Design of an E-Attendance Checker through Facial Recognition using Histogram of Oriented Gradients with Support Vector Machine

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Abstract— **The usual way of checking the attendance in a class has its own drawbacks. To be able to resolve it, automated attendance systems were introduced. In this paper, the design and development of an e-attendance checker using a facial recognition system were implemented. It can scan the faces of multiple students in a standard classroom setup. A commonly used approach for face detection called Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM) was applied to examine the effect of luminance of the surrounding, the facial orientation of the student and so as their distance from the camera in the facial detection and recognition. The obtained attendance will then be uploaded to a database with authentication. It was found that the system has an accuracy of 95.65% and can detect and recognize up to 37 students. It is suggested that the classroom should have a luminance level of about 217.39 lux or higher to achieve a better accuracy performance of the system. As for the analysis of the effect of distance in the system, it is claimed that the distance of the student does not affect the accuracy of the system. Lastly, it is suggested that the face angles of the subject should be directly facing the camera to achieve a more accurate recognition result.**

Keywords: Histogram of Oriented Gradients, Support Vector Machine, facial recognition system, e-attendance checker

I. Introduction

The checking of student attendance correlates with the academic performance in educational institutes. However, the maintenance of a manually checked attendance is a tedious and difficult job to do for the instructors and the institute as well [1] since the conventional method of monitoring class attendance requires a considerable amount of time and is vulnerable to errors and proxy attendances [2].

In order to resolve this problem, automated attendance management systems were introduced in the recent years. In Lukas' et al. (2016) study on face recognition, the researchers utilized the Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), and the Radial Basis Function Network (RBFN) in order to extract the facial features of a person for the system to recognize them. It was discussed that the automated student attendance system using face recognition works quite well with 82% of accurately recognizing facial images in the classroom [3].

Existing articles have already conducted actual facial recognition systems with different techniques and algorithms. However, it did not extensively consider some external factors that can significantly affect the accuracy of the face detection and recognition. This was concluded in the study of Okokpujie's et al. [4], stating that the different lighting conditions and orientations of the face resulted in the variations of the accuracy to their system. Optimizing these external key factors could be beneficial to the accuracy of the system.

The main purpose of this paper is to design an electronic attendance (E-Attendance) checker through facial recognition system using Histogram of Oriented Gradients with Support Vector Machine by considering its (a) conceptual framework, (b) process flow, and (c) implementation while considering the camera and class size optimization. This research specifically aims (1) to determine the accuracy of the system based in a classroom environment, and to examine the effect of (2) varying lighting conditions, (3) varying distance and (4) varying face orientation on the accuracy of the system.

The significance of this study is that the application of a facial recognition-based attendance checker provides trustworthy attendance monitoring that will not affect the lecture, for it is non-intrusive. It means that the checking of attendance will be made faster and more efficient. Also, it provides authentication through the facial features of each person inside the classroom that will eliminate the possibility of having proxy attendance.

The focus of this research is to provide an alternative way of attendance checking by using a facial recognition system in a classroom environment. The attendance obtained from the said system is stored in a database that can be accessed by the professors and administrators. A delimitation of this paper is that it does not consider counter measures in order to tolerate varying facial position that would diminish the accuracy of the system. Also, it does not provide any means for increasing the accuracy of the system, but rather finds the optimized conditions that can be considered to increase the accuracy of the system. Furthermore, the system can only accommodate a limited number of students and is only for a classroom-based environment.

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II. Review of Related Literature

Numerous face recognition attendance system researches have emerged in recent years. Each implementation differs from the algorithms that the researchers have used. Due to facial recognition being known as an efficient system that involves the identification of people researches like this has emerged. It is commonly used in schools, universities, working facilities, or any organization [5]. Facial recognition is an automated biometric system that can be used in checking student attendance since the traditional or manual system of attendance checking has many drawbacks considering an increased number of students. It was also implemented and proven in Dela Cruz' et al. study [6]. In this way, a fast and secure system of attendance checking can be developed which also reduces the chance of proxies in attendance.

The summarized table indicated below shows the algorithms used by previous researches while also considering the reliability or accuracy of their systems.

Table I. Algorithms used by Previous Researches

Author	Technique	Reliability of the System
Lukas et al. [3]	DWT, DCT, RBFN	Reliable 82% Accurate
Patel et al. [5]	Face_Recognizer class library in OpenCV	Reliable 99.38% Accurate (Sample size was not indicated)
Vispute et al. [7]	Viola-Jones Eigenface Algorithm PCA	Reliable
Mehta et al. [8]	LBPH	Reliable
Malik et al. [9]	Eigenface Algorithm PCA	Reliable
Varadharajan et al. [10]	Eigenface Algorithm PCA Preprocess: Background subtraction	Not reliable when the female students wore a veil.
Adouani et al. [11]	HOG-SVM Haar-like Cascade LBP	Reliable 92.68% 78.23% 39.64%, respectively

The systems implemented by the researchers, Patel et al. and Adouani et al., utilized a video feed input. The Raspberry Pi's memory and processing speed would limit the system's performance when using video as an input, compared to an image. Additionally, majority of the other research utilized the Eigenface algorithm. The Eigenface algorithm is very efficient in regards with the processing time and storage; however, a major drawback is that the accuracy of the system is sensitive to the varying light conditions and facial position.

For facial detection, the Histogram of Oriented Gradients stands out for its efficiency. As for the facial recognition algorithms, three of the more common techniques are assessed in a research done by Adouani et al. These three algorithms are namely Haar-like cascade, Histogram of Oriented Gradients (HOG) with Support Vector Machine and Linear Binary Pattern cascade (LBP). It was determined that the Histogram of Oriented Gradients (HOG) with Support Vector Machine algorithm outperforms the other two algorithms in terms of confidence factors. HOG with SVM is deemed to be the most accurate and efficient face recognition algorithm available in the OpenCV library.

III. Methodology

A. Face Recognition System

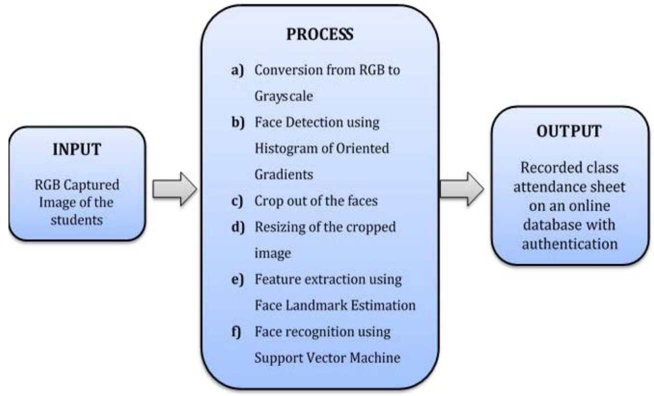

Fig. 1 Conceptual Framework

Two inputs would be required by the system; one would be the training images while the other input would represent the attendance of the student. For the training images, it would undergo a face landmark estimation and will be stored in a database. Data from this database will be pulled whenever a comparison for the facial recognition system will be processed. The image input that would serve as the attendance of the student would go through a conversion from RGB to Gray, then Facial detection via Histogram of Oriented Gradients extraction would occur to determine the faces of the image. Afterwards, the extracted face would be cropped and resized to enable face landmark feature estimation. Once this is done, the system would then proceed to compare the histograms derived from the SVM in order to determine the identity of the detected face. If the image is not identified, the system would drop that image and then restart the process, otherwise the system would update the attendance record and mark the student as present. In the case that the student is not in the class database where the pre-enrolled individual faces of the students are recorded, the system will then show that the student is 'unknown'. This record would then be uploaded to an online database via MySQL database.

B. Implementation

The two main hardware components that were used in this research, were the Raspberry Pi 3B+ and the Raspberry Pi Camera Module V2 to capture images.

Table II. Raspberry Pi Camera V2 Specifications

Video Capture resolution	1080p30, 720p60 and 640 × 480p60/90
Sensor resolution	3280 × 2464 pixels
Horizontal field of view	62.2 degrees
Vertical field of view	48.8 degrees
Still Resolution	True: 8MP
Camera Lens	0.45x Super Wide-Angle Macro Lens

A Raspberry Pi is a low cost and low energy gateway device that has the ability to facilitate the necessary computations and functions needed for the face recognition system. During this paper's research and implementation,

Table IV. Face Detection with Different Camera Positions

	Camera Position					
	Left of reference	Right of reference	Reference	Above the reference	Below the reference	Total
Successful Detection	7	9	15	7	9	47
Unsuccessful Detection	11	9	3	11	9	43
Total	18	18	18	18	18	90

The null hypothesis for this test is that the camera position does not affect the number of successful face detection. Again, a significance level of $\alpha = 0.05$ was used.

Using Fisher's Exact Test of Independence, the acquired P-value is 0.0442. Since the P-value is less than the significance level, the null hypothesis is rejected, and it is concluded that the camera position does affect the number of successful face detection, with the reference position having the greatest number of successful detections. With this result, the reference point which has the greatest number of successful detections will then be used for the testing and implementation of the system.

To assess the general performance of the system, several students were invited to participate in this study and asked them to sit in random seats in the room and look at the camera when taking the images. Starting with ten students, the number of participants was increased by one in each trial. Several factors such as the luminance level inside the room, the distance of the participants from the camera, and the participants' face orientation were uncontrolled at this point. Fig. 5 shows a sample image taken from this test.

Additionally, larger class sizes would require more training images as compared to smaller class sizes. Larger class sizes are more susceptible to misrecognition given that the system examines more identities. More training images are used in order to compensate for this issue.

Table V. Accuracy in a Classroom Environment

Number of Students	No. of Successful Recognition	No. of Unsuccessful Recognition	Accuracy (%)
10	8	2	80
11	9	2	81.82
12	10	2	83.33
13	11	2	84.62
14	13	1	92.86
15	12	3	80
16	13	3	81.25
17	14	3	82.35
18	16	2	88.89
19	17	2	89.47
20	19	1	95
21	20	1	95.24
22	21	1	95.45
23	22	1	95.65
24	21	3	87.5
25	23	2	92
26	24	2	92.31
27	23	4	85.19
28	25	3	89.29
29	26	3	89.66
30	26	4	86.67
31	26	5	83.87
32	28	4	87.5
33	29	4	87.88
34	29	5	85.29
35	28	7	80
36	30	6	83.33
37	30	7	81.08
Total: 658	570	88	86.63

Fig. 5 Sample Image with 23 Students

With the data gathered in Table V, the number of students was grouped into two categories, smaller class sizes, and larger class sizes. For this test, the smaller class size will consist 10 to 24 students, while the larger class size will consist 25 to 37 students. Considering the said categories, data from Table V can be simplified into Table VI where a statistical test was done. The goal of this test is to determine if the successful recognition of larger class sizes is statistically less than that of smaller class sizes.

Table VI. Accuracy in a Classroom Environment

	Successful Recognition	Unsuccessful Recognition	Total	%
Smaller Class Size	226	29	255	88.63
Larger Class Size	347	56	403	86.10
Total	573	85	658	87.08

The null hypothesis is that the successful recognition of larger class sizes is the same with smaller class sizes. Using a significance level of $\alpha = 0.05$ and Fisher's Exact Test of Independence, the P-value is 0.40. Since the P-value is greater than $\alpha = 0.05$, the null hypothesis will not be rejected and conclude that the successful recognition of a larger class size is the same with the smaller class size. The different characterizations/ conditions were studied to improve the accuracy of the system, particularly the lighting, the distance and the face angle.

C. *Varying Light Condition*

When a facial recognition system is used as an attendance system, one of the factors that should be considered is the lighting condition of the environment. The lighting of the classroom is considered as an external effect when the facial recognition process is done.

A test was conducted where the lighting conditions were varied and other external factors remained constant. A lux meter was used in order to measure the luminance level of the environment where the system was tested. Table VII shows the range of lux values obtained from successful and unsuccessful recognition. Note that the data considered in the statistical test are each of the lux values obtained per trial.

Table VII. Varying Lighting Conditions with Constant Face Position

Lux	Successful Recognition	Unsuccessful Recognition
0-125	13	11
126-250	25	4
251-375	11	4
376-525	7	1

Table VIII. Descriptive Statistics of the Varying Lighting Conditions with Constant Face Position

	Successful Recognition	Unsuccessful Recognition
Mean ($\bar{x}$)	217.3929	138.4000
Standard Deviation (s)	128.8565	154.1661
Count (n)	56	20

In the analysis of the varying light condition data, the T-test for independence was used. The null hypothesis for this test is that there is no statistically significant difference between the Lux in successful and unsuccessful recognition.

For this test, a significance level of $\alpha = 0.05$ was used. The degree of freedom is computed to be $n_1 + n_2 - 2 = 56 + 20 - 2 = 74$. The null hypothesis is rejected if the computed Test Statistic T_0 is greater than $T_{0.05,74} = 1.99$. Because $T_0 = 2.23 > T_{0.05,70} = 1.99$, the null hypothesis is rejected, and it is concluded there is sufficient evidence to support the claim – there is a statistically significant difference between the Lux in successful and unsuccessful recognition.

Generally, keeping the classroom uniformly lit with 300 to 400 lux is preferred, as it is also the regular lighting inside a classroom. It is seen that only two out of twenty unsuccessful recognitions are within this range. Blocking off uncontrolled luminance sources that can add contrast with the luminance inside the classroom is also recommended.

D. Varying Distance of the Participant to the Camera

The more apparent external factor that affects the success of face recognition is the distance of the subject to the camera. As the distance of the subject gets further away from the camera, the pixel group involving the subject's face gets smaller. A test was conducted to tell if the distance within an enclosed standard-sized classroom space is enough for it to affect the accuracy of the system, and if so, to tell at what distance the accuracy starts to decline.

For the data gathering of this test, 18 students were invited to participate in this study. Each student would initially be positioned at the center of the front most row seat, moving back a row for each succeeding trial, with a total of five trials per student – resulting in a total of 90 trials. This is done while the lux and face orientation of a person is held constant in each trial.

Table IX shows the gathered data, the columns being the distance of the students from the camera and two rows indicating the success and unsuccessful recognition of their entry.

Table IX. Varying Distance of the Participant to the Camera

	Distance (m)					
	2.14	**3.13**	**4**	**4.94**	**5.88**	**Total**
Successful Recognition	18	17	18	17	17	87
Unsuccessful Recognition	0	1	0	1	1	3
Total	18	18	18	18	18	90

The null hypothesis for this test is that the successful recognition of the system is not dependent on the distance. For this test, a significance level of $\alpha = 0.05$ was used. Using a Microsoft Excel add-in, a P-value of 1.00 was obtained. Since the P-value = 1.00 > $\alpha = 0.05$, the null hypothesis is failed to be rejected. Then, it is concluded that there is insufficient evidence to support the claim that the recognition of the system is dependent on the distance between the subject and the camera.

The test was done with minimal students in the image. If the classroom is filled with students in each of the rows, the result would mostly be the same since the system individually considers the faces it detects and would not affect the result of the other detected faces.

E. Varying the Face Orientation relative to the Camera

Another external factor that should be considered in the implementation is the position of the face in terms of the angle relative to the camera. The rotation of a subject's head relative to the reference may cause the failure of recognition due to hidden key features of the face. A test was conducted to see if the successful recognition of the system is statistically dependent on the orientation of the face relative to the camera. The horizontal and vertical face orientations were considered separately.

For the data gathering of the horizontal face orientation, five students were asked to participate in this test. Each student was asked to look at points that horizontally deviates from the camera, consisting of five trials each – resulting to a total of 25 samples.

Table X conveys the gathered data for this test, considering the horizontal orientation. The column represents degrees at which the face horizontally deviates from the camera, and the two rows categorize the success and unsuccessful recognition of their entry.

Table X. Varying the Horizontal Face Orientation relative to the Camera

	Horizontal Degree of Difference					
	90° left	**45° left**	**0° center**	**45° right**	**90° right**	**Total**
Successful Recognition	1	3	5	3	0	12
Unsuccessful Recognition	4	2	0	2	5	13
Total	5	5	5	5	5	25

Like the test previously done, the gathered data are unpaired and nominal. The Null Hypothesis for this test is that the successful recognition of the system is not dependent on the angle. This test will also use a significance level of $\alpha = 0.05$. Again, using the Microsoft Excel add-in, a P-value of 0.00967 was acquired.

Since the P-value = 0.00967 < $\alpha = 0.05$, the null hypothesis is rejected, and it is concluded that there is sufficient evidence to support the claim that the recognition of the system is dependent on the horizontal angle at which a face is oriented relative to the camera.

Now, considering the vertical face orientation, five students were asked to participate, this time, they were asked to look at points that vertically deviates away from the camera.

Table XI conveys the gathered data for it. The column represents the degrees at which the face vertically deviates from the camera, while the row simply categorizes the data to successful recognition and unsuccessful recognition.

Table XI. Varying the Vertical Face Orientation relative to the Camera

	Horizontal Degree of Difference					
	70° down	40° down	0° center	10° up	50° up	Total
Successful Recognition	0	0	5	5	1	11
Unsuccessful Recognition	5	5	0	0	4	14
Total	5	5	5	5	5	25

Through Fisher's Exact Test, the acquired P-value is 0.000034. Since the P-value = $0.000034 < \alpha = 0.05$, the null hypothesis is again rejected, and it is concluded that there is sufficient evidence to support the claim that the recognition of the system is dependent on the vertical angle at which a face is oriented relative to the camera and where the face directly facing the camera is the optimal orientation.

Additionally, students that are not facing the camera would not affect the result of those who are directly facing the camera, for each is individually considered by the system. However, it is recommended that all of the students would directly face the camera as observed in the gathered data.

IV. Conclusion

In this paper, a design of an e-attendance checker was established using HOG and SVM algorithms for face detection and face recognition, respectively. The process flows from taking an image and then implementing face detection via HOG which transpires and ends with the face recognition using the SVM algorithm. Its output was shown in an online database that includes the names of the students and the date and time the attendance was taken.

The implementation of the system also considered camera and class size optimizations. For the camera optimization, different lenses, and different positions, where the camera could be placed, were considered. As a result of the different lenses to be considered showed in Table III, 0.45x Wide Angle Lens provided the best result. As for the camera position, the reference point showed the greatest number of successful detection.

Based on the results of the test done for the accuracy of the system in a classroom environment (as shown in Table V), the maximum number of the successful detection that the system was able to analyze was 37, and the highest recognition accuracy was attained with a total number of 23 students having 95.65% accuracy. The suggested classroom luminance level is found to be around 217.39 lux for a better performance of the system. The accuracy of the system in varying the distance of the participant to the camera displays that there are no relevant evidences to support its relationship with the accuracy of the system. For the accuracy of the system in varying the face orientation of the participant relative to the camera, it shows that the angle in which the face orientation yielded the best result is when it is at 0° in reference to the camera – when they are directly facing the camera.

Lastly, given the current COVID-19 situation, the accuracy of the system will be affected. The accuracy of the system will increase for which the students will have social distancing lessening the interference of the faces. On the other hand, the accuracy will also decrease as students will now be wearing face masks and face shields that will affect the face detection and recognition of the system. With this, it is best to add more data or training images to overcome the effect of the face masks and face shields.

V. References

[1] P. K. Pani and P. Kishore, "Absenteeism and performance in a quantitative module A quantile regression analysis," *J. Appl. Res. High. Educ.*, vol. 8, no. 3, pp. 376–389, Jul. 2016.

[2] H. Rathod, Y. Ware, S. Sane, S. Raulo, V. Pakhare, and I. A. Rizvi, "Automated attendance system using machine learning approach," 2017 International Conference on Nascent Technologies in Engineering (ICNTE), 2017.

[3] S. Lukas, A. R. Mitra, R. I. Desanti, and D. Krisnadi, "Student Attendance System in Classroom Using Face Recognition Technique," 2016 Int. Conf. Inf. Commun. Technol. Converg., pp. 1032–1035, 2016.

[4] K. Okokpujie, E. Noma-Osaghae, S. John, K. A. Grace, and I. Okokpujie, "A face recognition attendance system with GSM notification," 2017 IEEE 3rd Int. Conf. Electro-Technology Natl. Dev. NIGERCON 2017, vol. 2018–Janua, pp. 239–244, 2018.

[5] S. Patel, P. Kumar, S. Garg, and R. Kumar, "Face Recognition Based Smart Attendance System Using IOT," Int. J. Comput. Sci. Eng., no. 5, pp. 871–877, 2018.

[6] J. C. Dela Cruz, A. C. Paglinawan, M. I. R. Bonifacio, A. J. D. Flores and E. V. B. Hurna, "Biometrics based attendance checking using Principal Component Analysis," 2015 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Cebu City, 2015, pp. 1-5.

[7] S. Patole and Y. Vispute, "Automatic Attendance System Based On Face Recognition," pp. 16009–16016, 2017.

[8] D. Mehta, B. Dedhia, and B. Kothari, "Automated Attendance Monitoring System Using Face Recognition," vol. 7, no. 1, pp. 99–103, 2015.

[9] R. Malik, P. Kumar, A. Verma, and S. Rawat, "Prototype model for an intelligent attendance system based on facial identification," 2016 Int. Conf. Inf. Technol. InCITe 2016 - Next Gener. IT Summit Theme - Internet Things Connect your Worlds, pp. 40–43, 2017.

[10] E. Varadharajan, R. Dharani, S. Jeevitha, B. Kavinmathi, and S. Hemalatha, "Automatic attendance management system using face detection," Proc. 2016 Online Int. Conf. Green Eng. Technol. IC-GET 2016, pp. 1–3, 2017.

[11] A. Adouani, W. M. B. Henia, and Z. Lachiri, " Comparison of Haar-like, HOG and LBP approaches for face detection in video sequences", 2019 16th International Multi-Conference on Systems, Signals & Devices (SSD'19), pp. 266-271, 2019.

[12] K. Jain, S. Narang, Arora, and M. Saxena, "Comparison of Face Recognition Algorithms Using Opencv for Attendance System," Int. J. Sci. Res. Publ., vol. 8, no. 2, p. 268, 2018.