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An android based course attendance system using face recognition

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ABSTRACT

Student attendance system is needed to measure student participation in a course. Several automated attendance systems have been proposed based on biometric recognition, barcode, QR code, and near field communication mobile device. However, the previous systems are inefficient in term of processing time and low in accuracy. This paper aims to propose an Android based course attendance system using face recognition. To ensure the student attend in the course, QR code contained the course information was generated and displayed at the front of classroom. The student only needed to capture his/her face image and displayed QR code using his/her smartphone. The image was then sent to server for attendance process. The experimental result shows that the proposed attendance system achieved face recognition accuracy of 97.29 by using linear discriminant analysis and only needed 0.000096s to recognize a face image in the server.

1. Introduction

Student attendance is an important factor for students to succeed in a course. In a certain university, student attendance in a course is also used as one of requirements for student to take the exam (Islam et al., 2017). A conventional approach to record student attendance is performed by asking every student to sign on an attendance list that passes through all students during the beginning of lectures. However, this approach is inefficient in term of time and can potentially lead to a fraud especially in a large class, where a student can sign on the attendance list for other students who are not present in the class. To avoid the happening of fraud, sometimes the lecturer calls out the names of students who have signed on the attendance list one by one. This method will take the lecture time and will have an impact on the effectiveness of lecture (Mohamed and Raghu, 2012). A modern approach to record attendance is by using automated attendance system. Several automated attendance system have been proposed by employing biometric recognition, such as fingerprint recognition (Mohamed and Raghu, 2012; Rao and Satoa, 2013; Soewito et al., 2015; Zainal et al., 2016; Zainal et al., 2014), face recognition (Chintalapati and Raghunadh, 2013; Fuzail et al., 2014; Mehta and Tomar, 2016; Raghuwanshi and Swami, 2017; Sayeed et al., 2017; Wagh et al., 2015; Wati Mohamad Yusof et al., 2018) and palm vein recognition (bayoumi et al., 2015) to recognize students who are present and record their attendance. The other proposed attendance systems used barcode (Noor et al., 2015), QR code (Rahni et al., 2015), RFID (Arulogun et al., 2013; Bhalla et al., 2013; Hussain et al., 2014; Rjeib et al., 2018) and near field communication (NFC) mobile device (Mohandes, 2017) to obtain student ID for attendance process. Some attendance systems were developed in portable device (Mohamed and Raghu, 2012; Zainal et al., 2016, 2014) and smartphone (Islam, et al., 2017; Mohandes, 2017; Noor et al., 2015; Rahni et al., 2015; Soewito et al., 2015).

Rao and Satoa (2013) have proposed an employee attendance management system using fingerprint recognition. Every check in and check out times, employees needed to scan their fingerprint to record attendance. Minutiae-based matching combined with alignment-based greedy matching was used to recognize scanned fingerprint in the proposed attendance system. Although the authors reported that the proposed system is easy to use and low cost, the proposed system is not appropriate for course attendance system since if there are a large number of classes in the same time then the system requires a large number of fingerprint recording devices. Moreover, if there are a large number of stu-

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dents in a course, then the system will cause a long and time consuming queue. Rao and Satoa (2013), Zainal et al. (2016, 2014) have proposed a portable device for student attendance system based on fingerprint recognition. The proposed systems asked student to scan his/her fingerprint to the device for attendance process. The attendance data was only stored on the device. The device was not directly connected to the server, as consequent the lecturer needs to back up the data to the server manually after class hour. In addition, many devices are needed if there are many classes at the same time. Soewito, et al. (2015) has proposed an employee attendance system on Android smartphone using fingerprint and GPS integrated with payment system. From the user smartphone, the system recorded fingerprint, attendance time, and the coordinate of position trough GPS that available on the smartphone to avoid a long queue and fake attendance. However not all Android smartphone are equipped with fingerprint scanner. Moreover, recording the user position through GPS on Android smartphone is inaccurate. According to Bauer (2013) GPS on Android smartphone had deviation about 10–93 m from the actual position. Therefore, employees who are outside the office but still close enough to the office can be recorded as present. Almost all proposed attendance systems based on fingerprint recognition did not report recognition accuracy except the system proposed by Zainal et al. (2016), which is 85% with total recognition time around 7–9 min for 27 students. Moreover, there is a drawback in attendance system based on fingerprint recognition. As reported by Zainal et al. (2016), the system cannot recognize a fingerprint if it is wet, dirty, or broken.

Chintalapati and Raghunadh (2013); Fuzail et al. (2014); Mehta and Tomar (2016); Raghuwanshi and Swami (2017); Sayeed et al. (2017); Wagh et al. (2015); Wati Mohamad Yusof et al., 2018 have proposed automated student attendance system based on face recognition. The proposed systems were used a camera to capture either all student faces at once (Fuzail, et al., 2014; Mehta and Tomar, 2016; Raghuwanshi and Swami, 2017; Wagh, et al., 2015) or one by one (Chintalapati and Raghunadh, 2013; Sayeed, et al., 2017; Wati Mohamad Yusof et al., 2018). Chintalapati and Raghunadh (2013) used principle component analysis (PCA) and local binary pattern (LBP) combined with some classifier to perform face recognition and achieved the best classification accuracy of 78% by using LBP and Euclidean distance for 80 students. Sayeed et al. (2017) have proposed a real time face recognition using PCA and Euclidean distance for attendance system. Wati Mohamad Yusof et al. (2018) have proposed a real time internet based attendance system using face recognition. The proposed system employed Haar-cascade for face detection combined with LBP for face recognition. The systems proposed by Chintalapati and Raghunadh (2013); Sayeed et al. (2017); Wati Mohamad Yusof et al. (2018) are not efficient since they only used a camera to capture student face image one by one. Fuzail et al. (2014); Wagh et al. (2015), Mehta and Tomar (2016), and Raghuwanshi and Swami (2017) employed a camera to capture all students face in a classroom at once. This strategy can avoid the occurrence of queues during attendance process. However, the attendance systems that use this strategy had a low accuracy on face recognition as reported by Raghuwanshi and Swami (2017), that were 53.33% and 60% using principle component analysis (PCA) and Euclidean distance and linear discriminant analysis (LDA), respectively.

The using of barcode (Noor et al., 2015), QR code (Rahni et al., 2015), RFID (Arulogun et al., 2013; Bhalla et al., 2013; Hussain et al., 2014; Rjeib et al., 2018), and NFC (Mohandes, 2017) is another alternative to record student identity in an attendance system. Attendance process in the systems proposed by Arulogun et al. (2013); Bhalla et al. (2013); Hussain et al. (2014); Noor et al. (2015); Rahni et al. (2015); Rjeib et al. (2018) was very simple, students only needed to scan their student card contained barcode, QR code, or RFID using the system to record attendance. While in NFC based attendance system (Mohandes, 2017), students placed their NFC phone near lecture's NFC phone when entering classroom. This process can lead to a long queue during attendance process. Fake attendance can also be occurred since student card contained barcode, QR codes, or RFID and NFC phone are easily transferable from one student to another. In addition, not all smartphones are equipped with NFC systems. To overcome this problem, the using of palm vein can be considered to recognize student in attendance system as proposed by Bayoumi et al. (2015). However, not all cameras can be used to capture the image of palm vein. Furthermore, the accuracy of palm vein recognition in attendance system proposed in (Bayoumi et al., 2015) was only 78%. Therefore, from the current state of the art of automated attendance system it can be found that face recognition is the best approach to recognize student in an attendance system.

Currently, the number of Android smartphone is growing rapidly. Almost all students have at list an Android smartphone equipped with camera. According to Pratama (2017), 95.24% of university students in Indonesia have their own smartphone in 2016. This phenomenon can be used to develop an attendance system using face recognition through Android smartphone. By implementing such a system, long queues occurred in previous automated attendance process can be avoided. However, it is necessary to create a mechanism to ensure that every student really attend in the course. Furthermore, the accuracy of face recognition also needs to be improved to guaranty the system can be implemented for several courses with a large number of students.

This paper proposed an attendance system using face recognition by employing Android smartphone to capture student face. The image was then sent to server for attendance process. Some innovations have been performed in the proposed system. First, every student only needed to capture his/her face image using his/her Android smartphone to avoid a long queue. Second, in case a student does not have a smartphone, the proposed system was designed such that the student who does not have a smartphone can use other student's smartphone to process his/her attendance. Third, the proposed system employed a simple classifier to recognize student face. The last, to increase face recognition accuracy, the proposed system only used a classifier in a certain course. The rest of the paper is organized as follow. Section 2 describes the required materials and method used in the proposed attendance system. The experimental result and its analysis are presented in Section 3. Finally the conclusion is drawn in Section 4.

2. Materials and method

2.1. Materials

The materials used to develop the proposed attendance system consisted of hardware, software, and face image data set. The hardware was Android smartphone, Raspberry Pi, monitor, and computer server. The proposed attendance system required an Android smartphone 4.3 (Jelly Bean) or later with camera and internet connection to open the attendance system by the lecturer and to process the student attendance. A Quad Core 1.2 GHz Broadcom BCM2837 64bit and 1 GB RAM Raspberry Pi 3 Model B was used to get the course information from the server and displayed it to the monitor at front of classroom. A 3.60 GHz Intel(R) Core (TM) i7-7700 and 16 GB RAM computer with Ubuntu Linux version 4.15.0-24-generic operating system was used as server.

Two Android applications were developed for the proposed attendance system, one for lecturer and one for student. The applications were developed in Android Studio. The applications employed Volley (Developers, 2018), an HTTP library for Android, and OpenCV (Bradski, 2000), a computer vision library, for networking with the server and image processing, respectively. A web client application was developed in PHP language to request information for opened attendance system by the Raspberry Pi from the server and to display the information on the monitor at the front of classroom. On the server side, an application was also developed in PHP language for communication with the Android smartphone and the Raspberry Pi. Moreover to carry out face recognition and attendance processing tasks in the server, a python based application was developed by employing OpenCV (Bradski, 2000) and Scikit-learn (Pedregosa et al., 2011) libraries for image processing and face image classification, respectively. All data used in the proposed attendance system were managed in the server using MySQL. The proposed attendance system used two connection types, Wi-Fi connection, to connect the Android smartphone and the server, and LAN connection, to connect the Raspberry Pi to the server.

2.2. Student registration

Every student in a course needed to register his/her face image and student registration number to the attendance system. The face image of every student was captured 10 times in the perpendicular direction to the smartphone camera with different expression, including normal, smiling, laughing, and sad using a menu in the Android application for student, as shown in Fig. 1. Before capturing his/her face image, the student needed to make sure that his/her face has been detected by the attendance system. The proposed attendance system employed Viola Jones algorithm (Viola and Jones, 2004) to detect face area in the image. Once his/her face detected the student was asked to capture his/her face image. The image was captured in RGB color space and cropped into 224×224 pixels such that the entire face is contained in the image. The cropped image was stored in PNG format with a unique file name related to student registration number. The image was then uploaded to the server to build a face image data set. The server is located in campus. This process was performed automatically by the proposed system without any intervention from the system administrator. The server is placed in campus and there is no one can access the face image database except the system and the system administrator. Therefore, the confidentiality of the face image database is really maintained.

Some students captured his/her face images in a very low lighting intensity. Consequently, some face image had a very low intensity. Therefore such images were removed from the face image data set. Finally, the face image data set consisted of 4209 face images was created and would be used to build a classifier for face recognition. The images were acquired from 423 students registered at 21 courses. The number of students and face images in a course were between 19 and 30 and between 186 and 300, respectively. Fig. 2 shows the example of face images in the data set. The authors have received permission from students whose face images are used in his paper.

2.3. Attendance process

The attendance process for the proposed attendance system consisted of several steps starting from system opening, followed by QR code generation, face capturing, face recognition, and attendance processing. The architecture and global steps for the proposed attendance system are shown in Fig. 3 and the details are explained as follow.

2.3.1. System opening

To open the attendance system of a course, the lecturer of the course needed to enable the system through his/her Android smartphone by choosing an appropriate course provided by the server. The data of chosen course was sent to the server through http protocol. An Android application was developed to facilitate the lecturer to take this step. From the application lecturer could also cancel the class, change class schedule, and obtain student attendance report. The user interface for the application can be seen in Fig. 4.

2.3.2. QR code generation

Once the server received the information about the opening of attendance system for a certain course, the server generated QR code contained information about course code, lecturer name, and schedule for the course using Simple QrCode (https://www.simplesoftware.io/docs/simple-qrcode). Every minute the Raspberry Pi located in the classroom requested the status of attendance system for the course that will be conducted in the classroom. If the attendance system has been opened by the lecturer then the Raspberry Pi downloaded the generated QR code from server and displayed it to a monitor located at the front of classroom. Fig. 5 shows the example of displayed QR code.

2.3.3. Face capturing

To enter the opened course attendance system, a student needed to capture the displayed QR code using the attendance sys-

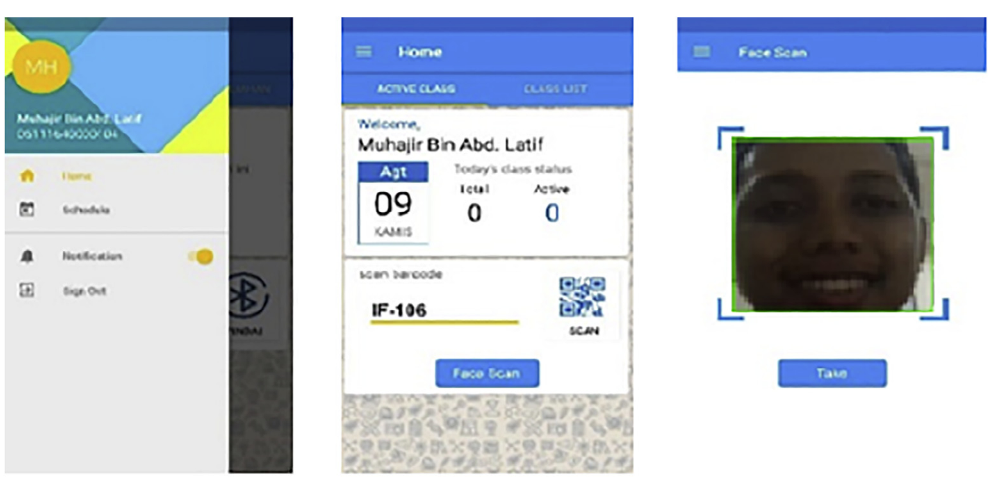


Fig. 1. The application for student registration.

Fig. 2. The example of face image in the data set.

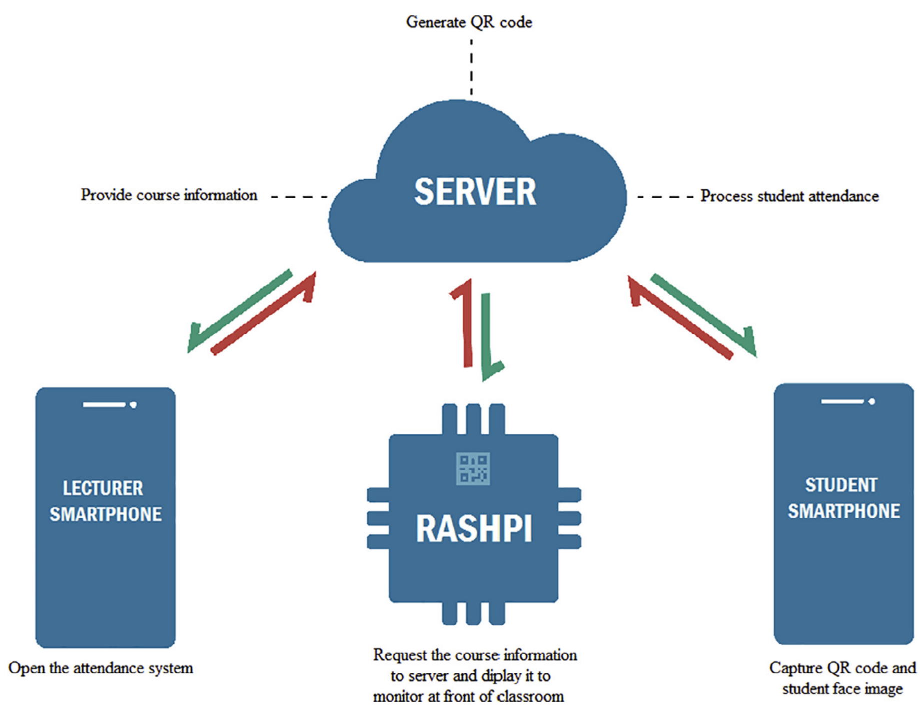


Fig. 3. The architecture and global steps for the proposed attendance system.

tem application installed in his/her own Android smartphone. This process was used to obtain the information of opened course and to make sure the student attend in the course. To minimize the possibility of cheating performed by students in attendance process, for example using QR code captured by other student, the system used campus intranet connection which is divided into several Wi-Fi segments for communication between smartphones and server. Therefore, the students who are not on Campus would not be able to process their attendance. The system used QRCodeScanner (https://github.com/blikoon/QRCodeScanner), a QR scanning library for Android, to scan displayed QR code. The student was then asked to input his/her student registration number, and capture his/her face using the attendance system application. The image was captured in RGB color space and stored in PNG format. If the captured image contained a face then the image was cropped into a 224 $\times$ 224 pixels image such that the entire face is contained in the cropped image. To perform the cropping process, the Viola Jones algorithm (Viola and Jones, 2004) was also used to detect face region in the image. Fig. 6 shows the example of captured and cropped images. The cropped image, course information, and student registration number were then uploaded to server for face recognition and attendance process.

2.3.4. Face recognition

In the server, the cropped image was converted to grayscale image and resized to a 96 $\times$ 96 pixels image. The grayscale value for every pixel in the grayscale image was transformed into a 9216 dimensional vector, as shown in Fig. 7. This vector was used as input feature to a classifier for face recognition. In this step, student registration number was used as class label or the target variable of classifier. The proposed attendance system used some simple classifiers for face recognition, including logistic regression

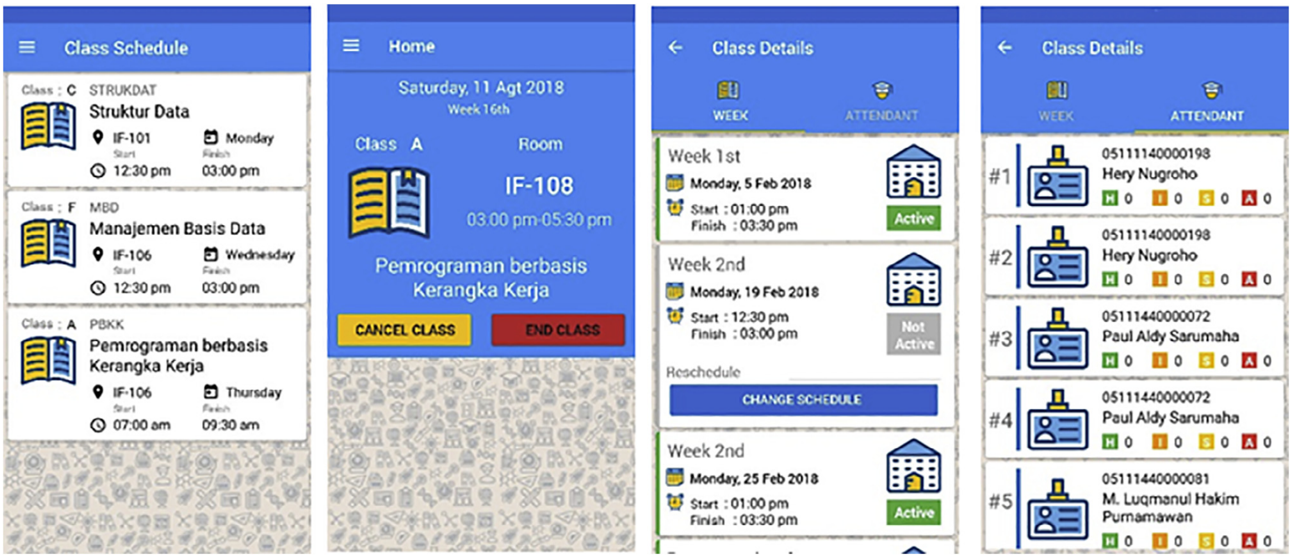


Fig. 4. The application for lecturer.

Fig. 5. The example of displayed QR code.

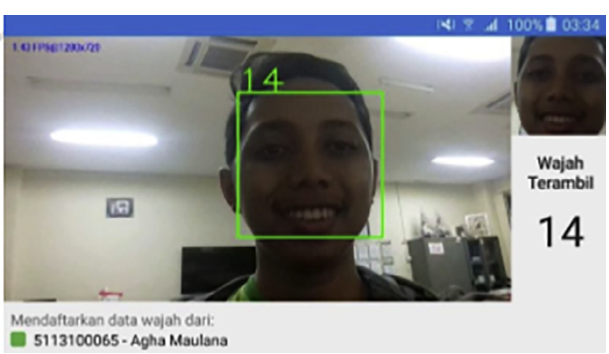


Fig. 6. The example of captured and cropped image.

(LR), linear discriminant analysis (LDA), and k-nearest neighbor (k-NN). Such classifier was chosen since it does not require a high computational cost and a high computer resource. Therefore the load of server was not too heavy either during classifier training or during simultaneously accessed by many students for attendance processing.

2.3.4.1. Logistic regression. Logistic regression is a simple binary classifier that can be extended to multiclass classifier by implementing the one versus the rest strategy. Logistic regression assigns an unknown sample to a class C_i that has highest class posteriors distribution $P(C_i|\boldsymbol{x},\boldsymbol{w},b)$ as in equation.

$$P(C_i|\boldsymbol{x},\boldsymbol{w},b) = \frac{1}{1+e^{-y(\boldsymbol{w}'\boldsymbol{x}+b)}} \qquad 1$$

where $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$is input feature, $(\boldsymbol{w}, b)$is weight, and $y \in \{-1, 1\}$ is the class label. The proposed system estimated weight $(\boldsymbol{w}, b)$using the implementation of trust region Newton method (Lin et al., 2007) in LIBLINEAR library (Fan et al., 2008) by minimizing a cost function defined in equation.

$$f(\boldsymbol{w},b) = \frac{1}{2}[\boldsymbol{w},b]'[\boldsymbol{w},b] + C\sum_{i=1}^{l}\log\left(1+e^{-y_i(\boldsymbol{w}'\boldsymbol{x}_i+b)}\right) \qquad 2$$

where $C > 0$ is a penalty parameter, $y_i \in \{-1, 1\}$is class label, $\boldsymbol{x}_i, i = 1, 2, \ldots, l,$ is feature vector for training example, and l is the number of training example.

2.3.4.2. Linear discriminant analysis (LDA). LDA perform classification by determining linear decision boundaries that maximizing between-class scatter and minimizing within-class scatter. LDA assume that the class-conditional density of input feature $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$ in class C_i is normal multivariate with mean $\boldsymbol{\mu}_i$ and covariance matrix $\sum$ for all $i = 1, 2, \ldots, k$, as in equation.

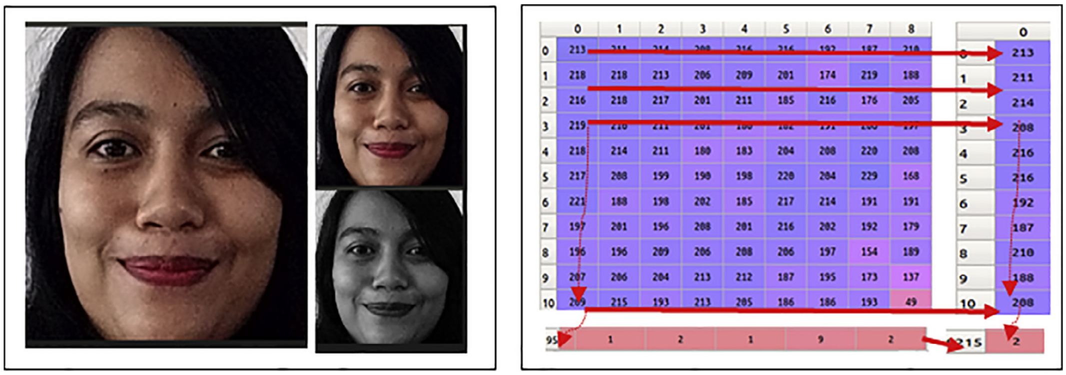
$$P(\boldsymbol{x}|C_i) = \frac{1}{(2\pi)^{n/2}|\sum|^{1/2}} e^{-1/2(\boldsymbol{x}-\boldsymbol{\mu}_i)'\sum(\boldsymbol{x}-\boldsymbol{\mu}_i)} \qquad 3$$

By using this assumption LDA assigns an unknown sample to a class C_i if it has greatest linear discriminant value (Hastie et al., 2009). The linear discriminant function of class C_i is calculated using equation.

$$\delta_i(x) = \boldsymbol{x}'\sum^{-1}\boldsymbol{\mu}_i - \frac{1}{2}\boldsymbol{\mu}_i'\sum^{-1}\boldsymbol{\mu}_i + \log\pi_i \qquad 4$$

where $\boldsymbol{\mu}_i$ is the prior probability of C_i.

2.3.4.3. k-nearest neighbor (k-NN). k-NN classifier assign an unknown sample to a class that has maximum number of examples close to the sample among k neighbors (Alpaydin, 2014). In the experiment, the proposed system used $k = 1$ and the distance between the sample and its neighbors was measured using Euclidean distance as in equation.



(a) (b)

Fig. 7. The example of transformation (a) from cropped image into gray scale image and (b) from gray scale image (96x96) into gray scale vector (9216 × 1).

$$d(\boldsymbol{x}, \boldsymbol{x}_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2} \quad 5$$

where $\boldsymbol{x} = (x_1, x_2, ..., x_n)$and $\boldsymbol{x}_j = (x_{j1}, x_{j2}, ..., x_{jn})$are the feature vectors for the unknown sample and the jth neighbor $j = 1, 2, ..., k$, respectively, and n is the dimension of feature vector.

2.3.5. Attendance processing

If student registration number resulted from step 4 match with student registration number inputted by student in step 3 then the student got a notification from the attendance system that his/her attendance has been recorded. Otherwise, the student was asked to capture his/her face once again. The result of attendance process was then reported to lecturer through the attendance system application installed in his/her Android smartphone, as shown in Fig. 8.

Fig. 8. The attendance report in lecturer's application.

2.4. Experimental setup

An experiment has been carried out in the laboratory to find the best classifier in two training scenarios. The first scenario, a classifier was used in attendance system for all courses. In this scenario all face image samples from all students registered at all courses were used to train the classifier. The second scenario, a classifier was only used in attendance system for a certain course. Therefore, if there were n courses, face image samples were divided into n sub samples according to the list of course participants. Each sub samples was used to train the classifier for attendance system in the corresponding course. The result of this step was student registration number related to the recognized image.

To validate the accuracy of the classifier for face recognition, the proposed attendance system used stratified k-fold cross validation in the training and testing processes (Alpaydin, 2014). The face image data set was randomly divided into k mutually exclusive subsets with equal size such that the number of face images in every class has same proportion for all subsets. A subset was used as testing data and the remaining $k - 1$ subsets were used to train the classifier. The training and testing processes were repeated k times such that every subset is used as testing data on exactly once iteration. Fig. 9 depicts the cross validation process.

For every testing data, the accuracy of the classifier was calculated using equation.

$$Acc_i = \frac{cc_i}{N_i} \times 100\% \quad 6$$

where Acc_i, cc_i and N_i are the accuracy of classifier, the number of correctly classified sample, and the number of sample on ith testing data, respectively. The average of $Acc_i, i = 1, 2, ..., k$ was calculated to obtain the final accuracy for the classifier. In this validation, the proposed attendance system used 2-fold and 5-fold cross validations to validate the accuracy of classifier and to investigate the influence of increasing the number of sample in training data on classification accuracy.

3. Results and discussion

3.1. First experimental scenario

As stated in section 2, in the first experimental scenario all face image data were used to train a classifier for face recognition process. The classification results for every classifier with the first

Fig. 9. *k*-fold cross validation process.

experimental scenario are tabulated in Table 1. As can be seen from Table 1, LR produced higher classification accuracy, which were 93.22% and 95.21% for 2-fold and 5-fold cross validation respectively, compared to LDA (93.17% and 93.36%) and k-NN (86.06% and 88.37%). In 2-fold cross validation 50% image data set was used as training data, while in 5-fold cross validation used 80% image data set. It can be observed in Table 1 that by increasing 30% training data, k-NN achieved the most significant increasing in classification accuracy (2.31%) followed by LR (1.99%) and LDA (0.19%). Therefore, it can be inferred that increasing the number of training data would significantly improve classification accuracy for k-NN and LR.

Although LR achieved the best classification accuracy, it was not efficient in term of computational time. As can be seen in Table 1, in 2-fod and 5-fold cross validation LR required 1339.89 s and 5143.99 s for training in the server, respectively, while LDA required only 27.80 s and 201.67 s. On the other hand, the classification accuracy of LR was not significantly different from LDA, which was only 0.05%. In this scenario, the server required about 0.000190 s, 0.000179 s, and 0.033409 s to recognize a face image using LR, LDA, and k-NN, respectively.

3.2. Second experimental scenario

In the second experimental scenario face image data set was partitioned into 21 sub data sets according to the list of course participant in 21 courses. The distribution of students and face images for all courses are depicted in Fig. 10. For classification task, there were 21 classifiers (one classifier for one course) used by the proposed attendance system to perform face recognition. Each classifier was trained using the corresponding sub data set. Table 2 summarizes the classification results for LR, LDA, and k-NN.

As can be seen from Table 2, on average LR produced higher classification accuracy, which were 96.53% and 97.48% for 2-fold and 5-fold cross validations respectively, compared to LDA (95.24% and 97.29%) and k-NN (91.86% and 93.05%). This result outperforms the recognition accuracy in attendance systems proposed in (Mohandes, 2017; Raghuwanshi and Swami, 2017; Zainal, et al., 2016). In 2-fold cross validation, the numbers of classifier that achieved classification accuracy greater than classification accuracy in the first experimental scenario were 20, 16, and 21 for LR, LDA, and k-NN, respectively. On the other hand, there were 15, 18, and 14 for LR, LDA, and k-NN, respectively, in 5-fold cross validation. Furthermore, it can be seen in Table 2 that by increasing 30% training data, on average LDA achieved the most significant increasing in classification accuracy (2.05%) followed by k-NN (1.19%) and LR (0.95%). Therefore, it can be concluded that by using the second experimental scenario, the classification performance could be improved about 2.07% until 5.80% both in 2-fold and 5-fold cross validations.

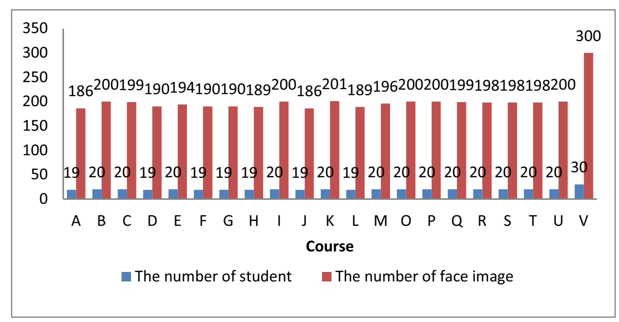


Fig. 10. The distribution of students and face image for all courses.

In the term of computational time, the second experimental scenario could reduce training time about 65.51% until 96.46% both in 2-fold and 5-fold cross validations, as shown in Table 2. However, LR still required more training time (48.98 s and 181.92 s) compared to LDA (9.59 s and 42.52 s) and k-NN (5.36 s and 7.42 s) both in 2-fold and 5-fold cross validations. In this scenario, the server required about 0.000042 s, 0.000096 s, and 0,001683 s to recognize a face image sample using LR, LDA, and k-NN, respectively. Therefore, based on classification accuracy and training

Table 1
The classification results for the first experimental scenario.

Classifier	2-fold cross validation		5-fold cross validation	
	Accuracy (%)	Training time (s)	Accuracy (%)	Training time (s)
LR	93.22	1339.89	95.21	5143.99
LDA	93.17	27.80	93.36	201.67
k-NN	86.06	60.96	88.37	52.599

Table 2
Classification results for the second experimental scenario.

Classifier	The number of classifier	2-fold cross validation		5-fold cross validation	
		Average accuracy (%)	Total training time (s)	Average accuracy (%)	Total training time (s)
LR	21	96.53	48.98	97.48	181.92
LDA	21	95.24	9.59	97.29	42.52
k-NN	21	91.86	5.36	93.05	7.42

Table 3
TPR, FNR, TNR, and FPR for LDA in the second experimental scenario.

Course	TPR (%)	FNR (%)	TNR (%)	FPR (%)
A	95.16	4.84	99.73	0.27
B	98.00	2.00	99.89	0.11
C	98.99	1.01	99.95	0.05
D	97.37	2.63	99.85	0.15
E	96.39	3.61	99.81	0.19
F	97.89	2.11	99.88	0.12
G	94.74	5.26	99.71	0.29
H	97.35	2.65	99.85	0.15
I	98.50	1.50	99.92	0.08
J	95.70	4.30	99.76	0.24
K	97.51	2.49	99.87	0.13
L	97.88	2.12	99.88	0.12
M	99.65	0.35	99.98	0.02
O	97.50	2.50	99.87	0.13
P	96.50	3.50	99.82	0.18
Q	95.98	4.02	99.79	0.21
R	98.48	1.52	99.92	0.08
S	100.00	0.00	100.00	0.00
T	98.99	1.01	99.95	0.05
U	98.00	2.00	99.89	0.11
V	95.67	4.33	99.85	0.15
Average	97.44	2.56	99.87	0.13

time, the proposed attendance system employed LDA resulted from the second experimental scenario for face recognition step. For further analysis the classification result of LDA in the second experimental scenario was divided into True Positive Rate (TPR), False Negative Rate (FNR), True Negative Rate (TNR) and False Positive Rate (FPR), as summarized in Table 3. As can be seen in Table 3, LDA produced TPR and TNR of 97.44% and 99.87% on average, respectively. It can be also seen in Table 3, on average LDA achieved low FNR and FPR of 2.56% and 0.13%, respectively. This results show that LDA could recognize the face of every student with a good performance. Based on these results, the system has been implemented to process the attendance of 21 courses for three semesters without any significant problem.

4. Conclusion

This paper proposes an Android based course attendance system using face recognition. The system asked every registered student to capture his/her face image and QR code displayed at the front of classroom using his/her smartphone. The captured image was then uploaded to the server for face recognition and attendance process. To achieve a good face recognition accuracy and efficient processing time, a classifier was only used to perform face recognition in a certain course. The experimental result shows that the proposed attendance system achieved face recognition performance of 97.29% by employing LDA and only needed 0.000096 s for face recognition process in the server. For future work, the investigation of the using of Bluetooth devise for measuring the distance between student's smartphone and Raspberry Pi located in classroom, to ensure students attend in a course, will be considered to minimize the possibility of cheating performed by students in attendance process.

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Declarations of interest

None.

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