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

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Abstract
This research was conducted to help answer whether a machine learning simulation can replace the human ability to recognize human faces, especially under challenges under travel industry requirements. The human ability to recognize faces was evaluated using a series of questions in a survey. The questions challenged the human respondents to recognize faces under similar looks, with hair and makeup disguises, only part of the facial area, and under dark lighting conditions. At the same time, a histogram of oriented gradient (HoG) combined with a support vector machine (SVM) was built for machine learning simulations. The machine learning was evaluated using two datasets, i.e., the Extended Yale B (EYB) Face dataset for challenge under dark lighting conditions and The Extended Makeup Face Dataset (EMFD) for challenge using face with makeup disguise. The results showed that machine learning simulation of the face recognition system yielded accuracy as high as 95.4% under dark lighting conditions and 70.8% under facial makeup disguise. On the contrary, only 48% of respondents accurately recognized human faces in dark lighting. The number was increased to 94-96% when the face images were adjusted first with the contrast adjustment method. However, only 36-37% of respondents accurately recognized human faces under face makeup disguise.

Keywords:
Face recognition;
Histogram of oriented gradient;
Human vs machine learning;
Machine learning;
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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 technology is beneficial 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. 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 Marriott International. To reduce the amount of time spent waiting in line, they have started to deploy technology, such as face recognition systems (FRS) [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. A profile of the frontal revise mapping (PTFRM) module was introduced, and this proposed method performed well.

A deeper look at facial recognition studies in the travel and tourism industry, the analysis in [10] concludes that multidimensional information processing through AI-based facial recognition technology can improve the travel and tourism sector socially, environmentally, and financially. The implementation of facial recognition check-in services in hotels is discussed in [11], emphasizing trust, security, and privacy. According to a study involving 391 hotel guests, privacy significantly impacts customer trust more than security. Guests' perceptions of security, privacy, and trust based on their previous interactions with facial recognition systems also influence their readiness to accept the technology. Meanwhile, the study in [12] empirically confirms a conceptual model that displays consumer intention to adopt facial recognition technology using information collected from a nationwide sample of hotel guests in the United States. The model is based on trust in the hotel, congruence with self-image, expected positive and negative emotions, and perceptual systems (including performance and effort expectations).

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 glimpse the answer: Can the machine learning system replace humans, especially on duty in the travel industry? Although the findings in this research cannot represent all human capabilities versus all methods in machine learning, this research also contributes to providing an understanding of this matter. The detailed contributions of this paper were as follows:

- Human abilities to recognize faces were challenged under variations, such as similar looks, using hair and makeup disguises, only part of the facial area being shown, and dark lighting conditions.

- Some of the images for the human respondents survey were using own-ethnicity and some were using other-ethnicity. We also provided compared results for both cases.
- The human ability to recognize faces under dark lighting conditions is also compared with using and without contrast adjustment methods to make it par with machine learning simulation.
- The machine learning simulation was evaluated using a combination of histogram of oriented gradient (HoG), contrast adjustment method (CLAHE and histogram equalization), and classification using support vector machine (SVM). The parameters for each method were also tested to find the best accuracy.

This research was conducted and summarized in this paper following an organization. While the Introduction Section already discussed the motivation of the study, research problem, and mentioned previous studies, Section Methodology explains the design of the research as well as the brief theory behind the methods. Section Results and Discussion provides the results and discussion from human respondents and machine learning simulations. Finally, the last section concludes with the findings.

METHODOLOGY

Design of the study

As mentioned, 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 the Machine Learning Simulation Section, pre-processing, HoG, classification, and performance calculation are described below.

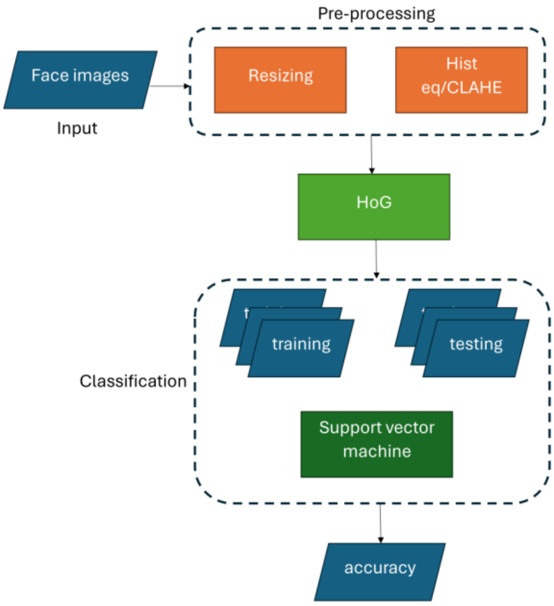


Figure 1. The design of the study of face recognition systems using machine learning.

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 [13].

Histogram of Oriented Gradient (HoG)

The pre-processed images were then extracted using a feature descriptor. Histogram of oriented gradient (HoG) [14] 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 (*c*) within each block (*k*) from *I(m,n)*.

The illustration of HoG can be seen in Figure 2. 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 [15].

$$Magnitude\big(I(m,n)\big) = \sqrt{I_m(m,n)^2 + I_n(m,n)^2} \quad (1)$$

$$Orientation\big(I(m,n)\big) = tan^{-1}\left(\frac{I_n(m,n)}{I_m(m,n)}\right) \quad (2)$$

Classification and Performance Calculation

We used 5-fold cross-validation to split the number of images in testing and training the classification process; hence, a 20:80 proportion was created, as the same ratio in [16]. We did not try other ratios, such as 70:30 [17] or 50:50 [18]. The details of the datasets analyzed in this research can be found in the next section. Support vector machine (SVM) was used for classification. Furthermore, the type of kernels in the SVM were examined to produce the best results. The SVM method aims to separate classes that can maximize the margin between these classes. Figure 3 [19] shows the illustration of SVM. It shows data from two classes and several hyperplanes that separate them. All hyperplanes can be separated, but SVM aims to find the best hyperplane that gives the maximum margin between these two classes.

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) [20].

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

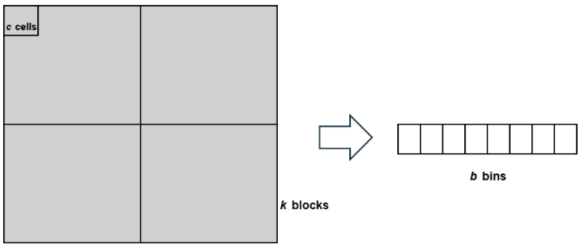


Figure 2. The illustration of HoG

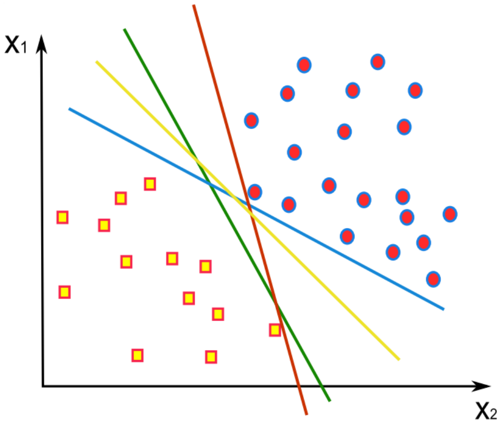


Figure 3. The illustration of SVM: several hyperplanes that separate two classes. The illustration is taken from [19]

RESULTS AND DISCUSSION

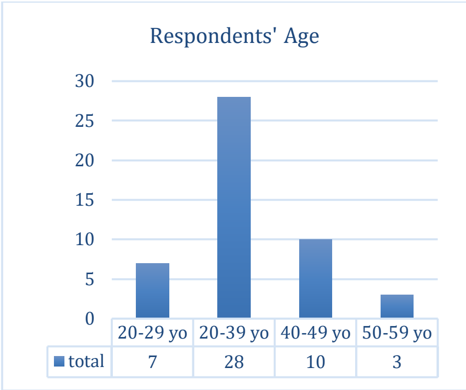
Human Survey

We created a small survey that assessed respondents' understanding of face recognition and tested their ability to recognize human faces in different conditions. Some images for human surveys are taken from the same face dataset used in this research to evaluate machine learning simulation.

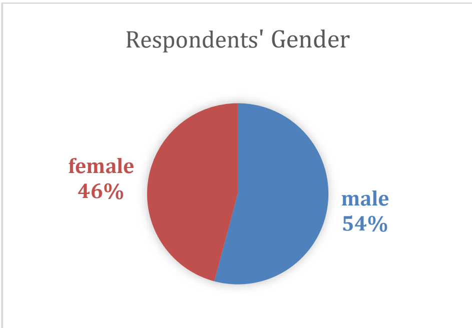
There were 48 respondents, 54% male and 46% female. All respondents are Indonesian. The respondents' ages varied from 20 to 59 years old, with 58.3% of respondents being between 20 and 39 years old. A total of 37.5% of respondents work in the travel industry. The details of the respondents' general information can be seen in Figure 4.

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 5.

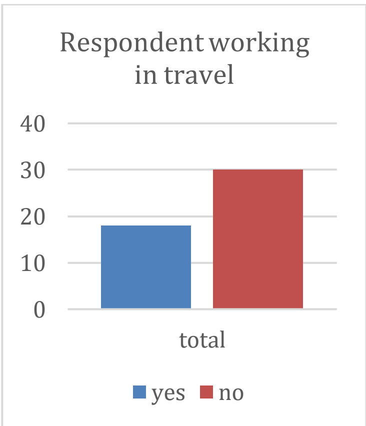
The respondents were then asked to answer 15 questions assessing their ability to recognize faces under different conditions. Each question in the survey showed two pictures of human faces that may be taken from the same person or other people. These pictures were taken from a variety of internet sources. Some of the pictures were taken from the same dataset that was used to evaluate machine learning simulation.



(a)



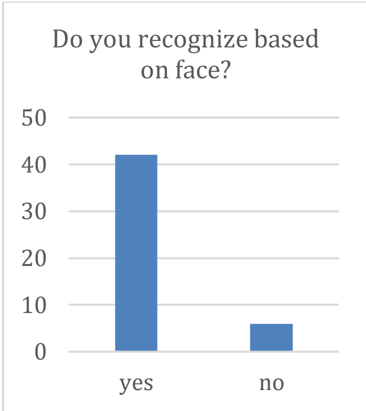
(b)



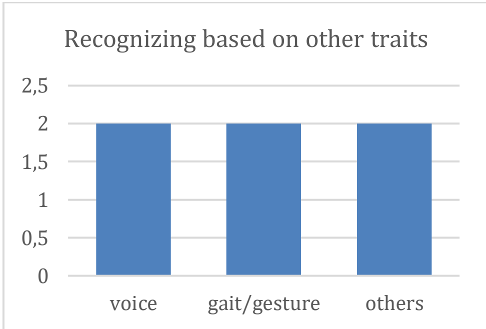
(c)

Figure 4. General Respondents' Information: (a) age, (b) gender, (c) respondents working in the travel industry.

It is worth noting that the respondents' ability to recognize faces may be biased toward their own-ethnicity [21][22]. Therefore, the survey questions sometimes used Asian faces to measure and compare the ability of respondents to recognize faces from own-ethnicity and other-ethnicity.



(a)



(b)

Figure 5. Respondents' Understanding of Face Recognition (FR): (a) understanding FR, (b) Recognizing based on face, (c) Recognizing by other traits.

Table 1 (Question #1-14) and Figure 6 (Question #15) display the human survey results. The first and second questions evaluated the respondents' ability to recognize similar faces in normal conditions. The third, fourth, fifth, and sixth questions assessed respondents' ability to recognize faces under makeup and hair disguises. The seventh to eleventh questions only provided the respondents with part of the facial areas (periocular/upper part and lower part). The twelfth question challenged the respondents' ability to recognize faces in dark lighting conditions. The thirteenth and fourteenth questions assessed the human ability to recognize faces after being manipulated with a contrast-adjusted process, e.g., CLAHE and histogram equalization, respectively. The last question was asked so the respondents could choose which method to recognize faces better (between CLAHE and histogram equalization).

Table 1. Respondents' assessment of recognizing faces under different conditions (Questions #1-14)

#	Conditions	Respondents' Answer: Are they the same person?		Summary
		YES (%)	NO (%)	
1	Two pictures of faces from two females with the condition of similar looks	43.8	56.3	56.3% of respondents correctly answered
2	Two pictures of faces from two males with the condition of similar looks	20.8	79.2	79.2% of respondents correctly answered
3	One picture of a face with makeup disguised and one picture of bare face from two female (Asian)	44.8	55.2	55.2% of respondents correctly answered
4	One picture of a face with makeup and hair disguised and one picture of a bare face with glasses from one female	37.5	62.5	62.5% of respondents wrongly answered
5	Two pictures of two females with similar hairstyles and hair colour while wearing glasses	39.6	60.4	60.4% of respondents correctly answered
6	One picture of a face with makeup disguised and one picture of bare face from one female (Asian)	35.8	64.2	64.2% of respondents wrongly answered
7	Two pictures of the periocular area (eyes and eyebrows) from two male	12.5	87.5	87.5% of respondents correctly answered
8	Two pictures of the periocular area (eyes and eyebrows) from two female	29.2	70.8	70.8% of respondents correctly answered
9	Two pictures of the periocular area (eyes and eyebrows) from two male (Asian)	9	91	91% of respondents correctly answered
10	Two pictures of the periocular area (eyes and eyebrows) from one male (Asian)	50.7	49.3	50.7% of respondents correctly answered
11	Two pictures of the lower facial area from two male	16.7	83.3	83.3% of respondents correctly answered
12	Two pictures of faces from one male with different lighting condition	47.9	52.1	52.1% of respondents wrongly answered
13	Two same pictures of faces from one male (Asian) with one dark condition and one contrast adjusted with CLAHE	94	6	94 % of respondents correctly answered
14	Two same pictures of faces from one female (Asian) with one dark condition and one contrast adjusted with histogram equalization	95.5	4.5	95.5% of respondents correctly answered

Table 1 shows that eleven out of fourteen questions were answered correctly. 56-79% of respondents correctly distinguished different but similar faces from male and female faces (questions #1-2). Only three questions are answered correctly from a total of five questions (question #3-7) under condition of makeup and hair disguised. 51-91% of respondents correctly answered if they were given only a partial area of the faces, i.e., upper and lower part (questions #8-11). 52% of respondents wrongly answered questions under dark lighting conditions (question #12). However, the number of respondents who answered correctly increased to 94-96% when the face images were adjusted with the contrast adjustment method (CLAHE for question #13 and histogram equalization for question #14). Between CLAHE and histogram equalization, as shown in Figure 6, 67% of respondents chose CLAHE as a method that gave them better results for recognizing faces.

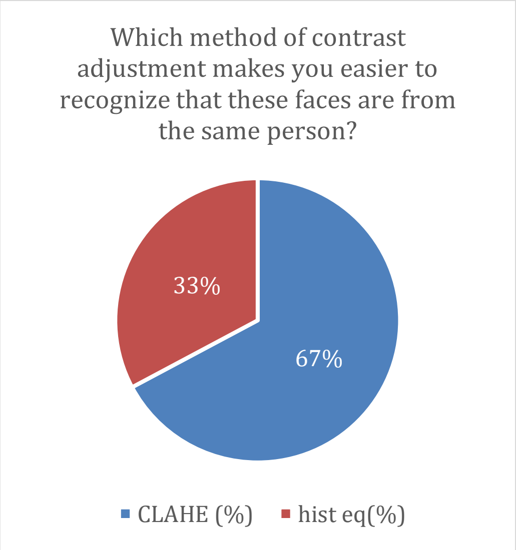


Figure 6. Question #15: between CLAHE and histogram equalization results.

The two questions that were answered wrong were under dark lighting (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 simulation.

Regarding own-ethnicity bias, from 14 questions (questions #1-14), six used Asian face pictures, and five were answered correctly (83%). The only question wrongly answered using an Asian face was when under makeup disguise. While eight questions used the other-ethnicity bias pictures, six were answered correctly (75%). The ratio of questions correctly answered while using own-ethnicity face pictures was higher. The ability of human respondents to recognize faces biased toward their own-ethnicity has occurred in this survey.

The next 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. 71% of respondents 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

Face Dataset

We know from the human survey results those two conditions caused the human respondents to fail to recognize faces. The conditions were makeup disguise and dark lighting. These two conditions were then assessed further by machine learning simulation of face recognition.

There were two different face datasets to analyze these conditions. To evaluate dark lighting conditions, we employed the Extended Yale B (EYB) Face dataset [23][24]. The EYB Face dataset consists of 2414 frontal-face images from 38 people, and for each person, there are 64 images. This EYB dataset gives variation in pose and lighting (illumination) conditions.

In this research, we chose four images from each person: one under a slight angle in illumination and three dark images (details about pose and illumination variation in the EYB dataset can be found in [23][24]). 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 7 shows the example of images from 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) [25]. The EMFD consists of 551 pairs of face images, one bare face (without makeup) and one image with makeup.

In this research, we chose two images from each person (one is a bare face image, and the other 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 8 shows the example of images from Dataset B used in this research.

Simulation Results

The experiments of machine learning simulation were conducted using Matlab 2024a (Update 5) with Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz 2.90 GHz and 16GB installed RAM. We used 5-cross validation in the classification process for all experiments that divided 20:80 between testing and training data. Table 2 displays all methods' parameters used in the experiments.

The first results from the experiment of first conditions, i.e., dark lighting 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 9 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%).

Figure 7. Example of images from Dataset A [23][[24]

Figure 8. Example of images from Dataset B [25]

Table 2. Simulation Parameters from The Experiments

Method	Parameter	Variation of Parameter
SVM	SVM kernel	Gaussian linear quadratic cubic
HoG	total feature with HOG (experiment #1)	16561
	total feature without HOG (experiment #1)	32256
	total feature with HOG (experiment #2)	1764
	total feature with HOG (experiment #2)	4096
	combination with contrast adjustment	HoG+CLAHE HoG+hist eq
CLAHE	region's size	[4,4] [8,8] [16,16] [20,20] [24,24] [28,28] [32,32]

experiment#1: dark lighting
experiment#2: face with makeup

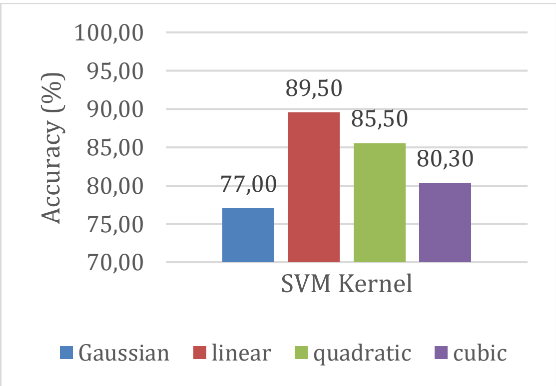


Figure 9. The accuracy using Dataset A with/without HOG and SVM of different kernels.

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 10 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.

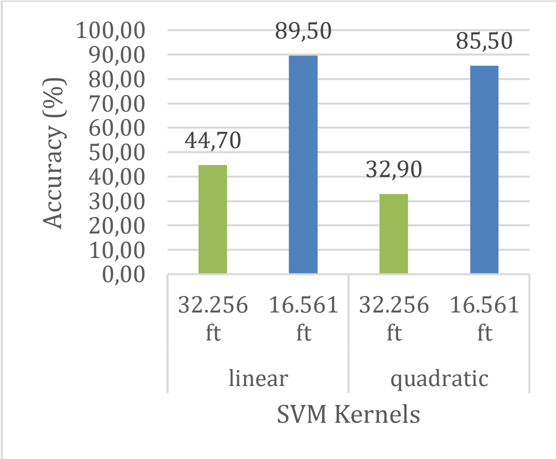


Figure 10. The accuracy using Dataset A without HoG (32256 features) and with HoG (16561 features)

Furthermore, we combined histogram modification methods, such as CLAHE and histogram equalization with HoG, in the following experiment. Figure 11 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.

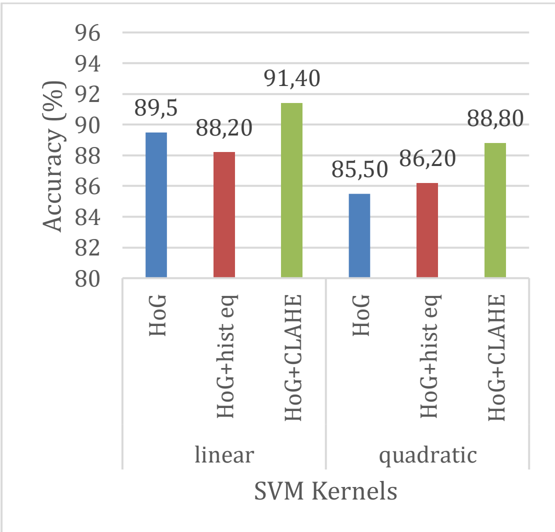


Figure 11. The accuracy of Dataset A using a combination of HoG with histogram equalization (hist eq) and CLAHE

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 variations 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 12 displays these variations in the size regions of the CLAHE results.

Going on to the following condition, i.e., face disguised with makeup, the experiment was conducted using Dataset B. We 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 13 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 14 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. To test this notion further, we explored and changed the 5-fold cross-validation to 2-fold cross-validation for this second experiment using Dataset B. The accuracy increased to 70.8% using 2-fold cross-validation.

Human respondents failed to recognize the faces in these conditions, i.e., dark lighting and face disguises (makeup). Table 1 shows that only 48% of respondents correctly identified the same faces in dark lighting. The number was increased to 94-96% when the face images were adjusted first with the contrast adjustment method.

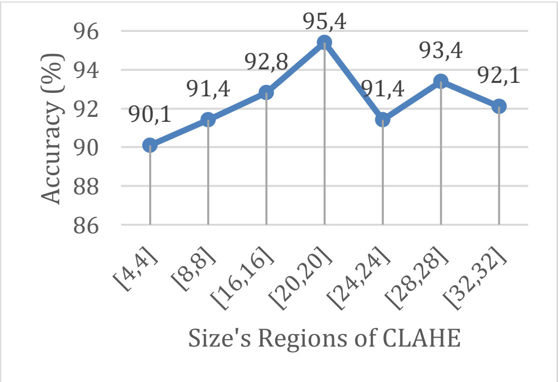


Figure 12. The accuracy of Dataset A using variations of CLAHE size's regions

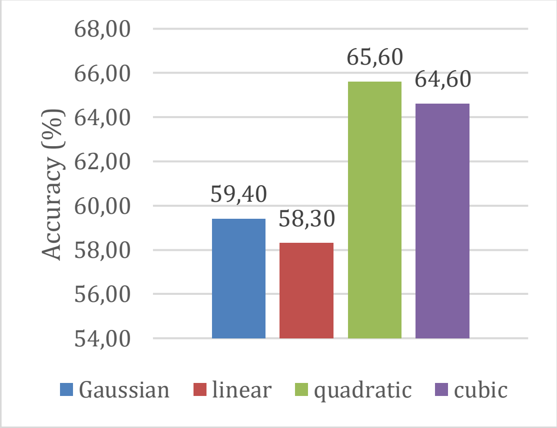


Figure 13. The accuracy using Dataset B with HOG and SVM of different kernels

In comparison, machine learning gave as high as 95.4% accuracy. Moreover, only a total of 36-37% of respondents accurately recognized human faces under makeup disguise, while machine learning gave 70.8% accuracy.

Table 3 compares our proposed machine learning simulation methods to recognize faces and other machine learning methods. The accuracy of simulations (%) and training time (second) were compared for dark lighting and face with makeup conditions. We can see that our proposed method surpassed other methods in accuracy results. However, our proposed method was not the fastest in the training process.

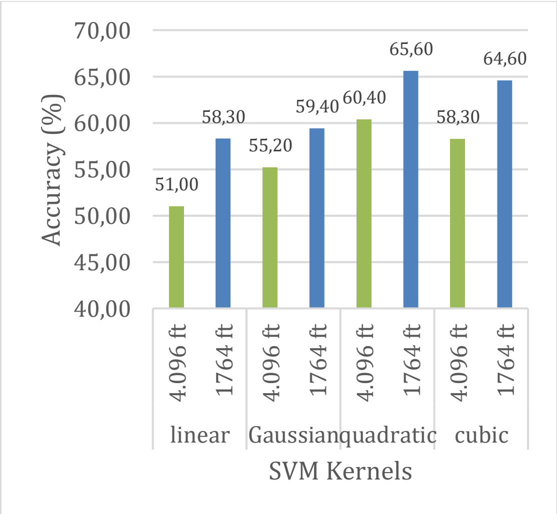


Figure 14. The accuracy of Dataset B without HoG (4096 features) and with HoG (1764 features).

Table 3. Comparison of the proposed method of machine learning simulation with other methods

#	Method	Variation in method	Accuracy (%)	Training time (s)
#1 dark lighting using 5-fold cross valida-tion	CLAHE+ HoG+SVM (proposed)	[20,20] size region in CLAHE with linear kernel in SVM	**95.4**	291.56
	HoG+ k-nearest neighbour	k=1, Euclidean distance	46.7	332.79
	HoG+ neural network	ReLU, 1000 iterations, first layer size 100	55.3	284.37
	HoG+ neural network	bilayered, number of fully connected layer 2, ReLU	23	526.3
#2 face with makeup using 2-fold cross valida-tion	HoG+SVM (proposed)	quadratic kernel in SVM	**70.8**	10.82
	HOG+ k-nearest neighbour	k=1, Euclidean distance	66.7	5.15
	HoG+ neural network	ReLU, 1000 iterations, first layer size 100	61.5	15.61
	HoG+ neural network	bilayered, number of fully connected layer 2, ReLU	20.8	24.12

CONCLUSION

In this research, we compared the human ability versus machine learning to recognize faces under several challenges. This comparison aims to contribute to understanding whether a machine learning simulation can replace the human ability to recognize faces, especially in the travel industry's requirement. The experiments conducted in this paper showed that the human ability to recognize faces was best under challenges such as similar looks, and only part of the facial area was shown. The own-ethnicity bias also occurred, especially under challenges such as dark lighting conditions and only part of the facial area was shown.

Although we cannot conclude that these numbers represent all human vs all machine learning methods, under this research setting, we showed that machine learning could recognize faces better compared to humans, especially under makeup disguises. The HoG, CLAHE, and linear SVM kernel combination from machine learning simulation produced 95.4% accuracy under dark lighting conditions. The same HoG and quadratic SVM kernel produced 70.8% accuracy under facial makeup.

There were some limitations to this study, so for future work, we suggest expanding the number of images in face datasets and the total number of respondents to the survey. The background of the respondents also needs to be extended. We also want to signify that the number of conditions to observe the ability of human vs machine learning needs to be expanded. The results from both also must be compared against own-race, own-age and own-gender.

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