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Enhanced Local Binary Pattern Algorithm for Facial Recognition Using Chinese Remainder Theorem

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Abstract

Current biometrics research focuses on achieving a high authentication success rate for identity management and discussing the threat of various security attacks. Local Binary Pattern (LBP), one of the methods for feature extraction, and Chicken Swarm Optimization (CSO), one of the strategies for feature selection, were used for user identification and authentication. LBP requires high computational time to extract features from the facial images. The Chinese Remainder Theorem (CRT) was used to reduce its computational time by formulating an Enhanced Local Binary Pattern (ELBP). Michael Olugbenga Banji Abolarinwa (MOBA) database was created specifically for this study. 600 frontal facial images of 200 people were collected, each with three images. 360 images were used for training while 240 images were used for testing. MATLAB (R2016a) was used to run the simulation. The time it took to classify the facial images when LBP and CSO were combined and when ELBP and CSO were combined were enumerated. The LBP-CSO achieved a false-positive rate (FPR) of 11.67%, a sensitivity (SEN) of 92.78%, a specificity (SPEC) of 88.33%, a precision (PREC) of 95.98%, and an

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accuracy of 91.67% in 119.10 seconds at 0.80 thresholds for face recognition. ELBP-CSO obtained an FPR of 5.00%, SEN of 95.00%, SPEC of 95.00%, PREC of 98.28%, and accuracy of 95.00% in 79.16 seconds. The results showed that LBP-CSO took an average of 119.10 seconds and ELBP-CSO took an average of 79.16 seconds. In conclusion, the performance of CSO-ELBP justifies the usage of LBP enhancement with CRT.

Keywords: Biometrics, Local Binary Pattern, Chinese Remainder Theorem, Chicken Swarm Optimization, Computational Time.

INTRODUCTION

Security is an important aspect of the present industry, accessing information requires the authentication of the person (Keerthi et al., 2016). Face recognition is an important biometric identification technology that detects human face images by comparing the face image with the face images in a database to find a matching face process to achieve the purpose of identification and assessment (Yanmei et al., 2018). For the system's efficiency, the time necessary to detect and validate such objects must be minimized. As a result, the computational time of dimensionality methods should be lowered (Madandola & Gbolagade, 2019).

In this study, the Local Binary Pattern (LBP) and Chicken Swarm Optimization (CSO) algorithms were used for feature extraction and feature selection, respectively. The LBP was enhanced with the Chinese Remainder Theorem, which is one of the Residue Number System (RNS) approaches, to reduce computation time. The main interest of the first computer based on residue arithmetic principleswas focused on the design and implementation of on-board processors (OBP) for space, avionic and military applications characterized byhigh reliability and very high reliability(Nannarelli & Re., 2018). Residue Number Systems (RNS) allow the spreading of large dynamic range computations over trivial modular rings, which allows the speed-up of computations(Mikhail, 2021).

Currently, available conversion algorithms are based on the Chinese Remainder Theorem or the Mixed Radix conversion techniques (Salifu, 2021). Chinese Remainder Theorem (CRT) is a proposition of number theory that expresses that if one knows the remainders of the Euclidean division of an integer n by several integers, then one can establish distinctively the remainder of the division of n by the product of these integers, under the condition that the divisors are pairwise coprime(Madandola&Gbolagade, 2019).According to (Salifu, 2021). CRT can be expressed as: Given the moduli set $\{n_1, n_2, n_3, \cdots, n_m\}$ with the dynamic range $N = \prod_{i=1}^{m} n_i$ and the RNSrepresentation of an integer X be represented as $\{x_1, x_2, x_3, \cdots, x_n\}$. Then the Chinese Remainder Theorem is as follows: $|X|_N = \left|\sum_{l=1}^{M} x_i \left|N_i^{-1}\right|_{n_i} N_i\right|_N$ (1)where $N = \prod_{i=1}^{n} n_i$, N is the product of the n_{mi} are the multiplicative inverse of Ni with respect to m_i $N_i = \frac{N}{n_i}$

Many researchers have proposed algorithms, and techniques involving facial recognition to address the challenges of identity management for security purposes using digital images and moving video images. Isnanto et al., (2021) suggested Multi-Object Face Recognition Using Local Binary Pattern and Haars cascade classifier on low-resolution images, histogram equalization, and median filter. For testing, the results obtained by the LBPH algorithm were equivalent to local and real-time stream video data. When the results were compared to previous work, the results were superior.

Qian et al., (2019) proposed facial image feature extraction using a local binary pattern (LBP) and the 2-D Gabor wavelet transform. The results of the inquiry suggest that the large-scale 2-D Gabor wavelet representation can achieve good classification accuracy. LBP was used to generate a 2-D Garbor wavelet representation of a face picture, which was collected with image block statistics, histogram statistics, PCA dimensionality reduction, and nearest neighbors' classification, and the approach improved classification presentation in dissimilar scales and instructions.

Liangliang et al., (2021) presented An Enhanced Multiscale Block LBP (MB-LBP) Three-Dimensional (3D) Face Recognition Method to improve the accuracy and speed of 3D face identification. The MB-LBP algorithm was used to extract the features of the 3D face depth image, and the average information entropy approach was utilized to extract the image's significant feature information. The extracted effective information was recognized using a Support Vector Machine method. According to the findings, the developed algorithm improved presentation in terms of accuracy and speed.

AL-Shatnawi et al., (2021) explored the Face Recognition Model based on the Laplacian Pyramid Fusion Technique. Face discovery, feature extraction, feature fusion, and face classification are the four essential steps involved in the methodology. Face detection and extraction of both local and global features are accomplished using Principal Component Analysis (PCA) and Local Binary Pattern (LBP). After that, the retrieved features are fused using the LP fusion technique and classified using the Artificial Neural Network (ANN) classifier. The FFLFRM model was validated using 10,000 face images from the Olivetti Research Laboratory (ORL) database. The FFLFRM outperformed three state-of-the-art face recognition models based on local, global, and Frequency Partition (FP) fusion approaches in terms of illumination, position, expression, occlusion, and low picture resolution problems. The results of the introduced FFLFRM identification were promising. The recognition accuracy was 98.2 percent.

Malathy et al., (2021) created a COVID-19 Diagnosis using Optimized PCA-based Local Binary Pattern Features to examine the chest X-ray for detecting the presence of COVID-19 using a Machine Learning algorithm. COVID-19 discriminant features were extracted using the LBP approach. The collected characteristics were fed into a number of classifiers, including Random Forest (RF), Linear Discriminant Analysis (LDA), k-Nearest Neighbor (kNN), Classification and Regression Trees (CART), Support Vector Machine (SVM), Linear Regression (LR), and Multi-layer Perceptron Neural Network (MLP). The introduced archetypal model produced an accuracy of 77.7%.

Chun-myoung et al., (2021) proposed Deep-learning-based face recognition for worker access control management in hazardous regions as a major function in access control systems used for identifying workers in limited and dangerous industries. The Scholars compared and scrutinized the presentations of traditional Deep-learning-based face Detection algorithms (DliD, SSD-Mobilenet V2) and FR algorithms (VGG, ResNet), with the goal of developing a FR algorithm with high forecast accuracy in a variety of scenarios (e.g., with subjects wearing a helmet, protective glasses, or both).The SSD-ResNet model (AP: 0.99) with the highest analyze field applicability (AP), a criterion for evaluating the presentation of face recognition algorithms, was chosen. The introduced algorithm's AP was found to be in the 0.683-0.863 range. In comparison to the recognition accuracy of human eyes (94.90%), the proposed algorithm was found to be insufficient for use in real-world industrial locations.

METHODOLOGY

In this study, the standard Local Binary Pattern (LBP) and the Chinese Remainder Theorem (CRT), an Enhanced Local Binary Pattern (ELBP) was created and used as a feature extraction approach. Also, a feature selection approach, Chicken Swarm Optimization (CSO) was used, and finally, a support vector machine (SVM) was used for classification. Following that, the performance evaluation of the classification across facial images was enumerated.Figure 1depicts the process flow ofthe Face Recognition Processing System while Figure2 depicts the schema of the Face Recognition System

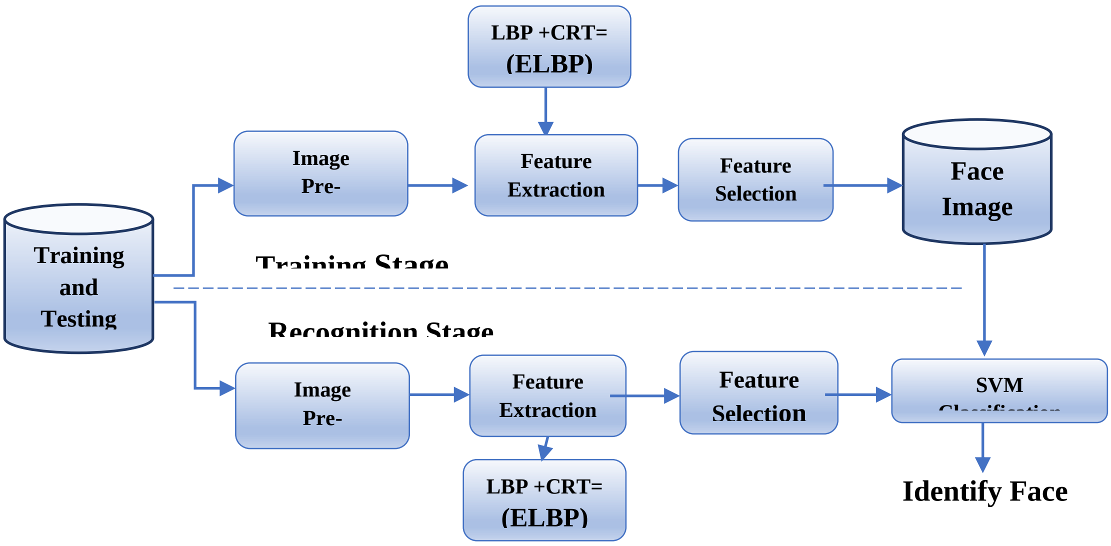


Figure.1: Process Flow of Face Recognition Processing System

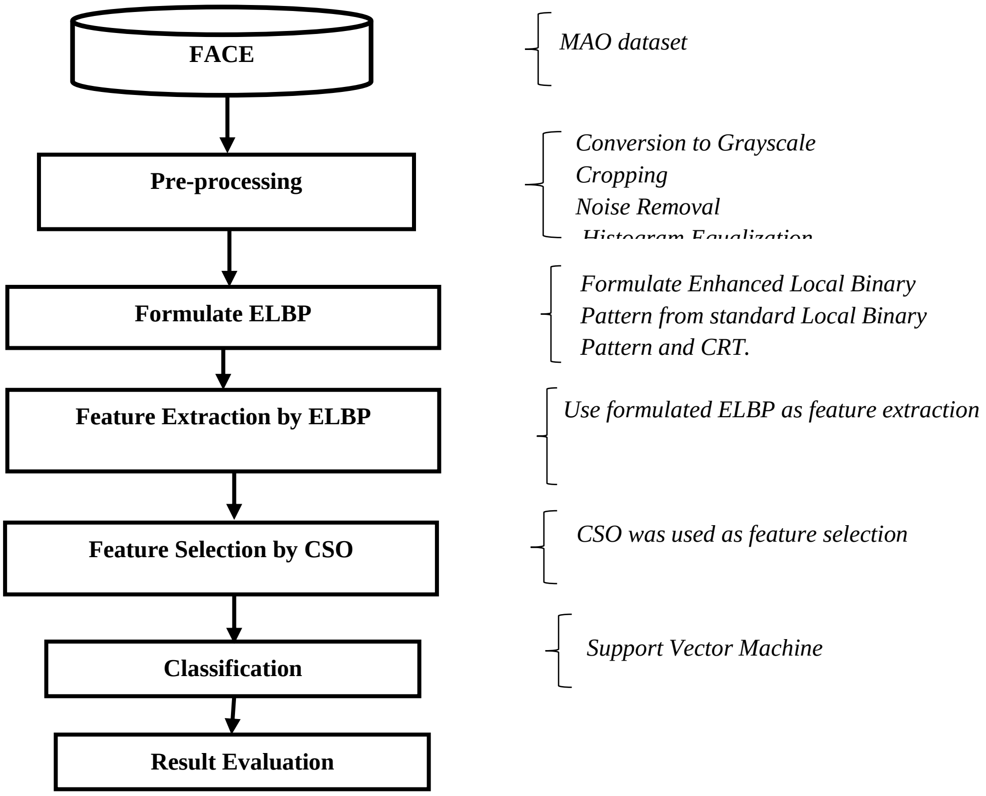


Figure. 2: The Schema of the Face Recognition System

Feature Extraction using existing LBP

Image Feature extraction was done using Existing Local binary patterns (LBP) and Enhanced Local binary patterns (ELBP).The existing LBP operator encodes the pixel-wise information in texture images, the existing LBP approach in a local binary pattern describing the relationship between a pixel and its neighbors. The existing LBP operator was defined by comparing the grey value of the central pixels with its 8 local neighborhood pixels. All neighbors that have a value higher or equal to the value of central pixels were given a value of 1, while all those lower values were given a value of 0.The binary values associated with the neighbors were then acquired sequentially, clockwise to form a binary number which was used to characterize the local texture.

Algorithm 1: Existing LBP Algorithm (Pseudocode)

Step 1: *Set g_c which corresponds to the gray value of the center pixel*

Step 2: *Set g_n as the gray values of the "n" neighbour pixels*

Step 3: *Set* $S = \begin{Bmatrix} 1, & if\ g_c \geq 0 \\ 0, & if\ g_n < 0 \end{Bmatrix}$

Step 4: *Compute LBP features as described thus;*

$$LBP_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} S(g_n - g_c) * 2^p \qquad (Eq.\ 3)$$

Where x_c and y_c represent the horizontal and vertical component of the image; Sg_n and Sg_c are neighborhood patterns, P representthe bit binary number resulting in 2^pdistinct values for the LBP code

Step 5: *Output selected LBP features*

Formulation of Enhanced Local Binary Pattern

In the enhanced LBP.ELBP operators were defined by comparing the gray value of unique center pixel solution up to a certain modulus with its unique neighborhood pixel solution up to another certain modulus.The binary values associated with the neighbors were acquired in parallel (simultaneously) by application of CRT.This would reduce the computational complexity and thereby resulted in decreasing the processing time.

Algorithm 2: CRT-LBP Algorithm (Pseudocode)

Step 1: *Set g_c which corresponds to the gray value of the centerpixel*

Step 2: *Set g_n as the gray values of the "n" which is one of theneighbour pixels*

Step 3: *Let g_c and g_n be coprime. The system of equations hasa unique solution of x_c modulo $g_c g_n$ where M is 1 or 0 which is one of the horizontal and vertical components of the image.*

$$x_c = M \ (mod\ g_c)$$

$$x_n = M \ (mod\ g_n)$$

The reverse direction is trivial: given $x_c \epsilon\ R_{g_c g_n}$ the study reduces x_c modulo $g_c$and $x_n$modulo g_n to obtain Eq. 4 and Eq. 5

Step 4: *Let $p_1 = g_c^{-1}(mod\ g_n)$ equation (4) and $q_1 = g_n^{-1}(mod\ g_c)\ Eq.(5)$.thesemust exist since g_c and g_n are coprime. Then this study claims that if y is an **integer**r such that*

$y_c = Mg_n q_1 + Mg_c p_1\ (mod\ g_c g_n)$ then y_c satisfied Eqs. 4 and 5

For modulo g_c, $y_c = Mg_nq_1 = M \ (mod\ g_c)$ *since* $g_nq_1 = 1\ (mod\ g_c)$

Similarly, $y_c = M\ (mod\ g_n)$. *Thus,* y_c *is a solution for* x_c

Step 5: *Set* $M = \begin{Bmatrix} 1, & if\ x_c \geq 0 \\ 0, & if\ y_c < 0 \end{Bmatrix}$

$LBP_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} M(y_c - x_c) * 2^p$ *Eq.6*

Where x_c *and* y_c *represent the horizontal and vertical componentof the image;*My_c *and* Mx_c *are neighborhood patterns, P represent the bit binary numberresulting in* 2^p*distinct values for the LBP code. P*

Step 7: *Output selected LBP features*

RESULT AND DISCUSSION

The results of the developed technique are evaluated based on the combination of ELBP-CSO and LBP-CSO. The result obtainable in Table 1 shows the performance of the LBP based on CSO. 240 datasets were used for testing. The result showcases the performance of the techniques evaluated at a threshold value of 0.25, 0.40, 0.60, and 0.80. It was discovered that the performance of the technique was identical for all threshold value ranges between 0-0.25, 0.26-0.40, 0.41-0.60, and 0.61-0.99, respectively. Hence, the optimum performance for each technique was achieved at a threshold value of 0.80. The results from Table 1 reveal that at a Threshold value of 0.80 for the face biometric; the CSO-LBP technique achieved an FPR of 11.67%, SEN of 92.78%, SPEC of 88.33%, PREC of 95.98%, and accuracy of 91.67% at 119.10 seconds.

Table1: CSO-LBP Result

Threshold	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time(sec)
0.25	23.33	94.44	76.67	92.39	90.00	119.54
0.40	20.00	93.89	80.00	93.37	90.42	116.14
0.60	16.67	93.33	83.33	94.38	90.83	119.47
0.80	11.67	92.78	88.33	95.98	91.67	119.10

The result obtainable in Table 2 depicts the performance of the CSO-ELBP based on face biometric traits. The results show that at a threshold value of 0.80 and above, the CSO-ELBP technique achieved an FPR of 5.00%, SENof 95.00%, SPEC of 95.00%, PREC of 98.28%, and accuracy of 95.00% in 79.16 seconds.

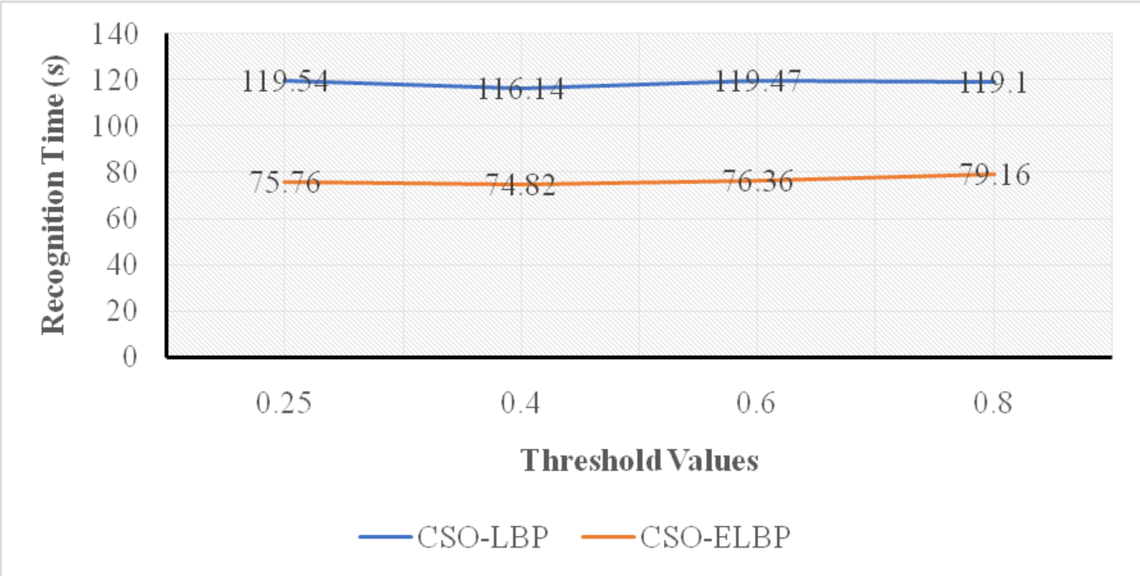
Table 2: CSO-ELBP Result

Threshold	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time(sec)
0.25	16.67	96.67	83.33	94.57	93.33	75.76
0.40	13.33	96.11	86.67	95.58	93.75	74.82
0.60	10.00	95.56	90.00	96.63	94.17	76.36
.80	5.00	95.00	95.00	98.28	95.00	79.16

At a threshold value of 0.8, Table 3.1 shows that the CSO-LBP technique achieved an FPR of 11.67%, SEN of 92.78%, SPEC of 88.33%, PREC of 95.98%, and accuracy of 91.67% at 119.10

seconds while from table 3.2 the CSO-ELBP technique got an FPR of 5.00%, SEN of 95.00%, SPEC of 95.00%, PREC of 98.28%, and accuracy of 95.00% at 79.16 seconds. The results shows that the CSO-ELBP technique better than the CSO-LBP technique in terms of FPR, SEN, SPEC, PREC, recognition accuracy, and time. This implies that the CSO-ELBP technique is more accurate and less computationally expensive with an average recognition time of 79.16 seconds.

This established that the time complexity associated with CSO-ELBP was less than that of CSO-LBP. Chinese Remainder Theorem (CRT) strategy in the standard CSO-LBP improve the sequential operation of LBP with parallelism (simultaneous) nonmodular thresholding of central pixel with neighboring pixels which allows the reduction in the recognition time to be achieved by the CSO-ELBP technique.



CONCLUSION

This study created a face recognition system by utilizing an Enhanced Local Binary Pattern algorithm for feature extraction and the Chicken Swarm Optimization technique for feature selection. A thorough investigation was conducted, and several threshold values were examined. The Chinese Remainder Theorem was applied to the existing Local Binary Pattern to reduce computational complexity and consequently decrease the processing time.

In all the evaluations conducted, the CSO-ELBP technique achieved a reduction of recognition time due to effective implementations of non-modular operations. The developed CSO-ELBP technique achieved improved recognition accuracy, FPR, SEN, SPEC, PREC, and recognition time. Hence, this is a justification that the developed technique reduces computational complexity and improved recognition performance due to the parallelism and simultaneous operation of the technique.

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CONFLICTS OF INTEREST

No conflict of interest was declared by the authors

REFERENCES

AL-Shatnawi A, Al-Saqqa F, El-Bashi M, & Nusir M. (2021).Face Recognition Model based on the Laplacian Pyramid Fusion Technique, *Int. J. Advance Soft Compu. Appl*, Vol.13, No.1

Chun-myoung N, Su-bong L & Jae-chul L.(2021). Deep-learning-based face recognition for worker access control management in hazardous areas, *Journal of Advanced Marine Engineering and Technology*, Vol. 45, No. 3, pp. 122~139.

Isnanto R.R, Adian F.R, Dania E, & Guntur D. C. (2021). Multi-Object Face Recognition Using Local Binary Pattern Histogram and Haar Cascade Classifier on Low-Resolution Images, *International Journal of Engineering and Technology Innovation*, vol. 11, no. 1,, pp. 45-58

Keerthi G, China R, Sowmya G, Anand T, &Meghana K, (2016). A Novel Approach to Identify the Facial parts using Local Binary Pattern and Combined LVQ Classifiers; *Advances in Computational Sciences and Technology* ISSN 0973-6107 Volume 9, Number 1 pp. 25-35

Liangliang S, Xia W, &Yongliang S; (2021). Research on an Improved MB-LBP 3D Face Recognition Method, *Journal of Software*, Volume 16, Number 6, pp306-314.

Madandola T.N & Gbolagade K. A. (2019). Reducing Computational Time of Principal Component Analysis with Chinese Remainder Theorem. *International Journal of Discrete Mathematics.* Vol. 4, No. 1, pp. 1-7.

Malathy J, Anbarasi LJ, Prassanna J, Jackson CJ, Manikandan R, Alzubi JA, & Dhanya D. (2021). Diagnosis of COVID-19 using Optimized PCA-based Local Binary Pattern Features, *International Journal of Current Research and Review Research Article*.

Mikhail S,(2021). Computationally Efficient Approach to Implementation of the Chinese Remainder Theorem Algorithm in Minimally Redundant Residue Number System. *Theory of Computing Systems*(2021) 65:1117–1140.

Nannarelli, A. & Re M. (2008). Residue Number Systems: a Survey. *Technical University of Denmark, DTU Informatics, Building 321. D T U Compute*. Technical Report No. 2008-04 pp3

Qian Z, Haigang I, Ming L & Lei D (2019); Feature extraction of face image based on LBP and 2-D Gabor wavelet transform, *Mathematical Biosciences and Engineering*Volume 17, Issue 2, pp.1578-1592.

Salifu, A.M. (2021) New Reverse Conversion for Four- Moduli Set and Five-Moduli Set. *Journal of Computer and Communications*, 9, 57-66.

Yassin K, Maher J, Ayman A.& Mohamed A. (2020): Face Recognition Systems: A Survey; *Sensors* 2020, 20, pp 342.