters generated for evaluation include accuracy, precision, recall, and face detection and recognition time. Accuracy, recall, and precision are calculated based on the confusion matrix generated from the study. Recognition time is calculated using a timer or system. Accuracy is used to indicate the percentage of correctness in face recognition. Precision and recall are used to indicate the consistency or closeness of research data conducted repeatedly [12].

IV. RESULTS AND DISCUSSION

Testing was conducted using an experiment using a combination of the Haar Cascade algorithm for face detection and the Local Binary Pattern Histogram (LBPH) for face recognition. The system was tested in various scenarios, including:

1) Number of faces in one frame (1, 2, ≥3 faces)
2) Light Condition (Normal Light and Low Light),
3) Facial angle (frontal, side ±30°),
4) Distance to camera (30cm, 50cm, 100cm).

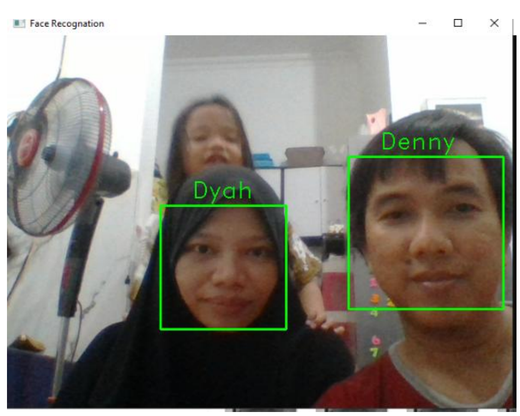

Fig. 6. Sample testing image of 2 person for normal lighting condition and a distance of 50 cm

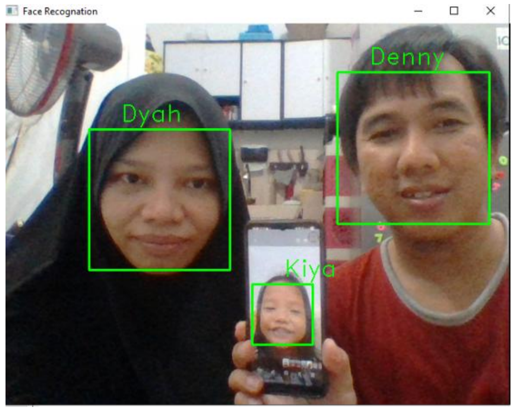

Fig. 7. Sample testing image of 3 person for normal lighting condition and a distance of 50 cm

Figure 6 and Figure 7 show a sample image from training under normal lighting conditions and a distance of 50 cm. The image shows three people, but only two are detected because the child's face is partially obscured by the adult in front of him. This indicates that the system has limitations in detecting facial patterns. If the facial pattern used as a characteristic in the Haar-Cascade algorithm is not met, the system is unable to detect the face. Table I shows a summary of the system performance based on the metrics of accuracy, precision, recall, and average recognition time per face:

TABLE I
PERFORMANCE RESULTS OF LBPH AND HAAR-CASCADE ALGORITHMS

Number of Faces (condition)	Light Condition	Distances	Accuracy (%)	Precision (%)	Recall (%)	Recognition time (milliseconds)
1 face	Low	30 cm	84.5	86.2	83.7	54
2 faces	Low	30 cm	83.7	85.3	82.3	55
3 faces	Low	30 cm	81.2	83.1	80.7	57
1 face	Normal	30 cm	**98.3**	**98.5**	**98.2**	**43**
2 faces	Normal	30 cm	96.7	97.0	96.5	47
3 faces	Normal	30 cm	92.8	93.1	92.4	58
1 face	Low	50 cm	83.1	85.4	82.5	55
2 faces	Low	50 cm	91.2	92.3	91.2	48
3 faces	Low	50 cm	88.1	90.2	87.5	55
1 face	Normal	50 cm	95.6	96.3	94.7	48
2 faces	Normal	50 cm	93.4	94.1	92.5	57
3 faces	Normal	50 cm	91.3	93.2	90.8	59
1 face	Low	100 cm	82.3	83.5	81.1	60
2 faces	Low	100 cm	80.1	82.5	79.6	65
3 faces	Low	100 cm	78.5	79.6	77.9	70
1 face	Normal	100 cm	89.2	90.3	88.7	55
2 faces	Normal	100 cm	88.6	88.9	87.5	59
3 faces	Normal	100 cm	84.9	85.4	83.2	65
30-degree tilted face	Normal	30 cm	87.3	88.1	86.7	56

The results show that the system accuracy tends to decrease as the number of faces in a frame increases, still achieving an accuracy of 80%-90% under normal conditions. This is due to the complexity of face detection increasing when many facial objects appear in the frame, the possibility of overlapping between faces, which reduces the quality of bounding box detection by Haar Cascade, variations in face size in the frame (depending on the distance to the camera), which affects feature extraction by LBPH. This finding is in line with the results of Pahlevi et al. [13], which showed a decrease in accuracy when faces are in close proximity or partially covering each other.

Lighting conditions significantly affect system performance. In low-light conditions, accuracy drops to 78.5% for a distance of 100 cm with face recognition of more than 3 people. This is because Haar Cascade relies on the contrast between facial features (eyes, nose, mouth), so bounding box detection can fail if the contrast is low. LBPH also has difficulty extracting clear texture patterns in dark images. The use of histogram equalization or CLAHE in preprocessing can help, as shown in the study of Salman et al. [7], where increasing contrast improves face recognition accuracy by 5%–8% in low-light conditions.

System performance decreases when the face is in a sideways position or when the subject is further from the camera (distance >1 meter). At a face angle of ±30°, accuracy drops to 87.3% at a distance of 30 cm. This decrease is caused by the Haar Cascade being trained to detect frontal faces, so detection can fail or the bounding box is not accurate in sideways poses. LBPH also performs better on frontal images because the texture pattern is more symmetrical and consistent. Smaller face resolution at long distances causes loss of texture detail, making the LBPH feature less accurate. Paul et al. [14] proved that too low a face resolution (<45px) causes LBPH accuracy to drop drastically, even up to 20%.

The average time required for the system to detect and recognize faces under normal conditions is approximately 40–60 milliseconds/face. Overall, the system is capable of operating in real time at approximately 8–12 frames per second (fps), depending on the number of faces and lighting conditions. This supports the system's claim to be a lightweight and fast solution, as also noted in the study [15] and [8].

The results of this study indicate that the combination of Haar Cascade and LBPH remains highly suitable for facial recognition applications, especially in systems with low-demand and real-time requirements, devices with limited resources, attendance systems, access control, or simple security. Although not as robust as deep learning methods, this combination has proven to be quite reliable, fast, and easy to implement, and has room for optimization through preprocessing and parameter adjustments.

For discussion, the findings of this study are largely consistent with previous research, particularly regarding the limitations of classical face recognition methods under challenging conditions such as multiple faces, low illumination, non-frontal poses, and increased distance. Similar to the observations reported by Pahlevi et al. [13] and Paul et al. [14], this study confirms that face overlap, reduced facial resolution, and pose variations negatively affect the performance of Haar Cascade and LBPH. However, the contribution of this research lies in its comprehensive evaluation of these factors within a single real-time multi-face recognition system, providing quantitative evidence that acceptable accuracy (80%–90%) can still be maintained under normal conditions and that performance degradation remains within predictable and explainable limits. In addition, the results reinforce prior findings by Salman et al. [7] regarding the sensitivity of LBPH to lighting conditions, while also highlighting practical preprocessing strategies that can be applied to mitigate this issue.

Compared to earlier studies that often focused on accuracy alone, this research adds value by jointly analysing recognition accuracy and computational efficiency in real-time scenarios. While deep learning-based approaches reported in recent literature achieve higher robustness, they typically require greater computational resources. In contrast, this study demonstrates that the Haar Cascade–LBPH combination can achieve real-time performance of 8–12 fps with processing times of 40–60 milliseconds/face, aligning with the lightweight performance claims reported in [8] and [15]. This comparative analysis underscores the continued relevance of classical approaches for resource-constrained environments, such as attendance systems and access control applications, and positions this work as a practical reference for selecting efficient face recognition methods when hardware limitations or real-time constraints are critical considerations.

V. CONCLUSION

Based on the results of research that has been conducted regarding the application of the Haar Cascade and Local Binary Pattern Histogram (LBPH) algorithms for real-time multiple face recognition using Python, several conclusions can be drawn as follows:

1. The system is able to recognize multiple faces simultaneously with high accuracy, above 90% under normal conditions (normal lighting, face frontal to the camera, distance of 30 cm). This shows that the combination of Haar Cascade and LBPH is quite reliable for light to medium scale real-time face recognition applications.
2. Face recognition times remain within the real-time range, between 40 – 60 millisecond/face, even when there are two or more faces in a single frame. This demonstrates the algorithm's efficiency and precise parameter optimization.
3. The combination of Haar Cascade and LBPH is suitable for systems with computational constraints, without requiring GPUs or deep learning infrastructure.

4. This research shows the advantages of the classical (non-deep learning) approach which is still relevant, especially in the context of attendance, access control, or surveillance systems with limited resources.

Suggestions that can be given for further research are:

1. Integration of adaptive preprocessing methods, such as CLAHE (Contrast Limited Adaptive Histogram Equalization), to improve system accuracy under poor lighting conditions.
2. Added multi-orientation face detection support, such as using the HOG (Histogram of Oriented Gradients) method or DNN face detector from OpenCV to overcome the limitations of Haar Cascade on extreme poses.
3. Testing in real environments such as classrooms, office entrances, or public areas, to test the robustness of the system broadly and realistically.
4. Development of a more interactive user interface (GUI) and integration with attendance databases or access logs for real implementation in attendance or security systems.
5. Combination with lightweight machine learning or deep learning methods (such as KNN, SVM, or Mobile Net-based embedding) can be considered to improve accuracy without significantly sacrificing efficiency.

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REFERENCES

[1] D. Hardiyanto, I. Prastyaningrum, U. Kholifah, and D. A. Sartika, “Identifikasi Penggunaan Masker yang Tepat pada Wajah Berbasis Deteksi Mulut dan Hidung”, *J. Nas. Tek. Elektro dan Teknol. Inf.*, vol. 11, no. 4, pp. 244–250, 2022, doi: https://doi.org/10.22146/jnteti.v11i4.3077.

[2] B. Yilmazer and S. Solak, “Cloud Computing Based Masked Face Recognition Application”, in *2020 Innovations in Intelligent Systems and Applications Conference (ASYU)*, IEEE, Ed., Istanbul, Turkey, 2020, pp. 1–5. doi: 10.1109/ASYU50717.2020.9259806.

[3] Suherwin, Z. Zainuddin, and A. A. Ilham, “The Performance of Face Recognition Using the Combination of Viola-Jones, Local Binary Pattern Histogram and Euclidean Distance”, in *2020 4th International Conference on Informatics and Computational Sciences (ICICoS)*, Semarang: IEEE, 2020. doi: 10.1109/ICICoS51170.2020.9299073.

[4] M. W. Tsigie, R. Thakare, and R. Joshi, “Face Recognition Techniques Based on 2D Local Binary Pattern, Histogram of Oriented Gradient and Multiclass Support Vector Machines for Secure Document Authentication”, in *Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, Coimbatore: IEEE, 2018. doi: 10.1109/ICICCT.2018.8473318.

[5] T. Septiana, N. Puspita, M. Al Fikih, and N. Setyawan, “Face Mask Detection Covid-19 Using Convolutional Neural Network (CNN)”, in *Seminar Teknologi dan Rekayasa*, Malang: Universitas Muhammadiyah Malang, 2020, pp. 27–32. doi: https://doi.org/10.22219/sentra.v0i6.3801.

[6] R. Soedarnadi, “Pengenalan Wajah Menggunakan Algoritma Local Binary Pattern Histogram (LBPH)”, medium.com. Accessed: Sep. 07, 2025. [Online]. Available: https://medium.com/@rahmasoed/pengenalan-wajah-menggunakan-algoritma-local-binary-pattern-histogram-lbph-82359410cede

[7] A. Salman, M. Hayaty, and I. N. Fajri, “Facial Images Improvement in the LBPH Algorithm Using the Histogram Equalization Method”, *JUITA J. Inform.*, vol. 10, no. 2, p. 217, 2022, doi: 10.30595/juita.v10i2.13223.

[8] N. Beri, V. Srivastava, and N. Malik, “Face Recognition Attendance Management System using LBPH

and Haar Cascade", *J. Trends Comput. Sci. Smart Technol. 6,* vol. 6, no. 3, pp. 257–273, 2024, doi: 10.36548/jtcsst.2024.3.004.

[9] H. Hadi, H. Radiles, R. Susanti, and M. Mulyono, "Human Face Identification Using Haar Cascade Classifier and LBPH Based on Lighting Intensity", *Indones. J. Artif. Intell. Data Min.*, vol. 5, no. 1, p. 13, 2022, doi: 10.24014/ijaidm.v5i1.15245.

[10] F. S. D. Cahyo, B. M. Basuki, and O. Melfazen, "Sistem Absensi Mahasiswa dan Dosen Menggunakan Pengenalan Wajah Dengan Metode Haar Cascade dan LBPH (Local Binary Patterns Histograms)", *Sci. Electro*, vol. 17, no. 4, 2024.

[11] D. S. Alfan, A. Rochman, M. Firdaus, N. Setiawan, and P. Rosyani, "Penerapan Metode Haar-Cascade Dan LBPH Untuk Face Detection dan Recognition", *J. AI dan SPK*, vol. 2, no. 1, pp. 96–104, 2024.

[12] D. Hardiyanto and D. Anggun Sartika, "Optimalisasi Metode Deteksi Wajah berbasis Pengolahan Citra untuk Aplikasi Identifikasi Wajah pada Presensi Digital", *Setrum Sist. Kendali-Tenaga-Elektronika-Telekomunikasi-Komputer*, vol. 7, no. 1, pp. 107–116, 2018, doi: 10.36055/setrum.v7i1.3367.

[13] R. A. Pahlevi and B. Setiaji, "Analysis Of Application Haar Cascade Classifier And Local Binary Pattern Histogram Algorithm In Recognizing Faces With Real-Time Grayscale Images Using Opencv", *J. Tek. Inform.*, vol. 4, no. 1, pp. 179–186, 2023, doi: https://doi.org/10.52436/1.jutif.2023.4.1.491.

[14] K. C. Paul and S. Aslan, "An Improved Real-Time Face Recognition System at Low Resolution Based on Local Binary Pattern Histogram Algorithm and CLAHE", *Opt. Photonics J.*, vol. 11, no. 04, pp. 63–78, 2021, doi: 10.4236/opj.2021.114005.

[15] A. 'Aatieff A. Hussin, A. R. Ismail, A. Jamalullain, A. M. A. Hamid, M. A. Asyraf, and M. Lubis, "Face Recognition based Attendance System using Haar Cascade and Local Binary Pattern Histogram Algorithm", *J. Adv. Res. Appl. Sci. Eng. Technol.*, vol. 59, no. 2, pp. 141–153., 2024, doi: https://doi.org/10.37934/araset.59.2.141153.