Communications on Applied Electronics (CAE) – ISSN : 2394-4714
Foundation of Computer Science FCS, New York, USA
Volume 7 – No. 37, January 2022 – www.caeaccess.org

ANN-based Age Detection System in Nigeria

Alowolodu Olufunso Dayo
Federal University of Technology, Akure, Nigeria
Cybersecurity Department

ABSTRACT
The Nigerian electoral system has witnessed a barrage of underage voting from time immemorial and the apex electoral body of the country has almost been incapacitated in providing a lasting solution to this menace of underage voter registration and voting. This act is commonly attributed to the northern part of the country where electoral officials were always under threat by politicians to allow children that are not up to eighteen (18) years of age to be registered as eligible voters. This has necessitated the proposal of an age detection system that will detect the age of an individual that wants to be registered for voting using iris biometric technology that employs Artificial Neural networks (ANN).

General Terms
Biometric authentication system Using Iris

Keywords
Biometrics, Artificial Neural Network, Iris, Underage, Voting System

1. INTRODUCTION
Underage voting has been a major issue in Nigeria's political discourse since the return of the government in 1999. This conundrum, which successive governments have not been able to resolve, has hindered the beauty of democracy in the country. Under the Constitution of the Federal Republic of Nigeria, people under the age of 18 are not allowed to vote or take part in elections. Although underage voting is common in some regions of the country, it is hardly visible in some parts of the country. Talking about underage elections in Nigeria, it would be easy to think about the northern part of Nigeria [13]. Underage voting has become a national problem and a danger to Nigeria's nascent democracy. Nevertheless, under the umbrella of the Independent National Electoral Commission (INEC), the country's electoral umpire could not do much to fix this persistent problem. The INEC Commissioner in Nigeria, Prof. Yakubu even stated that underage voting is illegal because there is a statutory age for eligibility of registration of voters. Underage voting is rampant, particularly in rural areas with minimal media attention. There, politicians use coercion and bribery to undermine INEC officials. Where this doesn't work, they resort to violence. INEC has admitted that its field workers are usually threatened by politicians who insist on registering and accrediting minors to vote [11]. The reverse is the case in counties where increment in the age range of eligible voters is being advocated to be reduced to between 16 and 17 years due to the low turnout of voters among the youth according to [7].

To combat this issue of underage voting, which is very rampant in the country today, the implementation and design of an age estimation system using iris biometric technology by employing an Artificial Neural Network (ANN) have become necessary. Biometrics is a computerized technique of identifying and confirming an individual based on a physiological or behavioral characteristic (what you are). Iris recognition can easily be considered the most accurate type of biometric technology compared to other biometric technologies, such as face, voice, and finger recognition. This was after a survey had been carried out and opinions were sampled [10]. Research had shown that Iris has a higher chance of accuracy among other classes of biometrics authentication forms because the use of iris as human identification has more benefits over other forms of human identification because it is considered to be the most inequitable of all facial biometrics available. [3]. Iris has some advantages, such as the highest proven accuracy, simplicity of the iris pattern, high information content, high-speed processing, durability, stability, versatility, ease of use, and reliability over other biometrics [9]. It cannot be borrowed, lost, or forgotten, and it is practically impossible to forge one. This has made Iris the suitable means of biometric identification in the age detection system to identify and prevent underage voting in the electoral system.

2. RELATED WORKS
In Nigeria, underage voting is rampant, particularly in rural areas with limited media attention. There, politicians use threats and bribery to undermine INEC officials, and where this doesn't work, they resort to violence. In some areas (mostly villages) INEC officials in Nigeria have been forced either to allow underage children to cast their votes or (in most cases) to be killed [6]. Underage voting has become a national problem and a danger to Nigeria's nascent democracy. Nevertheless, the electoral umpire, the Independent National Electoral Commission (INEC), has not been able to do much to fix this menace.

Nigeria registered the highest number of underage voters in 2015, especially in the Kano and Katsina States, where children under the age of 18 were allowed to cast their votes freely even in the presence of security agents [13].

The work of [1] proposed an innovative method of age group classification system based on the Correlation Fractal Dimension of the complex facial images. The system classifies them as young (less than 30 years), middle-aged (30–40 years), and aged (more than 40 years). The system could not correctly predict a person's age but could be identified as young, middle-aged, old. This approach cannot be used in a voting system where the actual age of the electorate needs to be used.

[2] worked on iris pupil thickness-based method for determining the age of a person. This study uses a Circular ROI crop algorithm for the iris segmentation and statistical techniques such as ANOVA and Turkey's pairwise comparison to find the confidence interval of Iris pupil

Communications on Applied Electronics (CAE) – ISSN : 2394-4714
Foundation of Computer Science FCS, New York, USA
Volume 7 – No. 37, January 2022 – www.caeaccess.org

thickness of different ages. A lesser range of age groups was not investigated and the factors that contribute to template aging.

[12] proposed a neural network-based iris recognition system using haralick features which include localization of iris using Hough transform algorithm, Normalization using Daughman's rubber sheet model, feature extraction using 2-D Haar wavelet. From the low-frequency data, Gray level co-occurrence matrix (GLCM) based Haralick features were computed and the probabilistic neural network (PNN) was used for matching purposes.

[4] opined that the use of a Personal Identification Number (PIN) or a password can no longer be relied upon as a means of securely identifying an individual. Iris recognition has been discovered to be a better form of biometric identification measurement among others and this has made it to be an interesting area of research focus. Iris recognition and authentication have a major code generation and verification accuracy issue.

[5] proposed an iris recognition system to enhance the e-security environment based on wavelet theory. The system is based on an empirical analysis of the iris image and is divided into several stages using local image properties. Unit measures capture the iris patterns; evaluate the position of the iris boundary; convert the iris boundary to the extended polar coordinate system; extract the iris code based on a texture analysis using wavelet transformations, and identify the iris code. The proposed system uses wavelet transformations for texture analysis. The system was implemented and evaluated using a dataset of 240 samples of iris data of varying contrast efficiency. The irises are localized and unwrapped to form a texture layer. Features are derived using multi-scale global texture analysis.

3. METHODOLOGY

3.1 System Design

The first phase of the method is the collection of a large database consisting of several iris images of minors and adults. The images will be captured using a CCD (Coupled Charged-Device) camera with a good resolution to create meaningful detailed images. Then the iris images are segmented by converting the iris images to grayscale images and Artificial Neural Network (ANN) will be used to train the iris images gotten during the second phase. The type of neural network used is a deep learning network with feed-forward propagation (FFP). A deep neural network means stacking many hidden layers and to learn more complex relationships in the data. This network is a four-layered network with nine (9) inputs in the input layer, the second third and fourth layers will have 3, 2, and 1 node respectively. The last node serves as the output which is the resultant age of the owner of the iris.

3.2 Iris Image Acquisition

The left side iris was considered in this work rather than using any of the iris from a different person. The iris images were captured from several people with the use of a CCD camera, which was placed at a distance of approximately 9cm from the user's eye. The captured images were of high resolution which is necessary for the accurate detection of the outer and inner circle boundaries.

3.3 Iris Image Preprocessing

The captured iris images were processed to increase the system performance. The processing methods include; Iris cropping, Iris Grayscale conversion, and Normalization of the iris images

i) Cropping: The captured iris images were cropped using 3-dimensional paint. Cropping out the iris images isolates the actual iris region from the digital image to remove all the irrelevant parts.

ii) Grayscale Conversion: The iris images were converted to grayscale to reduce the noise contained in the iris images, to reduce the space complexity, and also to make further processing faster. The images are converted to grayscale using:
Img = Image.open(file_name, "r")
Pix_Val = list(img.get data()

iii) Normalization: To unify input data with the various units, they are normalized. It helps to move the weights of the vectors towards a good solution using the formula below

For inputs:

The normalized value of a column =
$$\frac{real\ value\ in\ a\ column - mean\ of\ a\ column}{standard\ \ deviation\ \ of\ a\ column}$$

For Output:

Normalized age =
$$\frac{minimum\ \ age}{maximum\ \ age - minimum\ \ age}$$

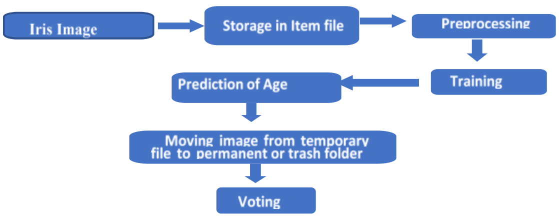


Figure 1: The system architectural design

3.4 The ANN Layers

From the diagram below, the network to be used has 4 layers with 9 inputs in the input layer, the second, third, and fourth layers have 4, 3, and 1 node respectively. The last node, which is the output, is the predicted age. The activation function used is tanh(x) and is non-linear from which the network can learn. Each node takes multiple weighted inputs, applies the activation function to the summation of these inputs, and in doing so generates an output. At the training, the input vector is presented to the network, which produced an output vector. This output vector is compared with the desired/target output vector. An error signal is generated if there is a difference between the actual output and the desired/target output vector. Based on this error signal, the weights are adjusted until the actual output is matched with the desired output.

Communications on Applied Electronics (CAE) – ISSN : 2394-4714
Foundation of Computer Science FCS, New York, USA
Volume 7 – No. 37, January 2022 – www.caeaccess.org

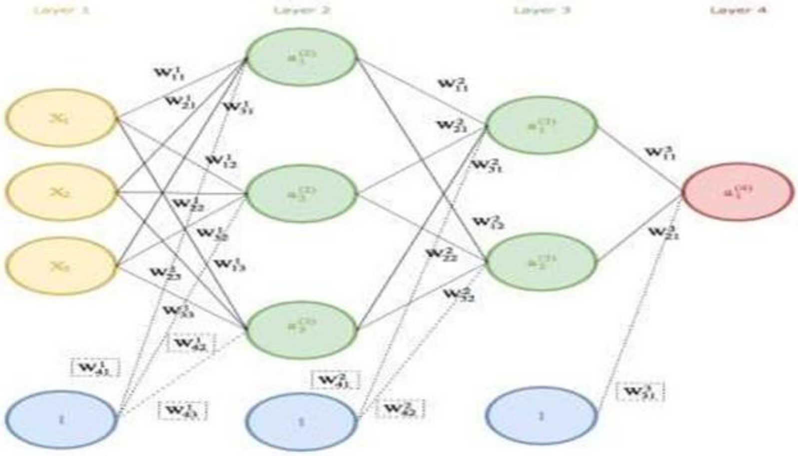


Figure 2: The ANN layers

Based on this error signal, the weights are adjusted until the actual output is matched with the desired output.
The values of the neurons of a hidden layer are called the activities of the hidden layer. To compute the values of neurons in the hidden layer, equations 1 and 2 are used while the values are saved into a matrix called $a^{(l)}$

$$Z^{l} = X^{l-1}.W^{l-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eqn\ 1$$

$$a^{(l)} = \tanh(Z)^{(l)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots Eqn\ 2$$

While *X* and *W* are supplied, weights are randomly generated initially. In the network, there are vectors W_1, W_2, and W_3. W_1 is a 2-dimensional vector of 10 rows and 3 columns, W_2 is a 2-dimensional vector of 4 rows and 2 columns, and W_3 is a 1-dimensional vector of 3 rows and 1 column. Z, a dot product of X and W, is computed for hidden and output layers. $a^{(l)}$, which is an output of hidden and output layers, are predicted outputs.

$$\delta^{4} = (-y).(1 - \tanh(z^{(4)2}) \ldots\ldots\ldots\ldots..eqn\ 3$$

$$\frac{\partial(J(w))}{\partial w_3} = \delta^{4}.a^{3} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn\ 4$$

$$\delta^{3} = (\delta^{4}.W_3^{T}).(1 - \tanh(z^{(3)2}) \ldots\ldots\ldots\ldots..eqn\ 5$$

$$\frac{\partial(J(w))}{\partial w_2} = \delta^{3}.a^{2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn\ 6$$

$$\delta^{2} = (\delta^{3}.W_2^{T}).(1 - \tanh(z^{(2)}) \ldots\ldots\ldots\ldots..eqn\ 7$$

$$\frac{\partial(J(w))}{\partial w_1} = \delta^{2}.X \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn\ 8$$

In the 4-layer network, eqn.3 is an error in the output layer. eqn.5 and eqn.7 are errors in the third layer and second layer respectively. eqn.4, eqn.6, and eqn.8 are for the rates of change of the cost concerning weights, $W_2, W_1,$ in the network. In other words, they give individual gradients for each input-output pair. The total gradients for the entire set of input-output pairs are:

$$\frac{\partial(J(W))}{\partial W_3}/m,\ \frac{\partial(J(W))}{\partial W_2}/m \text{ and } \frac{\partial(J(W))}{\partial W_1}/m$$

m is 80% of the image samples.

With regularization term included, the total gradients for the entire set of input-output pairs become:

$$\frac{\partial(J(w))}{\partial w_3}/m + \lambda.W_3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn\ 9$$

$$\frac{\partial(J(w))}{\partial w_2}/m + \lambda.W_2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn\ 10$$

$$\frac{\partial(J(w))}{\partial w_1}/m + \lambda.W_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn11$$

Using the learning rate and the total gradients, the weights are further updated as follows:

$$W_1 = W_1 - \alpha.(\frac{\partial(J(w))}{\partial w_1} + \lambda.W_1 /m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn12$$

$$W_2 = W_2 - \alpha.(\frac{\partial(J(w))}{\partial w_2} + \lambda.W_2 /m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn13$$

$$W_3 = W_3 - \alpha.(\frac{\partial(J(w))}{\partial w_3} + \lambda.W_3 /m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.eqn14$$

Communications on Applied Electronics (CAE) – ISSN : 2394-4714
Foundation of Computer Science FCS, New York, USA
Volume 7 – No. 37, January 2022 – www.caeaccess.org

α is the learning rate while is the regularization parameter. To check for the gradient,

The 38 elements are stored in a vector V_1

$$\frac{\partial(J(W))}{\partial W_1} = \begin{bmatrix} \partial w1_{11} & \partial w1_{12} & \partial w1_{13} \\ \partial w1_{21} & \partial w1_{22} & \partial w1_{23} \\ \partial w1_{31} & \partial w1_{32} & \partial w1_{33} \\ \partial w1_{41} & \partial w1_{42} & \partial w1_{43} \\ \partial w1_{51} & \partial w1_{52} & \partial w1_{53} \\ \partial w1_{61} & \partial w1_{62} & \partial w1_{63} \\ \partial w1_{71} & \partial w1_{72} & \partial w1_{73} \\ \partial w1_{81} & \partial w1_{82} & \partial w1_{83} \\ \partial w1_{91} & \partial w1_{92} & \partial w1_{93} \end{bmatrix}$$

$$\frac{\partial(J(W))}{\partial W_2} = \begin{bmatrix} \partial w2_{11} & \partial w2_{12} \\ \partial w2_{21} & \partial w2_{22} \\ \partial w2_{31} & \partial w2_{32} \\ \partial w2_{41} & \partial w2_{42} \end{bmatrix}$$

$$\frac{\partial(J(W))}{\partial W_3} = \begin{bmatrix} \partial w3_{11} \\ \partial w3_{21} \\ \partial w3_{31} \end{bmatrix}$$

4. RESULTS AND DISCUSSION

This research employed an application that was developed using some libraries in the python programming language that reads an iris image captured by a camera that was placed in a temporary folder on the laptop. The application reads the image, processes it, and evaluates it as shown in Figure 3 below.

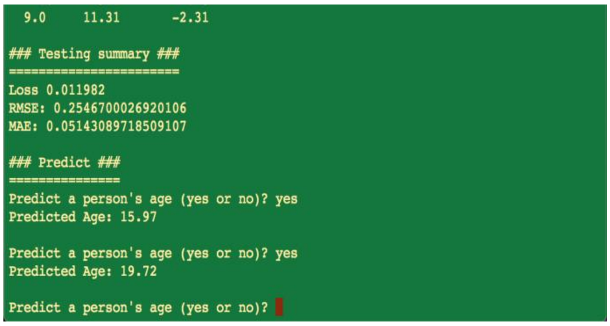


Figure 3: The app interface showing the running of the program

If the age is below voting age, the image is moved to a rejected folder, otherwise, the image is moved to an accepted folder. The temporary folder is cleaned for the next picture. Figure 4 depicts the accepted folder containing the images of eligible voters that are 18 years and above.

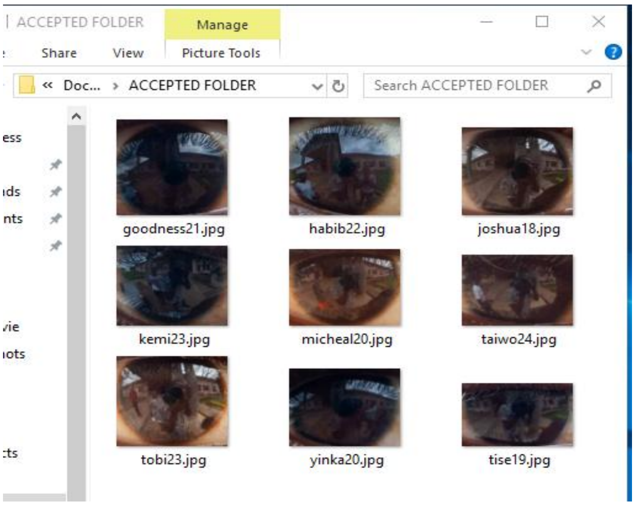


Figure 4: The Temporary Folder for the accepted image

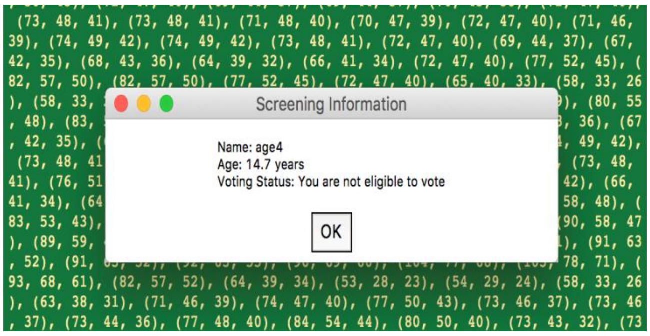


Figure 5. A message box showing that a person is not eligible to vote

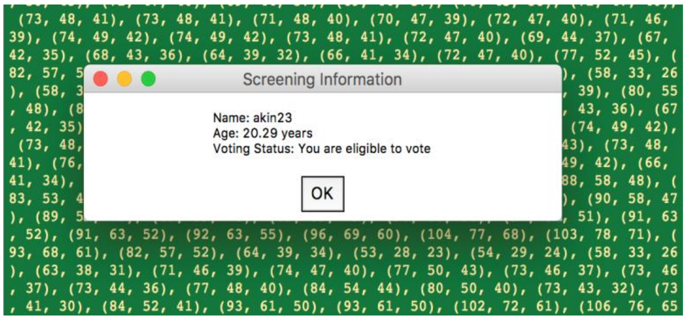


Figure 6. A message box showing that a person is eligible to vote.

The Dataset comprises of 240 set of Iris that was captured with a Coupled Charged-Device (CCD) camera with a good resolution to create meaningful detailed images. The system was able to correctly classify the Iris Images based on age as either an eligible or an ineligible voter using the following metrics: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN).

True Positive (TP) is a scenario whereby the system is accurately able to predict, determine and classify the age of a tested Iris as belonging to an eligible voter. The system correctly identified 215 sets of Iris correctly.

True Negative (TN) is a scenario whereby the system is accurately able to predict, determine and classify the age of a tested Iris as belonging to an ineligible voter. The system was able to correctly identify 18 Iris as ineligible voters.

False Positive (FP) is a scenario whereby the system is unable to accurately predict, determine and classify the age of a tested Iris hereby declaring an eligible voter as an ineligible voter. The system wrongly declared 5 iris as ineligible voters.

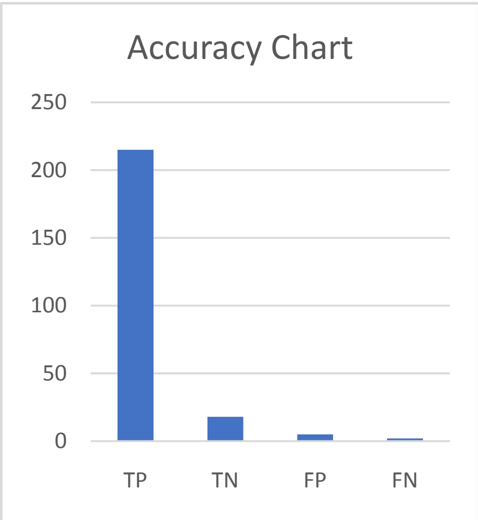
False Negative (FN) is a scenario whereby the system is unable to accurately predict, determine and classify the age of a tested Iris hereby declaring an ineligible voter as an eligible voter. The system wrongly declared 2 iris as eligible voters instead of the other way round.

Accuracy = TP +TN / TP + TN + FP + FN

Accuracy = 215+18 / 215 + 18 + 5 + 2

= 233/240 = 0.971

TP	TN	FP	FN
215	18	5	2



The system accurately predicted and determine the age of 233 iris while only 7 of the Iris were inaccurately predicted. This indicates that the system has 97.1% accuracy with only 2.9% inaccuracy.

5. CONCLUSION

This work had been able to prove that Iris as a model of biometric authentication is very suitable in estimating the age of an individual and at the same time used as a means of preventing under-age voting as the proposed system was able to generate 97.1% accuracy. The system could be used in enrolment platforms like national identity cards, SIM card registration, driver’s license registration, and so on. Schools could make use of it in their registration exercise to determine if an intending student meets the required age standard of getting admitted into a particular school. Also, the system could be applied in places where minors could be denied access to alcoholic drinks, tobacco products, and adult content websites.

6. REFERENCES

[1] Anuradha Yarlagadda, J.V.R. Murthy, M.H.M. Krishna Prasad (2015) A novel method for human age group classification based on Correlation Fractal Dimension of facial edges. Journal of King Saud University - Computer and Information Sciences, Volume 27, Issue 4, 2015, Pages 468-476, ISSN 1319-1578.

[2] Asima Abbasi and Muhammad Khan (2016) Iris-Pupil Thickness Based Method for Determining Age Group of a Person. The International Arab Journal of Information Technology, Vol. 13, No. 6, November 2016.

[3] Bramhananda Reddy, Dr & Vu, Goutham. (2018). Iris technology: A review on Iris-based Biometrics systems for unique human identification. International Journal of Research-GRANTHAALAYAH.6. 10.5281/zenodo.1162210.

[4] Habibah Adamu Biu, Rashid Husain, Abubakar S. Magaji (2018) “An enhanced iris recognition and authentication system using energy measure” African Journals Online (AJOLS) Vol. 13 No. 1 ISSN: 1597-6343

[5] Jafar M. H. Ali Aboul Ella Hassanien(2003) An Iris Recognition System to Enhance E-security Environment Based on Wavelet Theory’’ AMO - Advanced Modeling and Optimization, Volume 5, Number 20, 2003.

[6] John Owen Nwachukwu (2018) How I was nearly killed for trying to stop underage voting - Ex-INEC boss, Olurode - Daily Post Nigeria

[7] Mahéo, V., & Bélanger, É. (2020). Lowering the Voting Age to 16? A Comparative Study on the Political Competence and Engagement of Underage and Adult Youth. Canadian Journal of Political Science, 53(3), 596-617. doi:10.1017/S0008423920000232

[8] Mary Reni B (2015) Iris Recognition based Age Estimation in Security Systems using Canny Edge Detection’’ Research Journal of Pharmaceutical, Biological and Chemical Sciences, ISSN: 0975-8585, September - October 2015.

[9] Mehedi Hassan (2018) 25 Advantages and Disadvantages of Iris Recognition - Biometric Today

[10] Mehedi Hassan, (2016) Iris recognition is Most Accurate Biometric Modality (m2sys.com)

[11] Samson Toromade (2019) “INEC says its powers are too weak to punish politicians, political parties,” INEC says its powers are too weak to punish politicians, parties | Pulse Nigeria

[12] Sundaram R. M. and Dhara B. C. (2011), "Neural network-based Iris recognition system using Haralick features," *2011 3rd International Conference on Electronics Computer Technology*, 2011, pp. 19-23, DOI: 10.1109/ICECTECH.2011.5941793.

[13] Yusuf Luka (2019) Nigeria Decides: Underage voting and INEC's response as general elections kick off - Daily Post Nigeria, An excerpt from the Daily Post, A Nigerian Newspaper.