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Trimodal Biometric Security Systems Using Deep Learning Technique

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Unimodal, Bimodal, Trimodal, Convolutional Neural Network, Receiver Operating Characteristics.

Abstract

Biometrics refers to the automatic recognition of individuals based on their physiological and behavioural characteristics. These characteristics are unique to each individual and remain unaltered throughout human lifetime. Several unimodal, bimodal and trimodal biometric security systems have been developed using convolutional neural network but few of them have been able to handle the challenges of accurate recognition rates and processing time. In this work, a comparative study of the performances of unimodal, bimodal and trimodal biometric security systems using deep learning technique was carried out.

The System was tested on a database consisting of 1026 trained images and 684 probe images of face, ear and iris biometrics. All the images were preprocessed. Feature extraction and classification were carried out using deep learning technique, precisely, Convolutional Neural Network Algorithm (CNN). The results show that the unimodal, the Ear system produced highest value of 91.67% accuracy, Sensitivity of 93.57%, Specificity of 85.96%, Precision of 95.24% in in 114.10secs time. In bimodal system Ear-Iris produced highest value of 96.05 accuracy, Sensitivity of 96.49%, Specificity of 94.74%, Precision of 98.21% in 297.01 time, while the developed system propduced Sensitivity of 97.66%, Specificity of 98.25%, Precision of 99.40%, Recognition Accuracy of 97.81% but the Recognition Time of 455.54 Secs.

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1. Introduction

Biometrics according to [10] refers to the automatic recognition of individuals based on their physiological and behavioural characteristics. These characteristics are unique to each individual and remain unaltered throughout human lifetime. Utilizing biometrics for personal authentication is becoming more accurate than traditional methods (such as the utilization of passwords or Personal Identification Numbers - PINs) and more convenient (nothing to carry or remember). The etymology of biometrics is derived from the greek word "bios", which means life and "metron" which means "to measure", thus biometrics means life measurement [7].

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Most biometric systems deployed in real-world applications are unimodal, i.e., they rely on the evidence of a single source of information for authentication (e.g. single fingerprint or face). Multi-biometric systems are able to meet the stringent performance requirements imposed by various applications. They address the problem of non-universality, since multiple traits ensure sufficient population coverage. They also deter spoofing since it would be difficult for an impostor to spoof multiple biometric traits of a genuine user simultaneously. Furthermore, they can facilitate a challenge response type of mechanism by requesting the user to present a random subset of biometric traits thereby ensuring that a 'live' user is indeed present at the point of data acquisition.

Multimodal systems use a combination of two or more modalities to overcome the limitations that arise when using traditional approaches and single biometric trait to recognize individuals. Multimodal biometrics system involves various levels of fusion, namely, sensor level, feature level, matching score level, decision level and rank level [6]. Identity management system has a challenging task in providing authorized user with secure and easy access to information and services across a wide variety of networked system. [8] also suggested that future work should concentrate on how to reduce the computational complexity of the deep learning applications because it is still an open problem. The major challenge of any deep learning approach is the fact that it is computationally complex in nature. Thus, this work developed Convolutional Neural Network algorithm based trimodal biometric security systems.

2. Review of Related Works

Unimodal systems only make use of a single source of information for human recognition. For instance, [3] worked on the design of face recognition system using feed-forward neural network, they achieved a satisfactory result. [2] The paper presents a robust algorithm for ear recognition system based on self-organization Maps the results realized were satisfactory. [8] developed an iris recognition system with off the shelf CNN features. They worked majorly on the performance evaluation of some pre-trained CNN Models Alexnet, Googlenet, VGG, densenet, etc. The paper of [4] presented a design and implementation of a biometrically-controlled door system using iris recognition with power backup (case: Nigeria with epileptic power supply) where user's life property will serve as the key to granting access to a place or resource. Black iris data sets were used to simulate the iris recognition algorithms employed on the fabricated door prototype. The system was tested with a number of pre-enrolled templates and some fresh, incoming subjects. The door only unlocked for pre-enrolled subjects while for the latter, access denial was the case. The door system developed thus, answered only to iris signature. The researchers in [5] investigated the effectiveness of combining Independent Component Analysis (ICA) with Gabor algorithm (I-Gabor) as feature extraction. The features are extracted from eye and nose of known faces using Gabor and I-Gabor. The resultant features matrices were trained with support vector machine (SVM) for classification. The performances of the classification algorithms were evaluated with false acceptance rate, false rejection rate and accuracy.

Bimodal systems on the other hand makes use of two sources of information for human recognition. The authors in [1] developed a bimodal face-fingerprint biometric security system that fuses matching scores obtained from single face and single fingerprint recognition modules for result management. A total of 270 facial images and 270 fingerprint images were acquired using a digital camera and fingerprint scanner respectively. Features were extracted using the Modified Gabor Filter feature extraction technique. Matching scores were obtained for both face and fingerprint images using Euclidean Distance algorithm while Weighted Sum Rule fusion technique was used to compute the fused score. The results of evaluation showed that the developed system is highly effective in terms of the overall recognition accuracy, sensitivity and specificity of the system. More work can be found in [13].

Compound biometrics involves more than two evidences presented by different traits belonging to a user to form their identity as a whole and enhance authenticity efficiency. Although the system might be complex and cost higher due to the requirement of new sensors and longer time during recognition. The work of [15] instigated a multimodal biometric identification system based on features extracted from three biometric modalities including face, ear and gait using Gabor and PCA. Fusion at matching score was performed on ORL face database, USTB ear database and CASIA gait database. The paper evaluated three different kinds of normalization techniques experimentally and two kinds of fusion methods. Z-score method of normalization combined with weighed product method of fusion gave the best recognition performance of 97.5% at 0.1% FAR. The innovative approach outperformed the unimodal systems on a variety of image databases.

From the work of [12] face, ear and iris algorithms are tested individually and individual weight for face is found to be 92%, for ear 96% and iris 30%. The overall performance of the system has increased showing weight for face and ear to be 98.24% with FAR of 1.06 and FRR of 0.93 respectively. More work can be found in [14].

3. Materials

A. CNN Network Architecture

From literatures, it appears that choosing the network architecture is still an open problem and is application dependent. The main concern in finding the best CNN architecture is the number of the layers to employ in transforming from the input image to a high-level feature representation, along with the number of convolution filters in each layer. Figure 1 shows the architecture of CNN Model that comprises of one input layer, four convolutional layers, four max-pooling layers, two fully-connected layers and one output layer.

The input layer receives the input data which in this case is the result of fusing the feature vectors of face, iris and ear modalities. The convolution layer detects the local conjunctions of features from the previous layer and maps their appearance to a feature map. There are some layers between the convolution layer and the max-pooling layer, namely: non-linearity layer and rectification layer. The non-linearity Layer which consists of an activation function takes the feature map generated by the convolutional layer and creates the activation map as its output. The rectification layer performs element-wise absolute value operation on the input volume, generally the activation volume. The max-pooling or down-sampling layer was responsible for reducing the spatial size of the activation maps while the fully-connected layers mapped the activation volume from the combination of previous different layers into a class probability distribution. It is the output layer that gave the classification result [8].

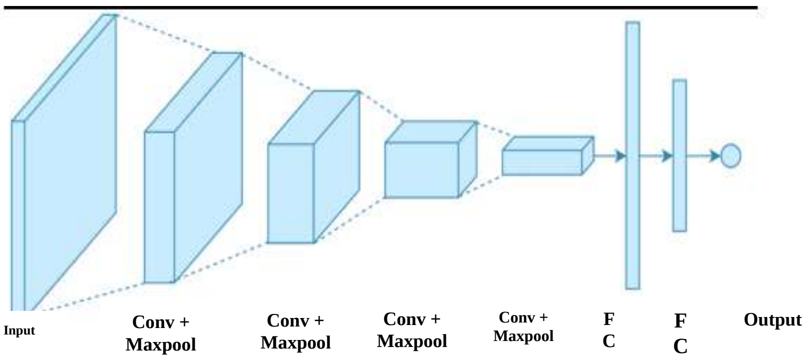

Figure 1: Architecture of CNN Model

B. Weighted Sum Rule Technique

According to Pour et al [9], weighted sum rule can be expressed as

$$Weighted\ Sum = \sum_{i=1}^{n} w_i\, S_i \qquad (1)$$

Where:

n is the number of preprocessed biometric modalities to be fused

S_i is the preprocessed biometric modality

w_i is the weight for each preprocessed biometric modality which can be calculated as follow:

$$Weight = \frac{EER_i}{\sum_i EER} \qquad (2)$$

Where EER_i is the unimodal biometric error,

C. Performance Evaluation Metrics

The following parameters were used to measure and evaluate the overall performance of the system:

Sensitivity (TPR): Ability to identify presence of images in the database,

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \qquad (3)$$

Specificity (TNR): Ability to identify absence of images in the database,

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \qquad (4)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \qquad (5)$$

$$\text{System Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total number of images}} \times 100\% \qquad (6)$$

Recognition Time: It is the measure of the time-taken for the training and classification of Images.

4. Method

The system architectural framework (as shown in figure 2) of the unimodal system is divided into (4) major phases, namely: Image capturing phase, Image preprocessing phase, feature extraction/classification phase and decision phase whereas the bimodal and multimodal biometric security systems are both divided into five major phases, namely: Image capturing phase, Image preprocessing phase, fusion phase feature extraction/classification phase and decision phase. Each of the phases isas shown in Figures 1 and succinctly discussed in subsequent sections.

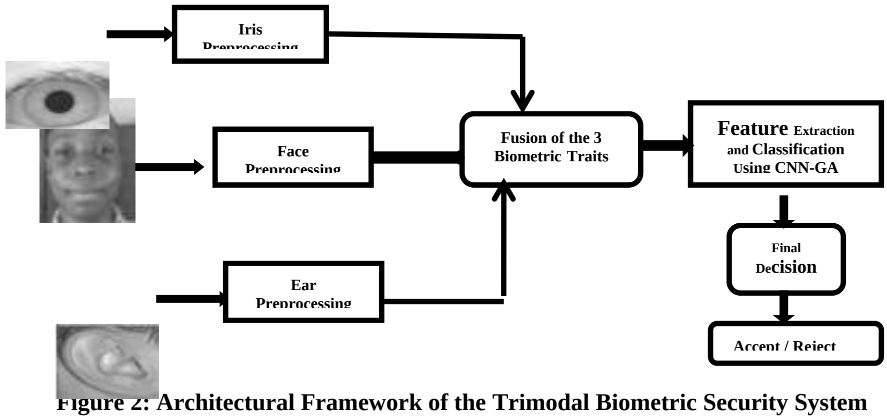

Figure 2: Architectural Framework of the Trimodal Biometric Security System

Image Capturing Phase

The user face, right-ear and right-iris images are captured using a high definition camera and an iris scanner. These were consequently stored in the databases created for the three identifiers, accordingly as "user templates". The total number of face images, right-ear images and right-iris images used for training and testing the multimodal system is 1,710 images of 190 individuals. Multiple instances (i.e. 3) of the images were captured for ease of training and classification. Only 171 of the 190 individual were used to train the system while the remaining 19 were added as part of the test images to eventually measure the performance of the system.

Image Preprocessing Phase

Image preprocessing is a fundamental step in image processing and computer vision. In this phase, the images were first cropped and resized, and thereafter enhanced using histogram equalization algorithm [17]. This includes primitive operations to reduce noise, contrast enhancement, image smoothing and sharpening, and advanced operations such as image segmentation.

(a) (b) (c)

Figure 3: Samples of Face Images Used: (a) Original (b) Cropped (c) Enhanced Histogram

(a) (b) (c)

Figure 4: Samples of Ear Images Used: (a) Original (b) Cropped (c) Enhanced

(a) (b) (c)

Figure 5: Samples of Iris Images Used: (a) Original (b) Cropped (c) Enhanced

Fusion Phase

Fusion of bimodal and multimodal biometric information was carried out by applying the weighted sum rule. The output of the Weighted Sum will be fed into the CNN model for feature extraction and classification.

Feature Extraction and Classification Phase

Deep learning algorithms can learn tasks directly from data, eliminating the need for manual feature election. Deep Learning is about learning multiple levels of representation and abstraction that help to make sense of data such as images, sound, and text. Deep learning performs end-to-end learning for feature extraction and classification. One of the commonly used deep learning techniques is the CNN. Once a preprocessed face, ear and iris images are obtained, and feature extraction carried out on each modality, classification shall be performed using Convolution Neural Network (CNN).

In this work, the structure of the modified CNN involves a combination of convolutional layers and subsampling max-pooling. The top layers in the modified CNN are two fully connected layers for the classification task. Then, the output of the last fully connected layer is fed into the Softmax classifier, which produces a probability distribution over the N class labels.

5. Discussion Of Results

A graphical user interface (GUI) was designed for the unimodal, bimodal and trimodal biometric security systems for ease of experimentation. Figure 6 shows the graphical user interface for the systems during feature extraction and classification using Modified CNN. The GUI has different segments such as the training, testing, classification segments and even others ones that display the images and show the results.

Figure 6: GUI of the developed System

Several experimental tests were conducted to validate the performance of the developed unimodal, bimodal and trimodal systems under varying conditions. Arbitrary constants termed threshold values of 0.76 was chosen.

As presented in table 1, the unimodal, the Ear system produced highest value of 91.67% accuracy, Sensitivity of 93.57%, Specificity of 85.96%, Precision of 95.24% in in 114.10secs time. In bimodal system Ear-Iris produced highest value of 96.05 accuracy, Sensitivity of 96.49%, Specificity of 94.74%, Precision of 98.21% in 297.01 time, while the developed system propduced Sensitivity of 97.66%, Specificity of 98.25%, Precision of 99.40%, Recognition Accuracy of 97.81% but the Recognition Time of 455.54 Secs.

TABLE 1: The Performance of the Unimodal, Bimodal and the developed Trimodal System at 0.76

BIOMETRIC TRAITS	Sensitivity (%)	Specificity (%)	Precision (%)	Recognition Accuracy (%)	Recognition Time (Secs)
Face Only	92.98	84.21	94.64	90.79	112.10
Ear Only	93.57	85.96	95.24	91.67	114.18
Iris Only	94.15	87.72	95.83	92.54	114.84
Face-Ear	95.32	91.23	97.02	94.30	222.93
Face-Iris	95.91	92.98	97.62	95.18	228.30
Ear-Iris	96.49	94.74	98.21	96.05	297.01
Face-Ear-Iris	97.66	98.25	99.40	97.81	455.54

Figure 7 shows the ROC curves of the developed trimodal system against the unimodal and bimodal counterpart. It was deduced from the curves that the trimodal system outperformed the unimodal systems as well as the bimodal systems in terms of sensitivity and specificity.

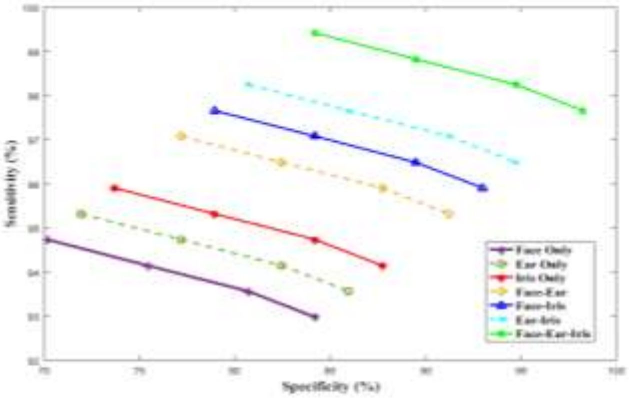

Figure 7: ROC Curve of the Trimodal Biometric Security System

6 Conclusion

This work has been able to establish the fact that no single biometric information is sufficient enough to authenticate individuals. The biometric information that were engaged in this work are face images, right ear images and the right iris images. All these were used because they are all passive biometrics and do not require active or full participation of individuals to be probed. Combining multiple sources of biometric information has proven to provide more reliability, accuracy and precision as established in this work. The three biometric traits of different persons were captured and integrated as seen in the experimental results, to enhance the performance of the bimodal and trimodal biometric systems that has been developed as against the unimodal systems. The results confirmed the trimodal system on the performed better than the bimodal and unimodal recognition systems based on sensitivity, specificity, precision, and recognition accuracy.

Further work can may be shifted to the hand region that comprises the fingerprint, palm print and finger-knuckles to further test the performance of the multimodal system. Future work can also consider integrating another optimization technique apart from genetic algorithm with CNN.

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