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Human vs machine learning in face recognition: A case study from the travel industry

Regina Lionnie[1*], **Vidya Hermanto**[2]
[1]Department of Electrical Engineering, Universitas Mercu Buana, Jakarta, Indonesia
[2]Panorama JTB Tours Indonesia

Abstract

This research was conducted preliminary to find an answer regarding whether a machine learning simulation can replace the human ability to recognize human faces, especially in travel industry requirements. A series of questions were asked of human respondents. At the same time, a Histogram of Oriented Gradient (HoG) combined with a support vector machine (SVM) with various kernels was built for face recognition simulations. There were two conditions focused on to be analyzed in this research, i.e., dark environments and face makeup; hence, two face datasets compatible with the total of human respondents were observed. The face recognition system by machine learning yielded better performance compared to the human ability to recognize faces under these two conditions. The face recognition system accuracy was 95.4% under conditions of a dark environment and 65.6% accuracy under facial makeup. While only 47.9% of respondents accurately recognized human faces in dark environments, only 37.5% of respondents accurately recognized human faces under disguised makeup. The potential of machine learning is high, but privacy and security concerns, as well as the inaccuracies and unreliableness of the system, are the concerns that people still question.

Keywords:
face recognition;
histogram of oriented gradient;
human vs machine learning;
machine learning;
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Corresponding Author:
Regina Lionnie
Department of Electrical Engineering, Universitas Mercu Buana Jakarta, Indonesia
Email:
regina.lionnie@mercubuana.ac.id

INTRODUCTION

Facial recognition technology, a type of biometric artificial intelligence, can identify or verify individuals using only their facial biometric data. It typically compares digital facial images to those stored in a database, matching facial features or skin textures. This technology is widely used across different fields; for instance, Facebook employs it to identify faces in digital images, and Apple's Face ID system authenticates user identity to prevent unauthorized access [1]. Additionally, it is frequently utilized in security, such as smart homes and automation lock systems [2,3].

Facial recognition technology is also increasingly being explored and utilized in travel and tourism. This is especially useful as tourism companies must deal with many tourists and customers, so any technology that can help speed up the process will greatly benefit. Additionally, security is a top concern in airports and hotels, and facial recognition can be used to identify people more quickly, give certain people access to places, and prevent others from entering. Moreover, instantly recognizing faces can also improve customer experience through better personalization.

One of the most obvious ways the travel industry uses facial recognition technology is to increase customer personalization. By matching faces in real-world environments with faces in databases, hotels, and other companies can quickly identify people and tailor their services. Hotels, for example, can offer guests the option to provide a photo of themselves during the booking process. When hotel cameras identify their faces upon arrival, hotel staff can greet them by name and use their booking information to ensure they receive specific services. It can also identify guests who have stayed at the hotel before so they can be given extra benefits. An example of this use case can be found at two Marriott Hotel properties in China, where guests can use facial recognition technology to check-in quickly and easily without queueing or waiting for a staff member [4]. The potential for using biometrics as identity identification in travel and tourism is enormous. However, several challenges in applying this industry also need to be considered. For example, the background of the image taken during the booking process is not necessarily the same as during hotel check-in. The condition of the face and attributes (hair, hair accessories, glasses, hats, makeup, etc.) also influence the system.

Looking at previous studies, such as research focused on recognizing similar faces and recognizing faces under different conditions, the study in [5] examines the characteristics that are essential for face recognition while concentrating on both known and unknown faces. The work contradicts the belief that distinct features are employed for known versus unknown face identification through a reverse engineering method. The authors show that the same high-perceptual-sensitivity (high-PS) features are used to match and recognize familiar faces. This suggests that all faces have a single perceptual representation, consistent with how deep neural network face recognition algorithms work. Unlike classic face recognition, the study in [6] presents a novel method for measuring perceived facial similarity between various individuals. The authors demonstrate the Lookalike Network and a brand-new dataset created especially for this purpose, proving that their approach is more effective at finding facial similarities than traditional face recognition networks. This study emphasizes the subjectivity of facial likeness. It offers potential uses in casting and entertainment, highlighting the necessity for specialized methods in computer vision. The study in [7] uses an artificial neural network method to analyze data regarding the application of makeup features on the face. The findings demonstrate that facial recognition systems can be more accurate by incorporating facial training sets with makeup features and additional challenges. The effects of facial plastic surgery and their impact on facial recognition systems were examined in [8]. The findings indicate that facial plastic surgery negatively impacts facial recognition system performance; however, when utilizing deep facial recognition, this impact is lessened compared to other approaches. A study in [9] investigates how changes in facial pose during data collecting significantly affect the identification.

In this research, we design the challenges of facial recognition, especially in the travel industry, for human respondents and machine learning simulation systems. We want to answer the following question: Can the machine learning system replace the human duty of receiving guests when checking in at a hotel? This research was conducted and summarized in this paper following an organization like this to answer this research question. While Section 1 already discussed the introduction, research problem, and mentioned previous studies, Section 2 explains the methodology of the research as well as the brief theory behind the methods. Section 3 discusses the results of both human respondents and machine learning simulations results. Finally, Section 4 concludes the findings.

METHODOLOGY

Design of the study

As mentioned previously, we compared the human ability to recognize faces and machine learning in a simulation system. Human ability was calculated using a series of questions in a survey. The face recognition system using machine learning was designed as in Figure 1. In Figure 1, we can see several parts of the simulation, such as pre-processing, feature descriptor using Histogram of Oriented Gradient (HoG), classification using support vector machine (SVM), and performance calculation of accuracy. While the input face image in our datasets is detailed in Section 3 (Machine Learning Results and Discussion), pre-processing, HoG, classification, and performance calculation are described below.

Pre-Processing

The input images were first processed to be resized, and some were contrast adjusted. We employed histogram equalization (hist eq) and contrast limited adaptive histogram equalization

(CLAHE) to pre-process some of the images in our datasets. Both histogram equalization methods were compared, so we observed the most suitable one for the conditions in our research. The histogram equalization improves the contrast of an image in one global region. To spread the image's brightness values, CLAHE reduces the contrast amplification and computes many histograms, each corresponding to a different image area. Moreover, CLAHE cropped the histogram at a predetermined value before calculating the cumulative distribution function to limit the amplification [10].

Histogram of Oriented Gradient (HoG)

The pre-processed images were then extracted using a feature descriptor. Histogram of Oriented Gradient (HoG) [11] counts the instances of gradient orientation in each local region while concentrating on an object's shape. The gradient's magnitude (1) and orientation (2) of an image (*I(m,n)*) are then used to create a histogram of b bins. HoG features are obtained by joining together all normalized histogram values of each cell within each block from *I(m,n)*. By analyzing the distribution of gradient orientations in specific local image patches, the HOG is a popular feature descriptor in computer vision that can be used for object detection and classification [12].

$$\text{Magnitude}\big(I(m,n)\big) = \sqrt{\mathrm{I_m}(m,n)^2 + \mathrm{I_y}(m,n)^2} \qquad (1)$$

$$\text{Orientation}\big(I(x,y)\big) = \tan^{-1}\left(\frac{\mathrm{I_n}(m,n)}{\mathrm{I_m}(m,m)}\right) \qquad (2)$$

Classification and Performance Calculation

We used 2-fold cross-validation to split the number of images in testing and training the classification process; hence, a 50:50 proportion was created. We did not use the common 80:20 proportion because the number of images in our datasets was limited. The details of the datasets analyzed in this research can be found in Section 3.2.1. Support vector machine (SVM) was used for classification. Furthermore, the type of kernels in the SVM were examined to produce the best results. To calculate the performance of the machine learning system, we only employed accuracy to level the performance of machine learning to human ability. The accuracy shows how many of the images are predicted correctly by the models; hence, the calculation is the sum of true positive (*TP*) and true negative (*TN*) divided by the total number of images in the dataset (*N*). The accuracy calculation is given in (3) [13].

$$\text{Accuracy} = \frac{TP+TN}{N} \qquad (3)$$

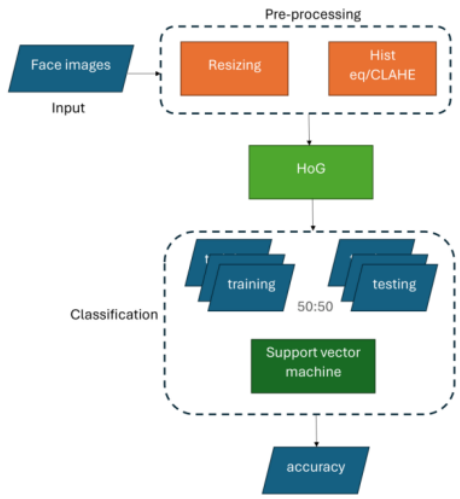


Figure 1. The design of the study of face recognition systems using machine learning.

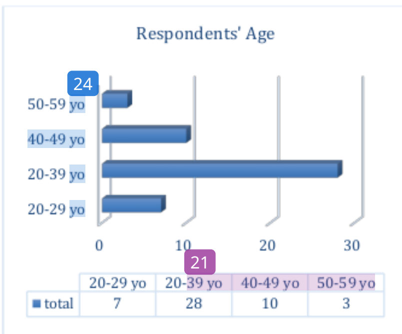
RESULTS AND DISCUSSION

Human Survey Results and Discussion

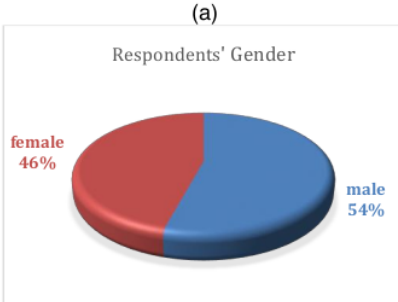
We created a small survey that assessed respondents' understanding of face recognition and tested their ability to recognize human faces in different conditions. There was a total of 48 respondents, 54% male and 46% female, with 37.5% of respondents working in the travel industry. The details of the respondents' general information can be seen in Figure 2.

The respondents were then asked whether they understood or tried the face recognition system daily. A total of 45 respondents claimed that they had tried the system and/or understood the face recognition system. Next, they were asked whether they recognized a person mostly from their face. Forty-two respondents agreed that the face is the most recognizable trait of a person. In comparison, six respondents didn't agree and chose voice, gesture, gait, etc., as the most recognizable trait. The details of this part of the survey can be found in Figure 3.

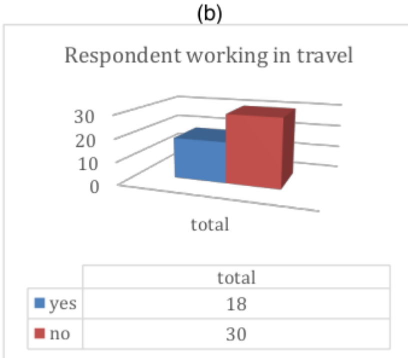
The respondents were then asked to answer a series of questions about their ability to recognize two similar faces under different conditions. There was a total of 8 questions assessing the respondents' ability. The first and second questions evaluated the respondents' ability to recognize similar faces from people in normal conditions. The third question challenged the respondents' ability to recognize faces in dark environments. The fourth, fifth, and sixth questions only provided the respondents with part of the facial areas (periocular/upper part and lower part). The last two questions assessed respondents' ability to recognize faces under disguise. Table 1 shows the results of this series of questions.



(a)

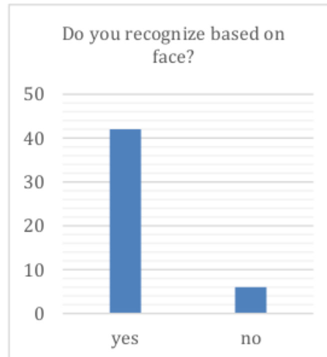


(b)

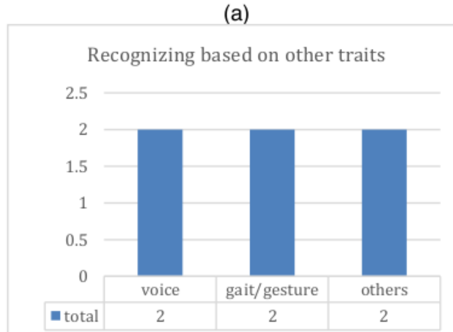


(c)

Figure 2. General Respondents' Information: (a) age, (b) gender, (c) respondents working in the travel industry.



(a)



(b)

Figure 3. Respondents' Understanding of Face Recognition (FR): (a) understanding FR, (b) Recognizing based on face, (c) Recognizing by other traits.

Table 1. Respondents' assessment of recognizing faces under different conditions.

No	Questions	Are they the same person?		Summary
		YES	NO	
1	 pictures from [5]	21	27	56.3% of respondents correctly answered that they are not the same person

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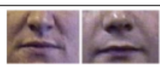
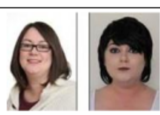
2	 pictures from [5]	10	38	79.2% of respondents correctly answered that they are not the same person
3	 pictures from [14,15]	23	25	52.1% of respondents **wrongly answered** that they are the same person
4	 pictures from [16]	6	42	87.5% of respondents correctly answered that they are not the same person
5	 pictures from [16]	14	34	70.8% of respondents correctly answered that they are the same person
6	 pictures from [17]	8	40	83.3% of respondents correctly answered that they are not the same person
7	 pictures from [18]	18	30	62.5% of respondents wrongly **answered** that they are the same person
8	 pictures from [18]	19	29	60.4% of respondents correctly answered that they are not the same person

Table 1 shows that six out of eight questions were successfully answered correctly. Respondents 56-79% correctly guessed similar faces from two different male and female face images (questions #1 and #2). Respondents then 70-87% correctly guessed if they were given only partial area of the faces, i.e., upper and lower part (questions #4 and #5). Respondents still 60% correctly guessed if two people were similarly styled, e.g., same hair color and same glasses (question #8).

The two questions that were answered wrong were under dark environments (question #3) and under the conditions of disguised using makeup (question #7). These two conditions were the challenges we wanted to compare thus given to the machine learning.

The last part of the survey was to question the respondents' opinions regarding whether they agreed with using the face recognition system in the travel industry, e.g., using a face recognition system as a check-in process in a hotel. A total of 34 respondents, or 70.8%, agreed that the face recognition system replaces the traditional check-in process in a hotel. At the same time, the rest of the respondents who disagreed with this process were asked to give their reasons. The reasons varied from privacy and security concerns to the inaccuracies and unreliableness of the system.

Machine Learning Simulation Results and Discussion

Face Dataset

From the human survey results (Section 3.1), we know that there were two conditions to be assessed further by machine learning, i.e., dark environments and face disguised (makeup). We need two different face datasets to analyze these conditions. To evaluate dark environments, we employed the Extended Yale B (EYB) Face dataset [14,15]. We chose 4 images (1 normal and 3 variations of dark images) from each. There were 152 images (4 images from 38 people), and we called this group of dark images Dataset A from here onwards. The size of each image was 168×192 pixels. Figure 4 shows the example of Dataset A used in this research.

The second face dataset was used to assess the condition of the face disguise (makeup). We employed The Extended Makeup Face Dataset (EMFD) [19]. We chose two images from each person (1 image is a bareface image, and 1 image is using makeup). There were 96 images (2 images from 48 people), and from here onwards, we called this group of disguised images Dataset B. We only analyzed 48 classes/people in Dataset

B to level the total number of human respondents in the survey. The size of each image was varied but resized to 64×64 pixels. Figure 5 shows the example of Dataset B used in this research.

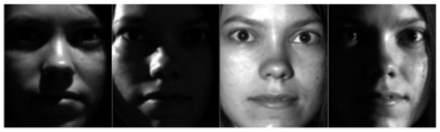


Figure 4. Example of images from Dataset A [14,15].

Figure 5. Example of images from Dataset B [19].

Results and Discussion

The first results from the experiment of first conditions, i.e., dark environments using Dataset A. We employed HoG with a total of 16.561 features for each image. The classification method used SVM with four kernels: Gaussian, linear, quadratic, and cubic. Figure 6 displays the accuracy results of the first experiment. The best accuracy came from the linear kernel (89.5%), followed by the quadratic kernel (85.5%).

We also compared the HOG of 16.561 features with a system that didn't employ HoG (32.256 features from the size of an entire image from Dataset A). Figure 7 compares accuracy using 16.561 features from HoG and 32.256 features using linear and quadratic kernels. Surprisingly, a full feature from an image did not yield a good result. In contrast, HoG, with only 51% of the total features, yielded the best results. The results from full feature images only gave 32.90% and 44.70% accuracy from quadratic and linear kernels, respectively.

Furthermore, we combined histogram modification methods, such as CLAHE and histogram equalization with HoG, in the next experiment. Figure 8 shows the accuracies for both methods, using linear and quadratic kernels. The best results came from combining HoG and CLAHE, 91.40% and 88.80% from linear and quadratic kernels, respectively. They improved by 2-3% from a system that only employed HoG. Combining HoG and histogram equalization improved the system accuracies but not as well as combining HoG and CLAHE. We suspected that since CLAHE adjusted the histogram based on the small regions of an image rather than the entire image, it performed better than histogram equalization. We then evaluate variation of size regions of CLAHE from [4,4] to [32,32]. We found that the best accuracy result, 95.4%, was obtained from [20,20]. Figure 9 displays these variations in the size regions of the CLAHE results.

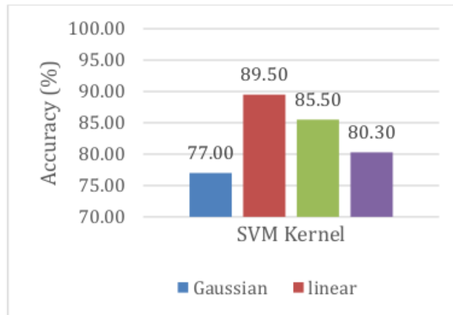


Figure 6. The accuracy using Dataset A with HOG and SVM of different kernels.

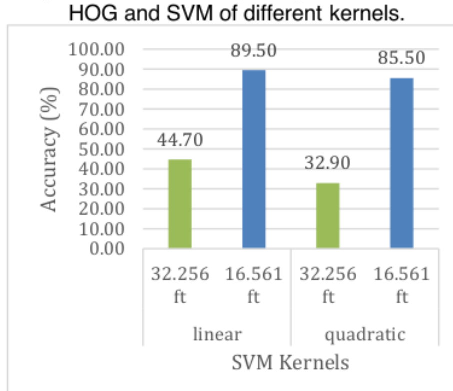


Figure 7. The accuracy using Dataset A without HoG (32.256 features) and with HoG (16.561 features).

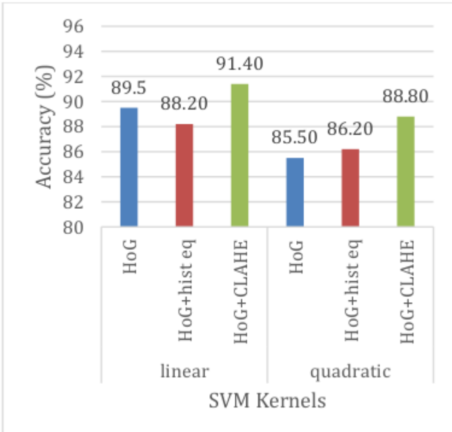


Figure 8. The accuracy of Dataset A using a combination of HoG with histogram equalization (hist eq) and CLAHE.

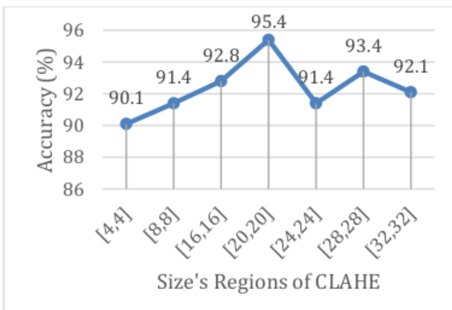


Figure 9. The accuracy of Dataset A using variations of CLAHE size's regions.

Going on to the following condition, i.e., face disguised with makeup, the experiment was conducted using Dataset B. We also employed HoG with a total of 1764 features for each image. The classification method used SVM with four kernels: Gaussian, linear, quadratic, and cubic. Figure 10 displays the accuracy results of this experiment. The best accuracy came from the quadratic kernel (65.6%), followed by the cubic kernel (64.6%).

We also compared the system without using HoG (a full of 4.096 features) with one that used HoG (1.764 features). Figure 11 shows these comparison results. Overall, a HoG system improved accuracy by 2-7%. Although we did not get satisfying results from Dataset B, we suspected this happened because we only had one training image and one testing image per person in Dataset B.

Human respondents failed to recognize the faces from these two conditions, i.e., dark environments and face disguised (makeup). Table 1 shows that 52.1% and 62.5% of respondents wrongly recognized the same faces in dark environments and under disguised makeup. We can say that only 47.9% of respondents accurately recognized human faces in dark environments. In comparison, machine learning gave as high as 95.4% accuracy. Moreover, only 37.5% of respondents accurately recognized human faces under makeup disguised, while machine learning gave 65.6% accuracy.

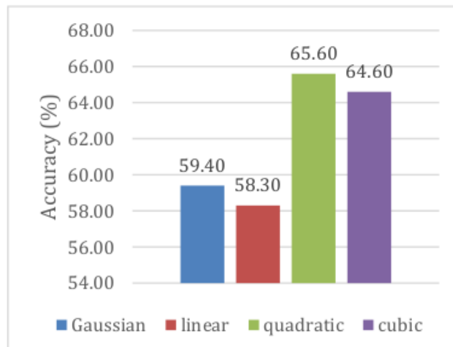


Figure 10. The accuracy using Dataset B with HOG and SVM of different kernels.

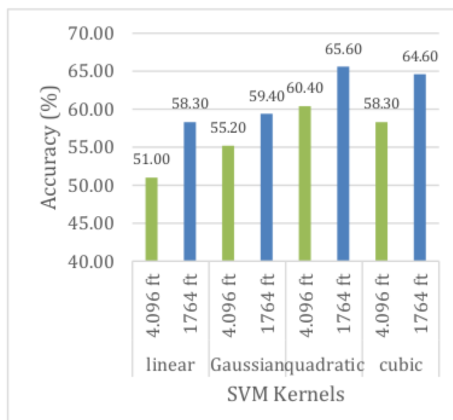


Figure 11. The accuracy of Dataset B without HoG (4.096 features) and with HoG (1.764 features).

CONCLUSION

In this research, we compared the human ability versus machine learning to recognize faces under dark environments and facial disguises (makeup).

This comparison aims to find an answer to the question of whether a machine learning simulation can replace the human ability to recognize faces, especially in the travel industry's requirement. The preliminary comparison conducted in this paper shows that the machine learning simulation (using a Histogram of Oriented Gradient and Support Vector Machine) yielded better performance in the accuracy of the system compared to the human ability to recognize faces (using a series of questions in a survey) under dark environment and facial makeup. The HoG, CLAHE, and linear SVM kernel combination produced 95.4% accuracy under dark environment conditions. The same HoG and quadratic SVM kernel produced 65.6% accuracy under facial makeup. Although we cannot conclude that these numbers represent all human vs all machine learning processes, from a preliminary comparison, we conclude that, in contrast, machine learning can recognize faces better under dark environments and makeup disguises. The potential of machine learning is high, but privacy and security concerns, as well as the inaccuracies and unreliableness of the system, are the concerns that people still question.

For future work, we suggest expanding the number of images in face datasets and the total number of respondents to the survey. We also want to signify that the number of conditions to observe the ability of human vs machine learning needs to be expanded.

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