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Research Article

# Modifications of Linear Regression Classification Method for Face Recognition with Image Resizing by Using Bicubic Interpolation

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ABSTRACT

Linear Regression Classification (LRC) is a method used in face recognition to identify a person by extracting features of a test image and comparing them with the features of representative images in a dataset. The LRC represents a test image vector as a linear combination of image vectors from each individual in the dataset, using the least squares method to find the minimum distance to the test image vector. The least distance from all the models of representative sets is used to identify the test image. However, the effectiveness of LRC depends on various facial variations. In this research, applied bicubic interpolation to resize images and extract new features from facial data, which enhanced the discriminative power of the extracted features. Also used K-means clustering techniques to select the most suitable representative images from each individual for the dataset. Additionally, used the Manhattan norm to measure distances during the identification process. Experimental results indicate that these suggested enhancements improve the efficiency of face recognition when integrated into the LRC algorithm.

**KEYWORDS:** Face recognition, Linear regression classification, Least squares method, K-means clustering.

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## 1. INTRODUCTION

Face recognition is a technology that involves identifying or verifying individuals based on their facial features, often used in security systems, access control, and biometric authentication. It works by analyzing unique characteristics of a person's face, such as the distances between eyes, nose, and mouth to distinguish one individual from another. Many face recognition methods, such as principle component analysis (PCA) (Turk & Pentland, 1991), linear discriminant analysis (LDA) (Belhumeur et al., 1997), independent component analysis (ICA) (Bartlett et al., 2002), and linear regression classification (LRC) (Naseem et al., 2010), have been proposed in the literature. The adaptive linear regression classifier (ALRC), leveraging the observation of similar subjects sharing comparable intra-personal variations, demonstrates superior performance over existing methods, particularly in handling variations such as expression, illumination, and disguise (Wang et al., 2013). Many studies research the impact of pre-processing on face recognition rates and present a qualitative overview of diverse pre-processing techniques and feature extraction methods, with results indicating the combined spatial and frequency feature extraction method outperforms individual approaches, demonstrating efficacy even in the absence of pre-processing (Dharavath et al., 2014). Face recognition using pre-processing techniques such as brightness adjustment and image resizing has been shown to achieve high recognition rates (Barnouti, 2016). The utilization of the K-means algorithm for facial feature analysis, followed by SVM classification, demonstrates high recognition performance with reduced feature numbers, highlighting its efficacy in enhancing face recognition accuracy and efficiency (Wei et al., 2018). The clustering method for face recognition effectively aligns feature domains globally while distinguishing target clusters locally demonstrating superior performance across various benchmark datasets (Wang & Deng, 2020). Face recognition algorithms combined with image super-resolution techniques improve the quality of low-resolution input images. Results demonstrate the effectiveness of the proposed approach in enhancing recognition accuracy for low-resolution face datasets. This significantly contributes to the advancement of face recognition technology for practical applications, particularly in scenarios where image resolution is limited (Bhadkare & Jotwani, 2024). The study of pre-processing methods with image resizing improves face recognition algorithm success. Image resizing is considered alongside other techniques like face detection, image cropping, and normalization as a part of the pre-processing stage to enhance facial recognition systems (Gülşen et al., 2024). The present research focuses on the LRC method, introduced by Naseem et al. (2010), which offers a straightforward and effective approach to face recognition. LRC represents a test image vector as a linear combination of image vectors for each individual in the dataset, with the optimal linear combination determined through regression or least-squares analysis. The method evaluates distances between the test image vector and the representative model for each individual, selecting the model of representative with the minimum distance, the performance of LRC contingent upon different facial variations.

This research improves face recognition using the Linear Regression Classification (LRC) method by: Employing image resizing to extract new features, applying K-means clustering to select representative images for the dataset, and utilizing different norms to compute distances during the identification process.

## 2. MATERIALS AND METHODS

### *2.1 The datasets*

The study focuses on four benchmark face datasets: Grimace, Faces95, Faces96, and Orl. Each dataset (Cambridge University Computer Laboratory, 1992-1994; Hond & Spacek, 1997) has details as shown in Table 1.

### *2.2 LRC algorithm*

The image used for face recognition is a gray-scaled image with the value of each pixel between $0-255.$ It is stored as a matrix of size $a\times b$ when $a$ and $b$ are the number of rows and columns respectively. Then it is converted into a column vector of size $ab\times 1$ by concatenation all its columns.

**Table 1** Details of 4 benchmark face datasets

| Dataset<br>Image size | Grimace<br>200 X 80 | Faces95<br>200 X 180 | Faces96<br>196 X 196 | ORL<br>112 X 92 |
|---|---|---|---|---|
| Number of people (individual) | n=18 | n=72 | n=147 | n=40 |
| Number of images for each individual | m=20 | m=20 | m=20 | m=10 |

The figures below show example face datasets which are used for the experiments.

**Figure 1** Sample facial images from the Grimace dataset

**Figure 2** Sample facial images from the Faces95 dataset

**Figure 3** Sample facial images from the Faces96 dataset

**Figure 4** Sample facial images from the Orl dataset

The LRC method can be described as follows. The dataset consists of $n$ individuals, where each individual has $m$ images. The dataset of all images is denoted by

$$X=\begin{bmatrix}X_1 & X_2 & \dots & X_n\end{bmatrix},$$

where $X_i=\begin{bmatrix}x_{i,1} & x_{i,2} & \dots & x_{i,m}\end{bmatrix}$ is the image vectors of the $i$ th individual for $i=1,2,\dots,n.$

Let $y$ be a test image vector. For each individual, the LRC will find the model of representative image

$$\hat{y}_i=X_i\beta_i,$$

which is the linear combination of the image vectors of the $i$ -th individual where

$$\beta_i=\begin{bmatrix}\beta_{i,1} & \beta_{i,2} & \dots & \beta_{i,m}\end{bmatrix}^T,$$

is a coefficient vector of size $m\times 1$ which obtained from solving the least squared distance $\hat{y}_i$ and $y.$ The coefficient vector is obtained by the least-squares method using the equation

$$\beta_i=(X_i^TX_i)^{-1}X_i^Ty.$$

The distance of $y$ and all $\hat{y}_i$ is calculated by the Euclidean norm

$$d_i(y)=\left\|y-\hat{y}_i\right\|_2,$$

then, the least minimum distance from all models of representatives for each individual is used to identify the test image $y.$

### *2.3 Bicubic interpolation method*

Reducing the size of the images used in the datasets helps to create unique features for each individual. It also helps to reduce the storage space for the datasets and the processing time for creating representative image sets for each individual.

The bicubic interpolation is a cubic interpolation for two variables or 2D interpolation by

$$f(x,y)=\sum_{i=0}^{3}\sum_{j=0}^{3}a_{ij}x^i y^j .$$

The bicubic interpolation estimates the value within the surface using surrounding points by normalizing the range into $-1\le x,y\le 2$.

Simply insert all $x,y=-1,0,1,2$ combinations to derive 16 equations.

$$f(0,0)=a_{00}$$

$$f(0,1)=a_{00}+a_{01}+a_{02}+a_{03}$$

$$f(1,0)=a_{00}+a_{10}+a_{20}+a_{30}$$

The system of equations can be rewritten in the form $F=CAC^T$,

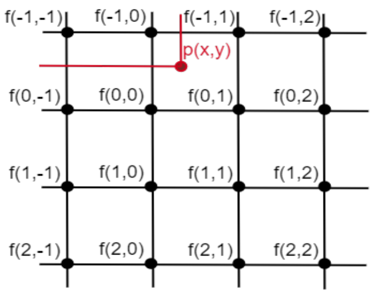
$$\underbrace{\begin{bmatrix} f(-1,-1) & f(-1,0) & f(-1,1) & f(-1,2)\\ f(0,-1) & f(0,0) & f(0,1) & f(0,2)\\ f(1,-1) & f(1,0) & f(1,1) & f(1,2)\\ f(2,-1) & f(2,0) & f(2,1) & f(2,2)\end{bmatrix}}_{F} =$$

$$\underbrace{\begin{bmatrix} 1 & (-1) & (-1)^2 & (-1)^3\\ 1 & 0 & 0^2 & 0^3\\ 1 & 1 & 1^2 & 1^3\\ 1 & 2 & 2^2 & 2^3\end{bmatrix}}_{C}\underbrace{\begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03}\\ a_{10} & a_{11} & a_{12} & a_{13}\\ a_{20} & a_{21} & a_{22} & a_{23}\\ a_{30} & a_{31} & a_{32} & a_{33}\end{bmatrix}}_{A}\underbrace{\begin{bmatrix} 1 & 1 & 1 & 1\\ (-1) & 0 & 1 & 2\\ (-1)^2 & 0^2 & 1^2 & 2^2\\ (-1)^3 & 0^3 & 1^3 & 2^3\end{bmatrix}}_{C^T}.$$

The coefficients $a_{ij}$ when $i,j=0,1,2,3$ are obtained from solving the system of equations by:

$$A=C^{-1}F(C^T)^{-1} \text{ or } A=C^{-1}F(C^{-1})^T .$$

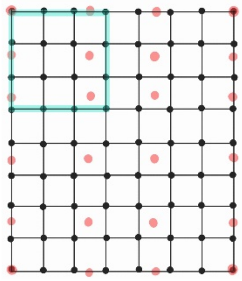
To compute the value of $p(x,y)$ within range $-1\le x,y\le 2$ refer to grid mask below,




the value of $f(0,0)$ represents the value of the image at position $(0,0)$ corresponding to the grid mask, the interpolation of $p(x,y)$ is obtained by:

$$p(x,y)=\begin{bmatrix}1 & x & x^2 & x^3\end{bmatrix}\begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03}\\ a_{10} & a_{11} & a_{12} & a_{13}\\ a_{20} & a_{21} & a_{22} & a_{23}\\ a_{30} & a_{31} & a_{32} & a_{33}\end{bmatrix}\begin{bmatrix}1\\ y\\ y^2\\ y^3\end{bmatrix}.$$

Example: resizing the image from its original size of $9\times 8$ to $6\times 4$.



**Step 1:** Calculate the position of all the new pixels (red points).

**Step 2**: Place the grid mask on the image by normalizing the range into $-1\le x,y\le 2$.

**Step 3:** Calculate the coefficient matrix $A$ from the system of equations $F=CAC^T$ where

$$A=C^{-1}F(C^T)^{-1} \text{ or } A=C^{-1}F(C^{-1})^T .$$

Each $f(x,y)$ represents the value of the image at position $(x,y)$ corresponding to the grid mask.

**Step 4**: Calculate all new pixels in the grid mask by normalizing the range into $-1\le x,y\le 2$ from

$$p(x,y)=\begin{bmatrix}1 & x & x^2 & x^3\end{bmatrix}\begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03}\\ a_{10} & a_{11} & a_{12} & a_{13}\\ a_{20} & a_{21} & a_{22} & a_{23}\\ a_{30} & a_{31} & a_{32} & a_{33}\end{bmatrix}\begin{bmatrix}1\\ y\\ y^2\\ y^3\end{bmatrix}.$$

**Step 5:** Shift the mask and repeat step 2 until all the new pixels are obtained.

**Note:** If the new pixels overlap with the original image, we use the original value.

### *2.4 K-means clustering method*

Choosing diverse image representatives from a dataset for each individual enhanced the efficiency of the LRC method. K-means clustering is therefore used in this step.


**Figure 5** Training-test split of the Grimace dataset (75% training ratio)

**Figure 6** Original-sized training set images from the Grimace dataset

**Figure 7** Training set resized to 30% of original images

**Figure 8** Training set resized to 20% of original images

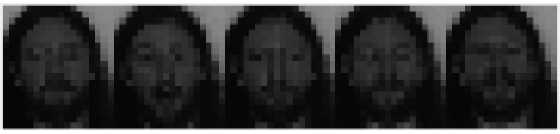


**Figure 9** Training set resized to 10% of original images

Let $X_i = \left[ x_{i,1} \quad x_{i,2} \quad \ldots \quad x_{i,p} \right]$ be the set of image vectors for the $i$ th individual. Select $m$ images to be the new dataset. The K-means method can be described as follows.

**Step 1:** Random $m$ image vectors from this class to be the initial centroids.

**Step 2:** Assign each of the remaining image vectors to the centroid which gives the least Euclidean distance.

**Step 3:** Compute the new centroid for each group using the mean of the image vectors in those groups.

**Step 4:** Repeat steps 2 and 3 until all the new centroids are not different from those in the previous round.

**Note:** A random sampling of different centers in the first round may produce varying data clustering results. If the results do not yield the desired number of groups, repeat step 1.

## 3. EXPERIMENTAL DESIGN

This section shows the experimental design to improve the performance of the LRC method for face recognition. There are three experiments for modifications of the LRC method. To evaluate the performance of the LRC method. Each experiment performs twenty independent tests. Each test uses the selected representative images as the training dataset and the remaining images as the test images to perform the identification and report the recognition accuracy which is calculated by the following.

$$\text{Recognition accuracy} = \frac{\text{The number of correctly identified images}}{\text{The number of all test images}}$$

The research has conducted a study on reducing the number of images as a training set and found that LRC still performs well in identifying identity and reduces the processing time of creating representative images in the group compared to using all images. From the benchmark face datasets, we found that we can reduce the number of images by 20%-25% depending on the characteristics of the dataset. In this case, we will use 25% for grimace, Faces95, and Faces96 because they have various image features, different facial distances, and backgrounds in the images, and 20% for ORL, which is appropriate with the number of images.

### *3.1 Studying LRC performances with bicubic interpolation for image resizing*

This study evaluates the performance of bicubic interpolation for resizing training and testing datasets and examines its impact on the accuracy

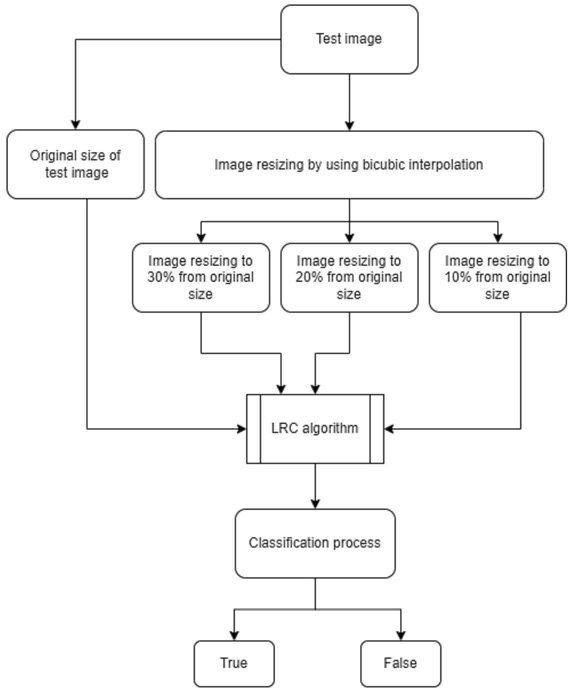



**Figure 10** Workflow of the LRC algorithm integrated with bicubic interpolation

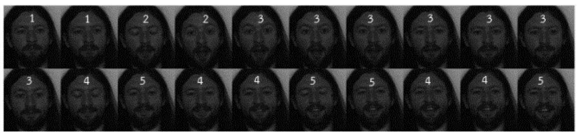


**Figure 11** Example: the numbers represent image labels for each group based on K-means clustering

**Figure 12** Examples: the image labels are the representative image closest to the centroids for each group

of identifying individuals at different reduction scales (30%, 20%, and 10% of the original size). After progressively resizing the images, the results are analyzed using the methodology outlined below.

1. For the benchmark face dataset, randomly choose five images for each individual to be representative of the training dataset and use the remaining fifteen images to be the test images except for the ORL dataset, which has only ten images per person, two images for representative images, and the remaining eight are the test images.

2. For each training and testing dataset, resize to 30%, 20%, and 10% of the original images, respectively.

3. For each size reduction, the least-squares method is used to create a model of representative for each individual $\hat{y}_i$. This model minimizes the distance from the test image $y$. The identification process involves all representative models, identifying which model provides the smallest distance from $y$. Finally, the recognition accuracy is calculated.

4. To ensure statistical reliability, twenty independent experiments were conducted. The average recognition accuracy and standard deviations were computed for each image resizing scale (30%, 20%, and 10% of the original dimensions).

### *3.2 Studying LRC performances with K-means clustering*

To compare the results of this experiment with 3.1, we set the grouping of each dataset to be the same as the last one. Using K-means clustering to select representative image sets helps reduce bias, as opposed to manual selection by researchers, which can affect the results and increase or decrease identifying identities for the LRC method. Additionally, using different initial random values in each group will result in different groupings by K-means, affecting the resulting suitable image representative in each group. To avoid this issue, operated twenty independent experiments for each dataset instead of just one experiment and summarized the results as follows:

1. For each benchmark face dataset, K-means clustering to classify images of each individual into five groups, except for the ORL dataset, which has only ten images per person, two groups are used for K-means clustering.

2. Each group will have a different number of images depending on the number of images that share similar characteristics. Select a representative image from the group based on the one closest to the centroid to be the training dataset for each individual.

**Note:** Centroids are average faces for each group, and images near the centroids refer to the image faces that are the closest to the average feature for each group. Thus, it contained almost all the characteristics of that group.

3. For the obtained training dataset, the least-squares method is used to create a model of representative for each individual $\hat{y}_i$. This model minimizes the distance from the test image $y$. The identification process involves all representative models, identifying which model provides the smallest distance from $y$. Finally, the recognition accuracy is calculated.

4. To ensure statistical reliability, twenty independent experiments were conducted.

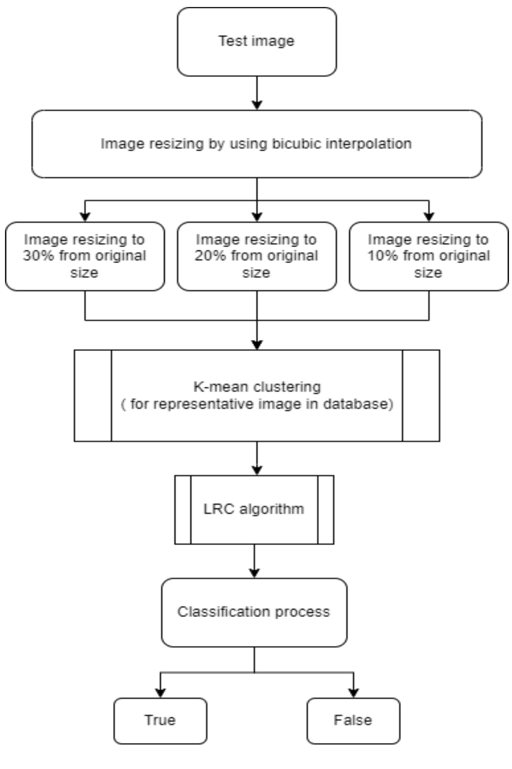



**Figure 13** Workflow of the LRC algorithm integrated with K-means clustering

The average recognition accuracy and standard deviations were computed.

***3.3 Studying LRC performances with Manhattan distance measurements (norm1)***

Studying the change in distance measurement in the LRC method to verify the effect of recognition rate when changing the distance measurement method.

1. Implementation of Manhattan Distance: The Manhattan distance metric is integrated into the LRC algorithm to measure the dissimilarity between a test image vector $y$ and the representative model $\hat{y}$ for each individual. The distance is calculated as:

$$d_i(y) = \|\hat{y}_i - y\|_1 = \sum_{k=1}^{n} |\hat{y}_{i,k} - y_k|,$$

where $y = [y_1 \quad y_2 \quad \dots \quad y_n]^T$ denotes the test image vector and the vector $\hat{y}_i = [\hat{y}_{i,1} \quad \hat{y}_{i,2} \quad \dots \quad \hat{y}_{i,n}]^T$ represents the reconstructed model for the $i$-th individual.

2. To ensure statistical reliability, twenty independent experiments were conducted. The average recognition accuracy and standard deviations were computed.

## 4. RESULTS AND DISCUSSION

***4.1 Recognition accuracy obtained from LRC with image resizing***

Results of experimentation 4.1 were found that reducing the size of the image did not decrease the effectiveness of the LRC method. However, it improved the ability to identify individuals and reduced the time to obtain the model representative for each group when solving the least-squares method. The recognition accuracy increased by 0.11%, 0.56%, 0.15%, and 1.18% for the grimace, faces95, faces96, and ORL datasets respectively.

**Table 2** Recognition accuracy of LRC with image resizing across benchmark datasets

| Database | Size of images | | | |
|---|---|---|---|---|
| | Original size<br>200 X 180 | Resize to 30%<br>60 X 54 | Resize to 20%<br>40 X 36 | Resize to 10%<br>20 X 10 |
| Grimace | 99.48% (sd=0.76) | 99.52% (sd =0.76) | 99.56% (sd=0.71) | 99.59% (sd=0.67) |
| Faces95 | 75.84% (sd=1.35) | 76.08% (sd=1.33) | 76.29% (sd=1.43) | 76.4% (sd=1.3) |
| | Size of images | | | |
| | Original size<br>196 X 196 | Resize to 30%<br>59 X 59 | Resize to 20%<br>39 X 39 | Resize to 10%<br>20 X 20 |
| Faces96 | 95.46% (sd=0.78) | 95.56% (sd=0.79) | 95.61% (sd=0.74) | 95.36% (sd=0.69) |
| | Size of images | | | |
| | Original size<br>112 X 92 | Resize to 30%<br>34 X 28 | Resize to 20%<br>22 X 18 | Resize to 10%<br>11 X 9 |
| ORL | 79.8% (sd=2.33) | 80.77% (sd=2.63) | **80.98**% (sd=2.38) | 78.3% (sd=2.31) |

**Table 3** Recognition accuracy of LRC with K-means clustering across benchmark datasets

| Dataset<br>Original size | Grimace<br>200 X 180 | Faces95<br>200 X 180 | Faces96<br>196 X 196 | ORL<br>112 X 92 |
|---|---|---|---|---|
| LRC method | 99.48% (sd=0.76) | 75.84% (sd=1.35) | 95.46% (sd=0.78) | 79.8% (sd=2.33) |
| LRC method and K-means | **99.83**% (sd=0.18) | **86.15**% (sd=0.85) | **98.68**% (sd=0.19) | **91.72**% (sd=1.36) |

**Table 4** Comparative analysis of LRC recognition accuracy using Manhattan distance across benchmark datasets

| Dataset<br>Original size | Grimace<br>200 X 180 | Faces95<br>200 X 180 | Faces96<br>196 X 196 | ORL<br>112 X 92 |
|---|---|---|---|---|
| LRC | 99.48% (sd=0.76) | 75.84% (sd=1.35) | 95.46% (sd=0.78) | 79.8% (sd=2.33) |
| LRC method and Manhattan distance | 99.81% (sd=0.25) | 80.06% (sd=1.61) | 95.94% (sd=0.75) | 83.06% (sd=2.34) |

**Table 5** Recognition accuracy of integrated LRC with image resizing, K-means clustering, and Manhattan distance across benchmark datasets

| Database | Size of images | | | |
|---|---|---|---|---|
| | Original size<br>200 X 180 | Resize to 30%<br>60 X 54 | Resize to 20%<br>40 X 36 | Resize to 10%<br>20 X 10 |
| Grimace | 99.48% (sd=0.76) | 99.93% (sd =0.15) | 99.94% (sd=0.14) | 99.85% (sd=0.19) |
| Faces95 | 75.84% (sd=1.35) | 89.76% (sd=0.91) | 89.92% (sd=0.76) | 90.28% (sd=0.67) |
| | Size of images | | | |
| | Original size<br>196 X 196 | Resize to 30%<br>59 X 59 | Resize to 20%<br>39 X 39 | Resize to 10%<br>20 X 20 |
| Faces96 | 95.46% (sd=0.78) | 98.74% (sd=0.23) | 98.84% (sd=0.2) | 98.76% (sd=0.21) |
| | Size of images | | | |
| | Original size<br>112 X 92 | Resize to 30%<br>34 X 28 | Resize to 20%<br>22 X 18 | Resize to 10%<br>11 X 9 |
| ORL | 79.8% (sd=2.33) | 93.84% (sd=0.9) | 93.41% (sd=1.11) | 93.28% (sd=0.99) |

### *4.2 Recognition accuracy obtained from LRC with K-means clustering method*

Results of experimentation 4.2 found that using k-means clustering to select representative dataset entries for each individual, rather than random selection, consistently yielded improved results across all experiments. It also significantly reduced the number of images in the dataset. Selecting appropriate group representatives still preserves the specific characteristics of almost all the images. The recognition accuracy increased by 0.35%, 10.84%, 3.22%, and 11.92% for the grimace, faces95, faces96, and ORL datasets, respectively.

### *4.3 Recognition accuracy obtained from LRC and Manhattan distance measurements (norm1)*

Results of experimentation 4.3 were found that changing the distance measurement method can slightly improve the efficiency of the LRC method compared to the two previous experiments. The recognition accuracy increased by 0.33%, 4.22%, 0.48%, and 3.14% for the grimace, faces95, faces96, and ORL datasets respectively.

### *4.4 Recognition accuracy obtained from integrated LRC with image resizing, K-means clustering, and Manhattan distance measurements*

The previous experiment results indicated that we could combine all methods to boost the maximum efficiency of each dataset in this research. Compared the experiment on the original size from Table 2 with the LRC method combined three processes: image resizing, K-means clustering, and Manhattan distance measurements. The recognition accuracy increased by 0.45%, 14.44%, 3.38%, and 14.04% for the grimace, faces95, faces96, and ORL datasets respectively.

## 5. CONCLUSION

In this research, our goal is to explore the workings of the LRC method to enhance the efficiency of facial recognition. We aim to identify the factors that contribute to improving the ability to identify individuals by thoroughly studying the working process of the LRC method at each stage and finding ways to enhance its efficiency. We found that the three main factors with the most significant impact are as follows:

1. Selecting diverse characteristics of representative images in the dataset for each individual enhances the efficiency of the LRC method and decreases the number of datasets for each individual. We use K-means clustering in this process.
2. Reducing the size of the images used in the dataset that makes the specific characteristics for each individual, as well as reducing the storage space and processing time to obtain the best representative image for each individual.
3. Changing the distance measurement method for the classification process to Manhattan distance improves the performance of distinguishing differences in each group and reduces the identification processing times.

## 6. LIMITATIONS AND FUTURE WORKS

The study's limitations include understanding the detailed working principles of each step of the LRC method to identify the main factors in correctly classifying individuals at each step. This understanding is crucial for selecting the appropriate improvement technique. The K-means clustering may not always result in the desired number of groups. It might be necessary to reinitiate the image sets until each individual is divided into five groups. Additionally, image resizing is necessary to solve the multiple times of the system of equations to obtain all the pixel values of the new image. The selected four benchmark datasets for our tests based on the hypothesis that choosing a good set of representative images, even when the dataset is similar, will enhance the recognition accuracy before expanding our approach to the complex situation of the dataset.

Future research directions could involve selecting novel grouping and image reduction techniques for the LRC method with specific situations of datasets or studying the working principles of other deep learning techniques, such as convolutional neural networks (CNN). That could involve identifying all factors that affect identity verification at each stage and finding suitable techniques for improvement.

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