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# Comparison of Different Classifiers for Drowsiness Detection Based on Facial Expression Recognition

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**Abstract:** Traffic accidents often occur due to the negligence of sleepy drivers. This study proposed a method to classify the normal expression and drowsiness expression as the first step in a driving safety system. In this study, a driver's facial expression recognition system was designed using Principal Component Analysis (PCA) as a feature extraction method and classifier comparison using K-Nearest Neighbor (K-NN) and Linear Discriminant Analysis (LDA) methods. PCA worked to reduce the data without eliminating important information in the image, and this process also caused system performance to be faster. The developed facial expression recognition systems can detect facial expressions and classify them into two types using data from the Yawning Detection Dataset (YawDD). They are normal expression and drowsiness expression using K-NN and LDA. The K-NN classification method has the advantage of being more effective and simpler computing with an accuracy rate of 97% from 200 test images using eigenface parameters on PCA and K value, equal to 1 using city block distance by 256 x 256 pixels. This paper proved that LDA has the same performance as the KNN classifier with an accuracy rate of 97 % using Bayes prior in size 128x82 pixels with the advantage that LDA is more compressible than KNN.

**Keywords:** Eigenface, Facial expression, PCA, K-NN, LDA, Drowsiness detection.

# 基于面部表情识别的睡意检测不同分类器的比较

**摘要**：由于困倦的驾驶员的疏忽，经常会发生交通事故。这项研究提出了一种将正常表情和困倦表情分类为驾驶安全系统的第一步的方法。在这项研究中，设计了使用主成分分析（PCA）作为特征提取方法并使用 K 最近邻（神经网络）和线性判别分析（LDA）方法进行分类器比较的驾驶员面部表情识别系统。PCA 致力于减少数据而又不消除图像中的重要信息，并且此过程还导致系统性能提高。开发的面部表情识别系统可以使用打哈欠检测数据集（偏航）中的数据检测面部表情并将其分为两种类型。它们是使用神经网络和 LDA 的正常表达和睡意表达。神经网络分类方法的优势在于，使用 PCA 上的特征面参数和 K 值从 200 张测试图像中得出的准确率为 97％，计算效率更高且更简单，使用 256 x 256 像素的城市街区距离等于 1。本文证明了使用大小为 128x82 像素的贝叶斯算法，LDA 具有与知识网络分类器相同的性能，准确率达到 97％，并且 LDA 比知识网络更具可压缩性。

**关键词**：特征脸，面部表情，主成分分析，K 最近邻，线性判别分析，嗜睡检测。

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# 1. Introduction

One of the main factors that caused traffic accidents is the drivers [1-3] instead of road construction [4]. This driver awareness is often regarded as the main reason for road accidents. Face detection is a human face recognition process using facial features that will be the first step before a whole face mechanism process. Areas of research consist of several things related to face processing such as face recognition, face authentication, face localization, face tracking, include facial expression recognition. Facial expression recognition is a technique used to recognize human emotions, seen from faces, as expressing non-verbal communication because of human feelings or emotions [5-6].

Research-based on face recognition is still has a big challenge due to the variation of facial expressions. Some remarkable studies of facial expressions were video-based fatigue classification by detecting blinking eye speed [7], yawning [8-11], emotion detection by using fuzzy rule classification [12], and SVM [13]. The one that was using sensors to obtained biosignal data combine with emotion detection, which had an accuracy of 71.9% [14]. Principal Component Analysis previously had been used for face recognition and emotion detection, in the research [15] with Backpropagation Neural Networks classification produced an accuracy of more than 90%. Another study [16] used the PCA method in dimension reduction with the best-proposed system capable of detecting 90.5% of indoor car test cases and 85% of outdoor car test cases.

Based on previous studies, face recognition was used for security on smart parking systems with an accuracy of 76.67% [17]. In this study, a face recognition system has been proposed, especially in emotion recognition for detecting drowsiness with the purpose was for safety while driving. The next project will be merged as part of the smart parking system. In this study, the data that came as a digital image captured from a web camera will be processed with the Principal Component Analysis method and the K-Nearest Neighbor classification to recognize the driver's facial expressions when he has drowsiness or normal expressions. This study had the aim to reduce the impact of traffic accidents so that they get an early warning to prevent the consequences of traffic accidents.

The Principal Component Analysis method was chosen as a feature extraction to reduce information without have eliminated important information in the image [18]. This process also caused faster system performance. K-NN classifier is chosen because it can be more effective and more straightforward computing with a high accuracy rate [19]. Many research LDA techniques have been used due to the large size of image dimensionality [20]. For example, some of them used for biometrics systems (preprocessing, feature extraction, and recognition) have been applied to face recognition [21-24]. LDA is a well-known linear technique for feature extraction, which can map high-dimensional samples onto a low-dimensional space. Thereby the combination between LDA, which has a lossless compression with PCA, is presented in this paper compared to the KNN classifier to give a more efficient, accurate, and stable method.

# 2. Materials and Methods

A whole system of drowsiness recognition can be seen in Figure 1.

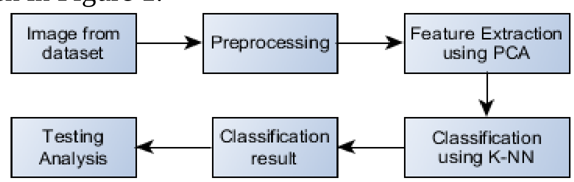



Fig. 1 System design of drowsiness recognition from facial expression

## 2.1. Preprocessing

The preprocessing process consists of several stages, shown in Figure 2. At this stage, the dataset form of a video frame had been cropped as an image. Then it was resized according to the predetermined size is 128 × 82 pixels. The data set also was compressed during an experiment to determine the effect on system performance. After it, face detection will be detecting the face area and marking the detected face with a red box using the Viola-Jones method. The last step in preprocessing is converting the color of data from RGB (Red Green Blue) to BW (Black and White). First, the RGB domain had been converting to grayscale, then grayscale converted to black and white.

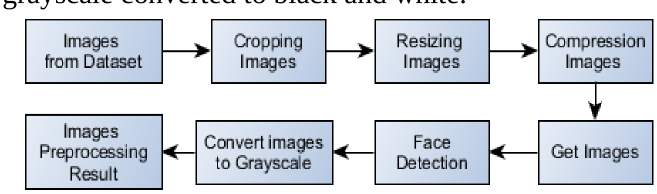



Fig. 2 Preprocessing design

## 2.2. Feature Extraction Using PCA

PCA is one of the statistical techniques used to analyze the data in a class and then summarise it. The shortest distance measurement on PCA based on eigenvalue considered as the first automatic face recognition technology. In this study, the eigenvalue was equal to eigenface, which became the main component in the feature extraction process of the initial training set of facial images. Each face image can be seen as a vector with the width and height pixels so that the component number of the vector is N = w × h. In this case, face images were represented as N-dimensional column vectors or N × 1 matrices. In this research, the steps that had taken in the PCA Eigenface process as follows [25]:

*2.2.1. Face Image with the Same Size and Format*

Collection of the training set face images amount of M images with width (w) and height (h) was represented as a vector of dimension N, where N = w × h. Where a set of facial images in a training set could be written as Ti = {T1, T2, T3, ...., TM}, where each Ti was a vector of dimensions N and M was the number of face images in the training set.

*2.2.2. Average Face Image Calculation*

The average image is the average of all training image pixels. Suppose that m is the number of training images with index I; the average image can be calculated using eq. 1.

$$\Psi = \frac{1}{m}\sum_{I=1}^{m} \Gamma i \quad , \tag{1}$$

where Y is an average matrix, and m is a sample of several training images, then the results of the average image would represent in a matrix below:

$$\Psi = \begin{bmatrix} \mu_1 \\ \mu_2 \\ : \\ : \\ \mu_N \end{bmatrix} \tag{2}$$

Two parameters obtained vector distance value, and they were the average face image value and matrix of face image Ti as seen in eq. 3:

$$\{\Phi_1, \Phi_2, \Phi_3 \dots, \Phi i\}$$
$$\Phi i = Ti - \Psi \tag{3}$$

Covariance between two datasets shows how close one to the other. In this case, the covariance of matrix C represented the relationship between the two matrices and the variants contained in the dataset as seen in eq.4, where *AT* is the transpose matrix of matrix A, and A is the difference (average face) between each training set's face image:

$$C = A \times A^T \tag{4}$$

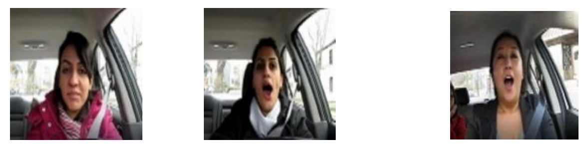
*2.2.3. Calculation of the Eigenvector and Eigenvalue from the Covariance Matrix C*

EV is the eigenvector's variable, and eval is the eigenvalue's variable. The vector had multiplied by *AT* matrix, so eigenface was obtained from the reference image in eq.5. This formula is the last step to find the eigenvalue or eigenface using PCA then would be continued to classify the data using K-NN classifier.

$$C \times eval = ev \times eval \tag{5}$$

Continue with the calculation flow of the eigenface value. The face vector used to find the Eigen Face value in an input image is as follows:

Take a set of training images as many as M pieces with the image format on JPG (same size) and used them as row vectors. The 2 × 2 matrices are assumed as a simple image, with each element considered as the pixel value of an image.



A = [7 42 8] B = [9 15 4] C = [3 72 6]

Fig. 3 Eigenvalue matrix illustration of an image

Furthermore, the entire image in Fig. 3 will be combined into one matrix, as shown in eq. 6.

$$im = \begin{bmatrix} 7\ 4\ 2\ 8 \\ 9\ 1\ 5\ 4 \\ 3\ 7\ 2\ 6 \end{bmatrix} \tag{6}$$

The next step is calculating the average face by adding the entire value of the image's pixel intensity and dividing it by the total number of face images in the picture. Each column of this matrix will be calculated for the average value.

$$\text{Column 1} = \begin{bmatrix} 7 \\ 9 \\ 3 \end{bmatrix} = \frac{1}{3}(7+9+3) = 6 \tag{7}$$

$$\text{Column 2} = \begin{bmatrix} 4 \\ 1 \\ 7 \end{bmatrix} = \frac{1}{3}(4+1+7) = 4 \tag{8}$$

$$\text{Column 3} = \begin{bmatrix} 2 \\ 5 \\ 2 \end{bmatrix} = \frac{1}{3}(2+5+2) = 3 \tag{9}$$

$$\text{Column 4} = \begin{bmatrix} 8 \\ 4 \\ 6 \end{bmatrix} = \frac{1}{3}(8+4+6) = 6 \tag{10}$$

The result is the mean row matrix [6 4 3 6]. Find out the difference in face image to average face and then obtain an A matrix (finding each reference image).

Feature A:

$$= \begin{bmatrix} 7-6 & 4-6 & 2-3 & 8-6 \\ 9-6 & 1-4 & 5-3 & 4-6 \\ 3-6 & 7-4 & 2-3 & 6-6 \end{bmatrix} \tag{7}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 3 & 0 & 2 \\ 0 & 3 & 0 \end{bmatrix}$$

Build the L matrix by optimizing the Eigen Face

Cov L= FiturAx $A^T$ (8)

$$\text{Cov L} = \begin{bmatrix} 1 & 0 & 0 & 2 \\ 3 & 0 & 2 & 0 \\ 0 & 3 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 1 & 3 & 0 \\ 0 & 0 & 3 \\ 0 & 2 & 0 \\ 2 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 5 & 3 & 0 \\ 3 & 13 & 0 \\ 0 & 0 & 9 \end{bmatrix}$$

Calculate eigenvectors and eigenvalues from the L matrix

$$|CovL - \lambda I| = 0 \quad (9)$$

$$\left| \begin{bmatrix} 5 & 3 & 0 \\ 3 & 13 & 0 \\ 0 & 0 & 9 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right| = 0$$

$$\left| \begin{bmatrix} 5 & 3 & 0 \\ 3 & 13 & 0 \\ 0 & 0 & 9 \end{bmatrix} - \begin{bmatrix} \lambda & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \lambda \end{bmatrix} \right| = 0$$

$$\det \begin{bmatrix} 5-\lambda & 3 & 0 \\ 3 & 13-\lambda & 0 \\ 0 & 0 & 9-\lambda \end{bmatrix} = 0$$

## 3. Classification Using K-NN

The result of PCA feature extraction would be an input to the K-NN classification process. The number of the neighbors determined the K value in the classification with the K-NN approach, and K Value was experimented with within this study to get the best results. The relationship between the K value and the number of comparisons was directly proportional. The classification process using K-NN is illustrated in Fig 4.

The K-NN classification method produces a sample image of several K values, which has a minimum distance from the test image and has a class label for each sample image. In this study, the test image would be classified to the class with the highest number of sample images from the K images sample. K value greatly influences the K-NN classification. To calculate the distance, KNN has some equations: Euclidean distance, city block distance, cosine distance, and correlation distance [26-30].

Euclidean Distance is a distance calculation used to calculate similarities in two vectors as shows in eq.10, where x1 is data sample, x2 is the data, d is a distance, and p is dimension distance.

$$d_i = \sqrt{\sum_{i=1}^{p} (x_{2i} - x_{1i})^2} \quad (10)$$

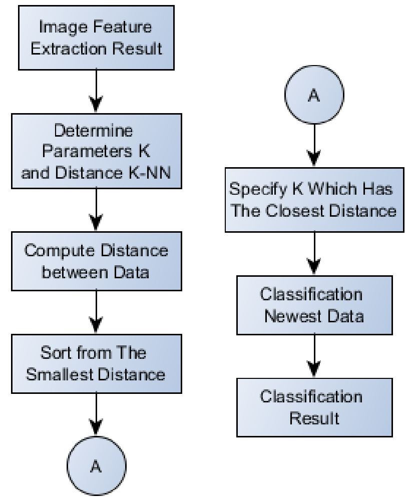



Fig. 4 Classification of normal and drowsiness expression using KNN

A city block is the same as Euclidean, which calculates the distance between two points. The difference only when calculating the distance between two points, as shown in eq below.

$$d_{s,t} = \sum_{i=1}^{n} |X_{sj} - Y_{tj}| \quad (10)$$

$$cos\theta = \frac{X_s X_t}{|X_s||X_t|} \quad (11)$$

$$d_{s,t} = 1 - cos\theta \quad (12)$$

Cosine distance is used to calculate similarities between two vectors of inner product space. Cosine distance has a range of values from -1 to 1, as a formula in eq.11. The last, correlation distance, calculates that process the points that are considered rows of values, where the distance between points $x_s$ and $x_t$ as given in formula eq.13 and eq.14, with $d_s$ is KNN distance.

$$d_{s,t} = 1 - \frac{(Xs - \overline{Xs})(Xt - \overline{Xt})}{\sqrt{(Xs - \overline{Xs}(Xs - \overline{Xs})}.\sqrt{(Xt - \overline{Xt})(Xt - \overline{Xt})}} \quad (13)$$

$$\overline{Xs} = \frac{1}{n} + \sum_j X_{sj} \text{ dan } \overline{Xt} = \frac{1}{n} + \sum_j X_{tj} \quad (14)$$

## 4. Classification Using LDA

The LDA method is a combination of the original predictors that create a new variable, maximizing the differences between the predefined groups concerning the new variable. The new variable form can be viewed as an excessive data dimension reduction technique with a normal distribution of discriminant scores [7].

There are three steps needed to be LDA method form:

a. Calculate the separability between different classes (mean) or between class matrix ($S_B$).

b. Calculate the distance between the mean and the samples of each class called the within-class variance ($S_W$).

c. Construct the lower-dimensional space, which maximizes the $S_B$ and $S_W$as in eq. 15 and eq. 16.].

$$\arg\max W = \frac{W^T S_B W}{W^T S_W W} \qquad (15)$$

$$S_W W = \lambda S_B W \qquad (16)$$

where W represents the matrix and λ represents the eigenvalues of W.

# 5. Results and Discussion

This system was tested to find out the system performance. The test scenario has been done in a non-real-time process, so the tested data should be stored in the storage media. The data used was 400 images in the JPG format, consisting of 200 images from the vehicle's dashboard and 200 images from the vehicle's mirror, then divided into 100 training images and 100 test images for the dashboard as well as the mirror. The facial expressions classification consists of drowsiness class and normal class. It was exhibited as many 20 different people examples of Yawning Detection Dataset (YawDD) [19] as shown in Fig. 4. The parameter testing goal was to obtain parameters with the best performance, more specific, and system accuracy. The test scenario is as follows:

In the first stage, the image acquisition process consists of cropping, resizing, and compression. The dataset used is Yawning Detection Dataset, which provides an image of a video stream frame with two expressions in sleepy and usual. The cropping process is used to cut an image from a frame video form dataset with a duration between 1 to 3 minutes. The cropping process is done by taking pictures on the video with different time intervals during sleepy and normal expressions and then saved in jpg format. After cropping, the dataset will resize the image according to the predetermined size, 128 × 82 pixels. The purpose of this process is for processing the same image pixels. To test the experiment, we also conducted resize with a size of 256 × 256 pixels, 512 × 512 pixels, and 1024 × 1024 pixels to determine the effect of changes in image size. The resized image is also compressed by 25%, 50%, 75% to see the impact on system performance. The image that has been through the image acquisition process is separated into a training image and the test image for the preprocessing stages for training and testing. Fig 5 below is one of the Yawning Detection Dataset image samples that has gone through the image acquisition process.

Fig. 5 YwDD image sample after the acquisition process

The second stage is the preprocessing stage, which consists of face detection and color conversion to grayscale. The algorithm used in this face detection process is the Viola-Jones method. Figure 6 below is an image sample that has passed the face detection stage.

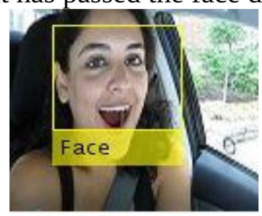



Fig. 6 Yellow bounding box on image samples after face detection

After going through the face detection process, the image will be changed from the initial image to an RGB image to a grayscale image. Figure 7 below is an image sample that has been converted into a grayscale image.

Fig. 7 RGB to grayscale conversion

Third Phase, after preprocessing, the data will go to the feature extraction stage using the Principal Component Analysis (PCA) method. This stage will acquire the Eigenface value and will store it in the whole transformation data, which is the transformation matrix.

In the fourth stage, after the results obtained from the feature extraction, which is PCA transformation data, the image classification will be performed using K-Nearest Neighbor. The distance parameters used are Euclidean distance, City Block distance, Cosine distance, and Correlation distance. The final stage for system testing is calculating the system's accuracy and optimal computing time with several test parameters.

## 5.1. K Parameters Impact in the K-NN Classifier

Table 1 shows that the highest results obtained at K=1 caused by a lot of neighborhood in the test data with training data could be classified according to the dominant class. Based on Table 1, it also can be concluded that the lowest accuracy had been done when K has an exact value with the same parameters that were the distance of the test characteristics and the training characteristics. The system would have good results when K had odd to determine the grade based on most of the number of training features.

Table 1 K-parameters testing result in K-NN

| K | *Camera* Position | Accuracy (%) |
|---|---|---|
| 1 | Dashboard | 97% |
| | Mirror | 100% |
| 2 | Dashboard | 92% |
| | Mirror | 88% |
| 3 | Dashboard | 85% |
| | Mirror | 81% |
| 4 | Dashboard | 78% |
| | Mirror | 71% |
| 5 | Dashboard | 75% |
| | Mirror | 66% |
| 6 | Dashboard | 50% |
| | Mirror | 50% |

Same as the Euclidean distance experiment, the test was done using city block, cosine, and correlation with PCA parameters the size of each image 128 × 82 pixels where the parameter of K value used was 1, 3, 5. It because in previous results, the odd K value had higher accuracy than the actual K value. The work is illustrated in Table 2 and Figure 8.

The data in Table 3 results from testing the image rescaling parameters to determine each size's effect on each image.

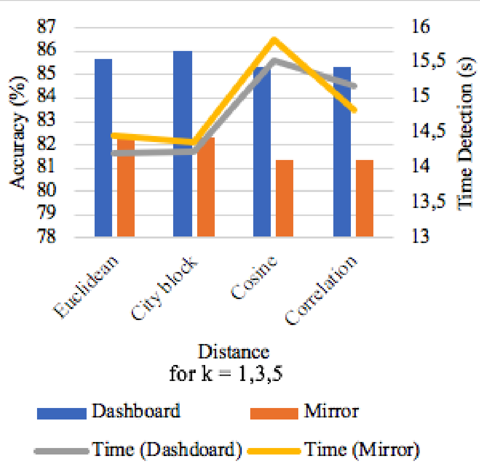



Fig. 8 Graph of comparison average accuracy and time detection of distance parameters in K-NN classifier

Table 2 Graph of comparison average accuracy distance parameters in K-NN classifier

| Dist. | K | Cam. Position | Acc | Time Comp. (s) |
|---|---|---|---|---|
| Euclidean | 1 | Dashboard | 97% | 13.9 |
| | | Mirror | 100% | 13.6 |
| | 3 | Dashboard | 85% | 14.3 |
| | | Mirror | 81% | 15.0 |
| | 5 | Dashboard | 75% | 14.6 |
| | | Mirror | 66% | 14.8 |
| City block | 1 | Dashboard | 98% | 14.4 |
| | | Mirror | 96% | 14.4 |
| | 3 | Dashboard | 85% | 13.7 |
| | | Mirror | 83% | 14.2 |
| | 5 | Dashboard | 75% | 14.6 |
| | | Mirror | 68% | 14.5 |
| Cosine | 1 | Dashboard | 96% | 16.0 |
| | | Mirror | 97% | 17.3 |
| | 3 | Dashboard | 85% | 15.7 |
| | | Mirror | 78% | 16.3 |
| | 5 | Dashboard | 75% | 14.9 |
| | | Mirror | 69% | 13.9 |
| Corr. | 1 | Dashboard | 96% | 15.0 |
| | | Mirror | 97% | 15.6 |
| | 3 | Dashboard | 85% | 15.6 |
| | | Mirror | 78% | 14.5 |
| | 5 | Dashboard | 75% | 14.9 |
| | | Mirror | 69% | 14.4 |

Table 3 Rescaling dimension parameters result

| Rescaling Dimension (pixels) | Camera Position | Accuracy | Average of accuracy |
|---|---|---|---|
| 256×256 | Dashboard | 97% | 95 % |
| | Mirror | 93% | |
| 512×512 | Dashboard | 96% | 94.5% |
| | Mirror | 93% | |
| 1024×1024 | Dashboard | 96% | 94.5% |
| | Mirror | 93% | |

The first experiment had been done using eigenface on PCA parameter, and K-NN using distance city block K=1 for the camera position on the dashboard and the camera position on the mirror was use the Euclidean distance K = 1. The highest accuracy approach is 97 % for the camera position on the dashboard in the smallest 256x256 pixels based on testing. Then continue to noising experimental as a result shown in Table 4 and Figure 9.

Table 4 Noise effect test result

| Type of Noise | Variance and density (0,1) | Variance and density (0,2) | Variance and density (0,3) |
|---|---|---|---|
| Gaussian Mean= 0,01 | 82% | 77% | 73% |
| Speckle | 80% | 76% | 74% |
| Salt & pepper | 79% | 76% | 69% |
| Poisson | 78% | 76% | 65% |

Based on Table 4, it can be concluded that the system most reliable against Gaussian noise than others. In the same variance and density of 0.1, Gaussian noise approach 82% of accuracy. Moreover, the worst noise is Poisson, which has the lowest level, 65% of accuracy invariance, and a density of 0.3.

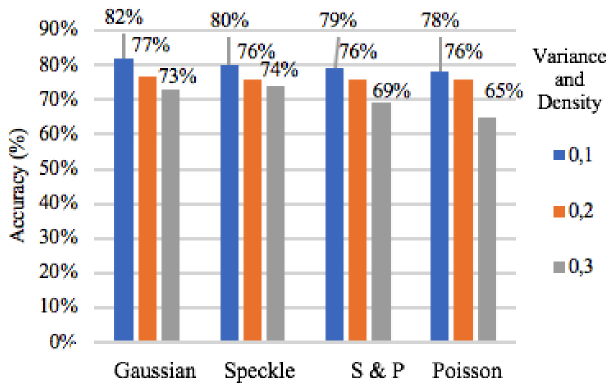



Fig. 9 Noise effect test result

This section is focused on comparing KNN and LDA when the PCA parameter using Euclidean distance for both classifiers. LDA was chosen in this experiment because it has the same character as PCA, which works linearly to reduce the dimension of data [6, 31, 32]. Based on Figure 10, only two parameters of KNN will be compared with LDA. They are Euclidean and City Block. While two of the LDA parameters used, Bayes prior and Euclidean distance, as shown in Table 5, shows Bayes prior is 93 % has higher accuracy than Euclidean (77%) in average for dashboard condition.

### 5.2. Comparison Based Experiment

Table 5 Accuracy of LDA classifier

| Cam. Position | LDA parameter | Accuracy of resizing images | | | |
|---|---|---|---|---|---|
| | | 128×82 | 256×256 | 512×512 | 1024×1024 |
| D | Bayes prior | 97% | 93% | 94% | 88% |
| | Euclidean | 91% | 87% | 76% | 52% |
| M | Bayes prior | 75% | 57% | 53% | 50% |
| | Euclidean | 76% | 68% | 55% | 50% |

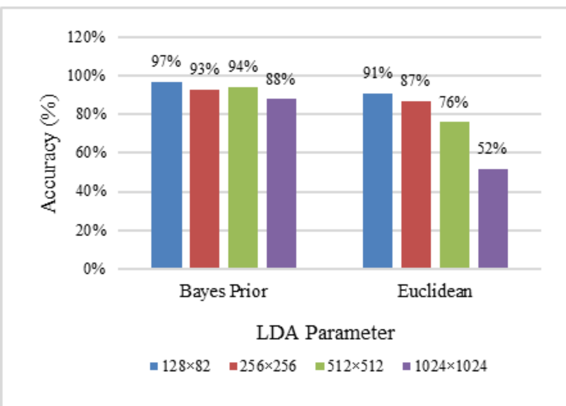



Fig. 10 LDA method performance

## 6. Conclusions

In this paper, facial expression recognition system for drowsiness detection using the PCA method with eigenface parameters as feature extraction and K-NN using the parameter K = 1 city block distance with an image size of 256 x 256 pixels produced the highest-level approach 97% of accuracy. The best K parameter on KNN was K = 1 for each test and then used for compressed images experimental. The best performance on the compression parameter was 95% accuracy, obtained from image compression of 25% (256x256). In comparison, the LDA approach with 97 % of accuracy in size 128x82 shows that LDA has better performance than the KNN regarding a face recognition system. The system was tested for the noise effect, and the result showed Poisson noise had the worst accuracy than other types of noise such as Gaussian, speckle, and salt & pepper noise.

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