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# An Enhanced Singular Value Decomposition System for Facial Feature Extraction Using Residue Number System (RNS)

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**ABSTRACT**
Facial Expression (FE) is a technique of extracting facial feature to identify people. There have been several investigations on how to speed up the SVD algorithm's computations for facial feature extraction and offer other improvements. Several technologies have been created that do facial expression recognition. However, it is a difficult task to realize the balance between computing time and accuracy of each approach in these systems In contrast, further research is still needed to speed up calculation and increase accuracy of the facial expressions technique. This study offers improved singular value decomposition using the residue number technique for the extraction of facial features. After the feature extraction procedure, the Manhattan classifier was utilized to categorize the facial features. Local database was setup which contained 90 facial images of 30 persons frontal faces with 3 images of each individual. The training set consisted of 60 images, whereas the testing set had 30 images. The experimental results indicated an average training time of 2.045 seconds for SVD and average training time of 1.045 seconds for SVD-RNS. Bar chart was used to show the graphical relationship between SVD and SVD-RNS Training time. The research revealed that RNS reduce SVD computational time.

**Key words:**Facial Expression, Residue Number System, Eigen Vector, Eigen Value, training time, Testing Time, Database.

## 1. INTRODUCTION

Biometrics in the context of computers simply means identity verification and safety measures based on measurable biological characteristics of the individual (Ross, 2019). An important step in expressing facial images, feature extraction can have a significant influence on recognition rates (Modiri, 2012). A popular and well-known example of feature extraction techniques includes, Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA) and Singular Value Decomposition (SVD).

False Acceptance Rate (FAR) and False Reject Rate (FRR) are the two main inaccuracies in biometric authentication accuracy. Olufemi (2017) defines FAR as the likelihood that the scheme will accept a false biometric credential as authentic. This might be a case of someone requesting access to a personal account but instead granting access to the account of another individual. Olufemi (2017) further defines FRR as the possibility that a valid biometric credential will be rejected by the scheme.

Ross, Nandakumar and Jain (2019) stated that when a legitimate person is denied access due to the biometric authentication scheme's inability to match the individual's live scan with every archive in the database, FRR becomes a worry.One of the issues that exist in various parts of the world is security. Criminal activity, especially in Nigeria, is caused by inadequate identity and verification processes (Madandola, Gbolagade & Yusuf-Asaju, 2019). Thus, in order to satisfy regulatory compliance requirements, a robust authentication system must be implemented.

In biometrics, facial expression (FE) is a natural way to identify someone. It uses a face's distinctive feature to identify a person. A specialized device, like a camera or film, is utilized to obtain the facial features (Daugman & Dowing, 2018). The application of FE for identification of an individual can be accomplished by a variety of methods, such as taking a photo of the face with a camera or using infrared patterns of facial heat emission. FE has several advantages, such as non-interfering, no interaction, and widespread acceptance (Bolle, 2020). The primary drawback of the FE system is the influence that the environment has on it as it is acquiring features. For instances bad illumination, resolution of camera and obstruction on image attempts for access (Olufemi, 2017).

Face detection is the process of extracting information from photos so that the algorithm might accurately identify a particular portion of the image as a face. Feature extraction is the process of extracting pertinent facial features from the extracts. Many technologies have been developed that do facial expression recognition in order to understand, relate to, and recognize human emotions. But finding the ideal balance in these systems between the speed and accuracy of each method can be challenging (Xingang, Shen & Lu, 2018).

Eigenface and Fisherface are two well-known and often used examples of facial feature extraction algorithms. Eigenface uses Singular Value Decomposition (SVD) to reduce the dimensionality of the input. Using the SVD method, images are converted into a low dimension space. Subsequently a linear matrix transformation is applied to find the data variance in the projection subspace (Tahir, Khan & Salem, 2015).

## 2. LITERATURE REVIEW

Rong, Jian, Liling, Heng, Honngran and Ming (2024) investigated singular value decomposition in conjunction with joint multi-subspace feature learning for reliable single-sample face recognition. K-NN classifiers (k-NN) in each subspace are used to identify face. Extensive experimental verification of the approach was conducted using various databases, including CUHK, Extended Yale B, FRGCv2, and AR. The results display high recognition accuracy of 98% on FRGCv2 database, 96% on Yale database and 94% on AR database. The experimental outcomes showed that the approach consistently achieves competitive performance when compared to other methods.

Seo and Byung (2021) suggested a reliable approach for detecting facial emotions that relies on the Multi-Rate Feature Fusion Scheme and Singular Value Decomposition.The singular value decomposition experiment was conducted on the JAFEE database with accuracy of 96.25% and 2.194 seconds for training features. These two algorithms were combined together to provide a low time and high accuracy rate.

Muhammed (2020) Facial Expression Recognition System Employing Manhattan Classifier and Singular Value Decomposition Techniques. The KDEF and JAFFE databases, which are used to calculate system performance, have undergone extensive testing. The results of the experiment shown that the proposed system can work in a wide range of conditions, including face details, different lighting conditions, and facial expressions. The results showed that the system has a long execution time of up to 6.3471 seconds and a high recognition rate with accuracy of up to 95.09% in the JAFFE database and 94% in the KDEF database. In order to reduce the computation time of SDV, future research may employ a method similar to Support Vector Machines (SVM) or another method.

Maafiri and Khalid (2018) proposed novel combination of Relevance Weighted Linear Discriminant Analysis (LDA) and Singular Value Decomposition (SVD) for face recognition The paper describes a strategy whose performance is improved by using wavelets for feature extraction. The singular values were replaced for the left and right singular vectors of the SVD in order to achieve a better performance. The results of the experiment show that the LDA method produces better results than the SVD. LDA training time and recognition rate is 1.999sec and 92% on ORL database while SVD training time and recognition accuracy is 2.421sec and 90% on GTFD database. Hence more improvement is needed in term of time and recognition accuracy.

## 3. METHODOLOGY

### 3.1 Formulation of Architectural Design Framework for Enhance SVD

SVD computational time rises through eigen value and eigen vector. In order to develop enhanced singular value decomposition. Figure 1 showed the research framework. The research frame work consists of four main stages. The first stage is image acquisition. The second stage is image normalization. The third stage, residue number system was embedded with singular value decomposition for quick feature extraction. Finally, In order to offer the closest categorization of the input picture, the Manhattan classifier was used to categorize the extract features:

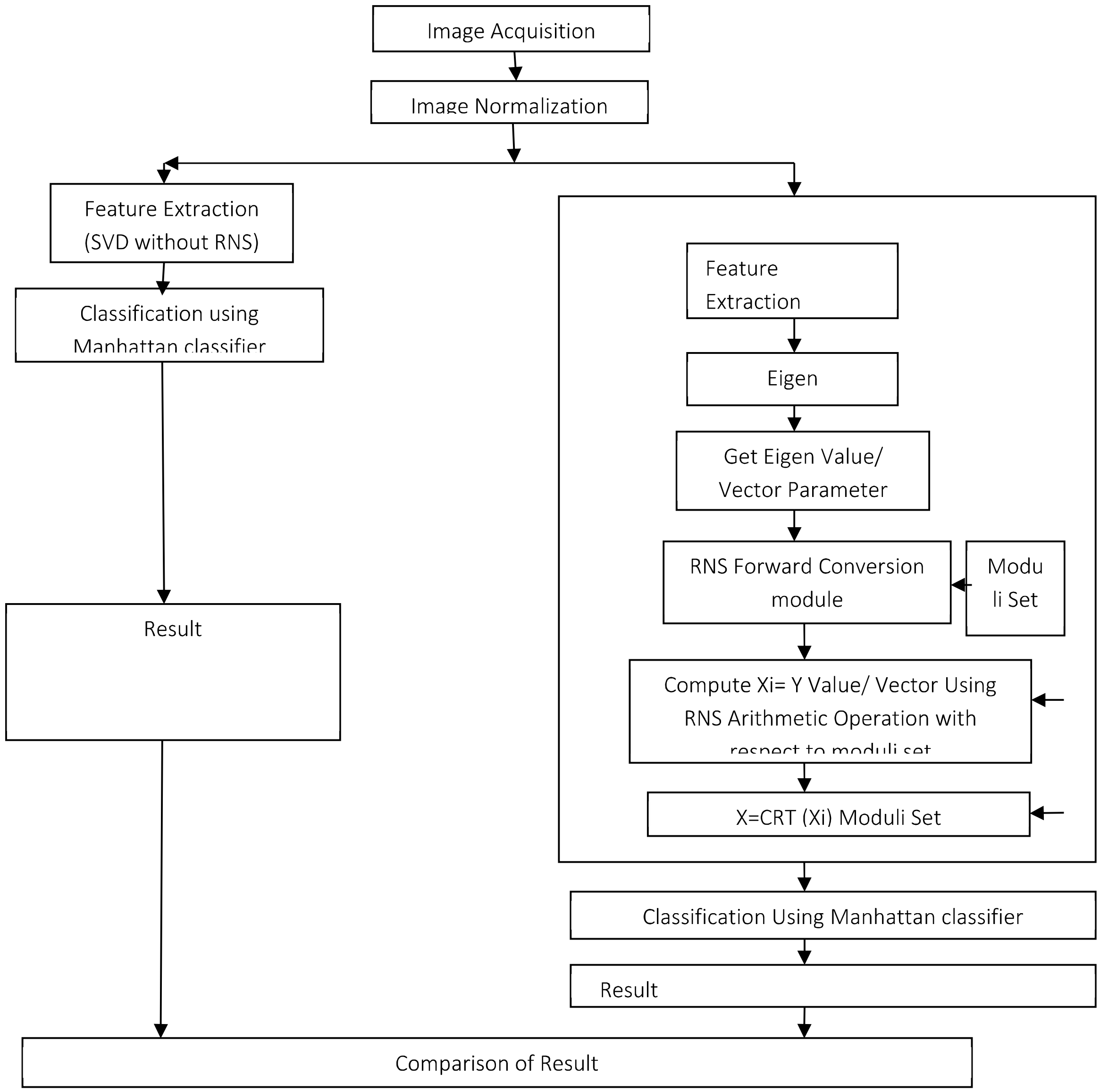


**Figure 1: Research Framework**

### 3.2 Image Acquisition

A30s Galaxy camera with 5mm lens length and 1/25 second exposure time was used to take pictures of various faces. The ninety photos were all originally taken with different sizes, but they were all later cropped to 70 × 70 pixels and stored in local databases.  Some selected image captured as shown in Figure 2.

**Figure 2: Samples of Captured Raw Images**

### 3.3 Image Normalization

Furthermore, the second phase in the suggested framework is normalization.Histogram equalization was used on the photos to adjust the intensity, remove noise, and enhance the contrast of the facial image.. Normalization is the initial step in the process of using dimensionality reduction methods for feature extraction in local databases.Some selected normalized image as shown in Figure 3:

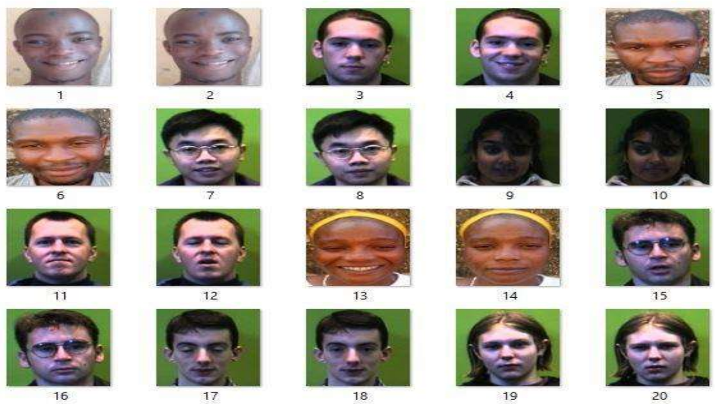


**Figure 3 Selected normalized images from Local Database**

### 3.4 Feature Extraction

Singular Value Decomposition (SVD) was employed as a technique for feature extraction. Later, the eigenvector estimate of each algorithm independently was accelerated by using the Residue Number System. in order to calculate the Eigen value and Eigen vector Each image in the training set is viewed as an n-dimensional vector$Xi, i = 1,2 \dots \dots . . N$ where $N$ the number of training pictures and $n$ is the number of pixels in an pictures. SVD finds a transformation $W_{SDV}$ such that is the number of pixels in an image. SVD finds a transformation $W_{SDV}$ such that

$$SVD\ (X) = (x - \mu_X)\mathrm{V} \tag{1}$$

Resulted to Vector Subspace;

$$\mathrm{Z} = SVD\ (x)(x - \mu_X)V; \text{ Then} \tag{2}$$

2. calculate covariance matrix X

$$\textstyle\sum_z = (x - \mu_X)^{\ T}(x - \mu_X) \tag{3}$$

$$\textstyle\sum_z = V(x - \mu_X)^{\ T}(x - \mu_X)V \tag{4}$$

$$\textstyle\sum_z = V^{\ T} \sum_x V$$

3. find [orthonormal] eigenvectors of Σ

$$v^{T} \sum_{X} v = v^{T} v\Lambda \quad (5)$$

$\sum_{z} = \Lambda$

The projected matrix Z is uncorrelated and its variables have no longer any linear dependency [because $\Lambda$ is a diagonal matrix].

$$.(f(x).\varnothing = (\mathrm{fx.} + \sum_{n=1}^{N} (a_n \, \mathrm{f(x)}) = \Sigma \mathrm{an\ k\ (x, xn)} \quad (6)$$

For the purpose of illustration, considering n = 2 for the moduli set {2n+1, 2n, 2n-1} the moduli set is {5,4, 3}. Assume class1 and class2 represent image 1 and image 2 then the residue are calculated as follow:

$$X = (x_1, x_2, x_3) \ \mathrm{RNS}(m_1/m_2/m_3) \quad (7)$$

$$X = (0,3,0)\ (5/4/3)$$

$$X = \left| \sum_{i=1}^{3} M_i \left| \mathrm{RNS} M_i^{-1} x_i \right| m_i \right|_{M}, \quad (8)$$

M = 5 x 4 x3 = 60 (Dynamic range)

$$M_1 = {}^{M}/_{m_1} = {}^{60}/_{5} = 12$$

$M_i^{-1} = |z.Mi|m_i \equiv 1$ (X = CRT (Xi) moduli ) (9)

$M_1^{-1} = |3\ x12|_5 \equiv 1,\ M_1^{-1} = 3$

$M_2^{-1} = |3\ x15|_4 \equiv 1,\ M_2^{-1} = 3$

$M_3^{-1} = |2\ x20|_3 \equiv 1,\ M_3^{-1} = 2$

$$X = \left| \sum_{i=1}^{3} Mi \left| M_i^{-1} xi \right| mi \right|.\mathrm{mod}\ (f(x).\varnothing = (\mathrm{fx.} + \sum_{n=1}^{N} \left(a_n \, \mathrm{f(x)}\right) = \Sigma \mathrm{an\ k\ (x, xn)} \quad (10)$$

**3.5 Image Classification**

Once the most relevant attributes had been obtained, one of the most well-known and simple photo categorization methods, the Manhattan Classifier, was applied. To measure the accuracy of the classification, this method uses the point distance rule to determine how similar the weights of the training data set and the input face picture are.The approach below was the mathematical approach to find Manhattan distances. Assuming we have 3D images and 1D images for both training and testing, the calculation of Manhattan distance, can be given by

$$\mathrm{distance} = f(x) = a_0 + \sum_{1=1}^{n} \mathrm{Xi} - \mathrm{Yi} \quad (11)$$

Considering our example

As we know

$$Ac = 3D \quad (12)$$

$$BC = 1D \quad (13)$$

$$\text{Manhattan Distance} = |3 + 1| = 4$$

$|AB = 4|$

## 4. ANALYSIS OF IMAGE USED IN SET-UP DATABASE

In this work one ninety images were captured for setting up a new research database. The images go through histogram normalisation in order to get better output. The total sample of images is 90 and 60 employed for training and 30 employed for testing while three were chosen as number of sample per person. Which as shown in Table 1 below.

The suggested system was put into practice by creating a computer program called a software application using MATLAB, which lets us build a code to process the input, which are photographs, and also construct a graphical user interface so that we can deal with the system. This work contains a number of modules: image acquisition, feature extraction, and recognition. In this work MATLAB R2015a was used to implement effect of SVD and SVD-RNS as shown in Figure 4 on Intel inside Pentium with 1.60GHz Processor speed.


| Variable | Frequency |
|---|---|
| Number of Persons | 30 |
| Number of Sample per Persons | 3 |
| Number of Total Sample | 90 |
| Number of Training Set | 60 |
| Number of Testing Sample | 30 |

**Figure 4: Developed system for SVD and SVD-RNS**

## 5. RESULTS AND DISCUSSION

**Table 2: Traning time (TT) of SVD with RNS on Set-up Database**

The results summarized in Table 2 indicate that the average testing time of SVD with RNS is approximately 1.045sec.

| IMAGE | SVD WITH RNS TRANING TIME (Sec) | IMAGE | SVD WITH RNS TRANING TIME (Sec) |
|---|---|---|---|
| 1 | 1.0309 | 16 | 1.5333 |
| 2 | 0.3478 | 17 | 1.4881 |
| 3 | 1.3276 | 18 | 1.9204 |
| 4 | 1.9021 | 19 | 1.3088 |
| 5 | 1.3398 | 20 | 1.7432 |
| 6 | 1.4501 | 21 | 1.5360 |
| 7 | 0.1365 | 22 | 1.5242 |
| 8 | 1.1342 | 23 | 1.1538 |
| 9 | 1.3828 | 24 | 1.4931 |
| 10 | 1.6706 | 25 | 1.2349 |
| 11 | 1.7894 | 26 | 1.9439 |
| 12 | 2.3491 | 27 | 1.6680 |
| 13 | 1.5264 | 28 | 1.9701 |
| 14 | 1.1348 | 29 | 2.4853 |
| 15 | 1.5361 | 30 | 1.5665 |

**Table 3: SVD without RNS Training Time on Set-up Database**

Table 3 shows the processing time for each of these steps for SVD on the face database. According to the findings listed in Table 3, the typical training time for SVD without RNS is around 2.045 seconds. The results of the developed system training time of SVD with RNS were compared with ordinary training time of SVD in figure 5 below.

| IMAGE | SVD TRANING TIME (Sec) | IMAGE | SVD TRANING TIME (Sec) |
|---|---|---|---|
| 1 | 11.1064 | 16 | 3.9471 |
| 2 | 4.7606 | 17 | 2.8743 |
| 3 | 3.5072 | 18 | 2.7801 |
| 4 | 4.6581 | 19 | 5.8356 |
| 5 | 3.8357 | 20 | 6.351 |
| 6 | 5.4461 | 21 | 2.4527 |
| 7 | 5.0753 | 22 | 10.634 |
| 8 | 10.6286 | 23 | 5.7821 |
| 9 | 7.4692 | 24 | 3.8460 |
| 10 | 6.2894 | 25 | 2.9160 |
| 11 | 3.8689 | 26 | 4.0721 |
| 12 | 7.2561 | 27 | 8.6651 |
| 13 | 5.0722 | 28 | 3.4253 |
| 14 | 8.7644 | 29 | 4.3821 |
| 15 | 4.8721 | 30 | 9.6020 |

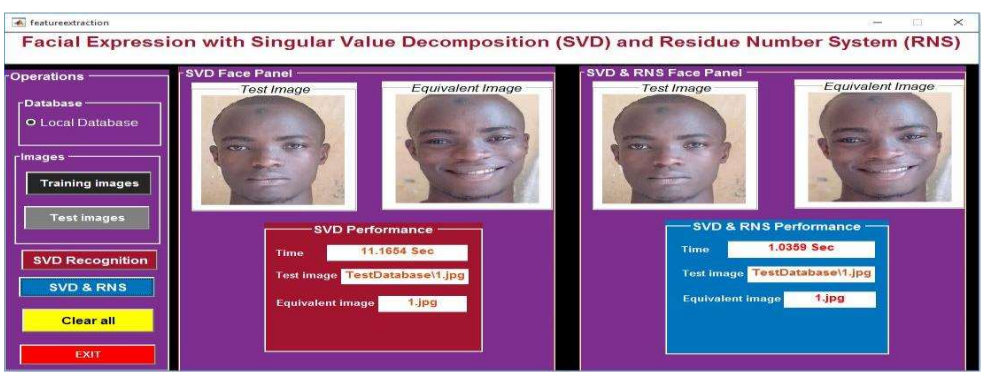

**Figure 5: Both SVD without RNS and SVD with RNS Training Time of Image 1 of Local Database Setup**

Figure 5 displays a training time of 1.0359sec for SVD with RNS on image one while SVD without RNS display 11.165sec on image one. The developed system (SVD with RNS) outperformed the existing system, as seen by the figure 5 above. Similarly, Figure 6 and 7 graphically displays the testing time gain during the feature extraction process for SVD with RNS and SVD without RNS.

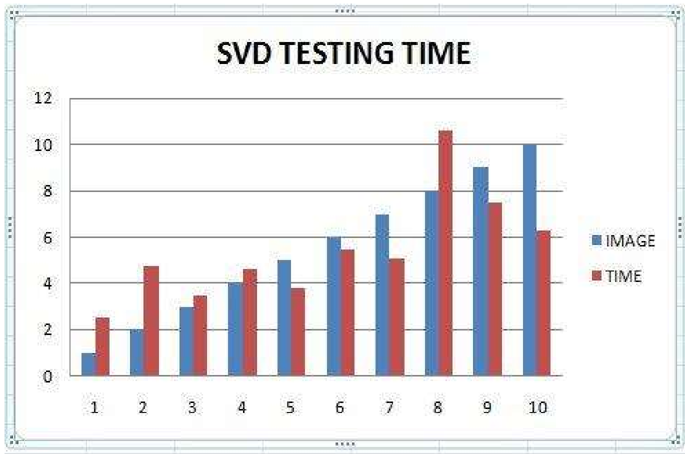


**Figure 6: TestingTime for SVD without RNS on Local Database**

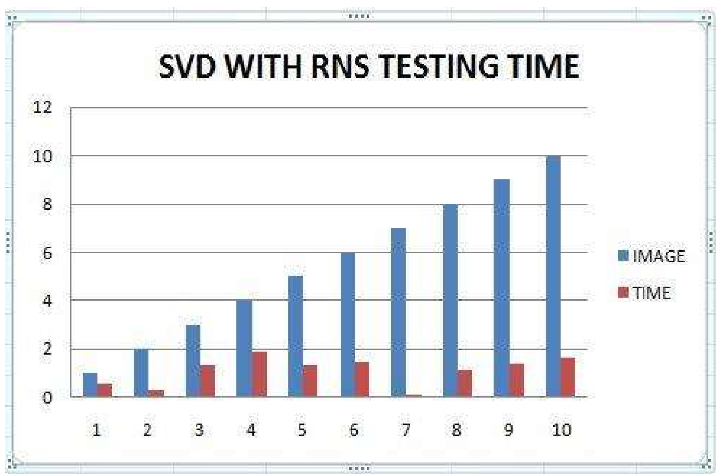


**Figure 7: TestingTime for SVD with RNS on Local Database**

However, Figure 6 illustrates the benefit of using the RNS with SVD technique, demonstrating how it offers quick computing speed with enough training and testing times. This observation indicates

the method used has a good accurate speed. Meanwhile, this figure 7 also help us to further prove that the added residue number system is useful and the
Proposed methods are efficient.

**Table 4: Performance Comparisons of SVD without RNS Recognition Index and SVD with RNS Recognition index**

| Method | Database | Recognition Index |
|---|---|---|
| SVD without RNS | Local Setup Database | 70%. |
| SVD with RNS | Local Setup Database | 90%. |

The findings revealed that the suggested system has a high recognition rate with accuracy up to 90% in the setup database, compared to SVD without RNS, which has a recognition rate of only 70% in the setup database.

## 6. CONCLUSION

In this work, chain of input images from local setup database were trained and tested to determine the effect of RNS on computational time of SVD for facial feature extraction. Training and testing time were used as performance metrics. The investigation shown that SVD uses more Training Time when RNS was not employed than when employed. SVD average testing time is 2.9770 seconds while the average training time for SVD-RNS is 1.1429 seconds. The experimental result revealed that SVD has 70.0% recognition accuracy and SVD-RNS has 90% recognition accuracy on the set up Local database. The experimental results demonstrate that this scheme outperforms the existing system as far as the time taken is concerned.

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Reference citation within the body of the paper is (Name, date) format, and should be listed in alphabetical order

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