© May 2023| IJIRT | Volume 9 Issue 12 | ISSN: 2349-6002

Biometric Authentication System using Human Ear

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Abstract -– In this paper, a fully-automated ear-based biometric authentication system is proposed. Biometric authentication technology has become widespread, with the mainstream methods being fingerprint authentication and face recognition. However, fingerprint authentication cannot be used when hands are wet, and face recognition cannot be used when a person is wearing a mask. Like the face and fingers, the ear as a biometric contains features that enable human identification and has been the subject of research on personal authentication. The advantages of using the ear as a biometric is that undamaged ears are more or less the same until a person reaches 70 years old. YOLOv3 (You Only Look Once) is used to segment each user's image. After segmentation, noise is eliminated using Gaussian blur. Different methods are then subsequently applied to the resulting binary contour image for the purpose of feature extraction. Prominent contours associated with the folds of the ear shell are detected. The extracted features are then compared with the existing features in the database using feature matching. Once verified, the user will be granted access.

Keywords — Authentication, Biometrics, Ear, Contour Detection, Feature vectors

I. INTRODUCTION

In the realm of secure authentication systems, biometrics has emerged as a groundbreaking approach, utilizing unique physical or behavioral characteristics to verify the identity of individuals. Biometric authentication methods, such as fingerprint and facial recognition, have made significant strides in ensuring robust security across various domains. However, in the quest for even more accurate and reliable identification techniques, researchers have begun to delve into the untapped potential of an often overlooked feature—the human ear.

The human ear, an organ primarily responsible for hearing, has long fascinated scientists and researchers with its intricate and distinctive structure. With its complex shape and a multitude of unique characteristics, the human ear presents a compelling opportunity for biometric authentication [1]. Leveraging the ear as a biometric modality offers several advantages, including a high level of uniqueness, stability over time, and ease of capture, making it an appealing alternative to existing authentication methods [2].

This paper aims to explore the concept of biometric authentication using the human ear, shedding light on its underlying principles, technological advancements, and potential applications. The rest of the paper is organized as follows. Section II details the design of the proposed system. Section III analyses the results and the conclusion is given in Section IV. Section V outlines potential directions for future research.

II. SYSTEM DESIGN

An overview of the enrollment and authentication stages of the proposed fully automated ear-based biometric authentication systems are conceptualised in Fig 1.

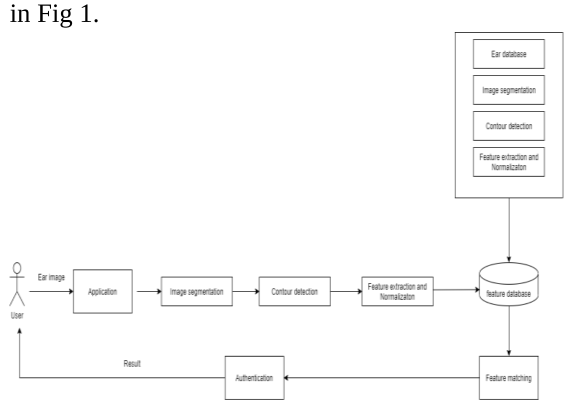


Fig 1: Architecture Diagram

A. Image Segmentation

A deep learning model architecture called YOLOv3 (You Only Look Once version 3) is employed for object detection in pictures and videos. It is a single neural network design that has great accuracy and real-time object detection capabilities. A single-layer neural network represents the most simple form of neural network, in which there is only one layer of input nodes that send weighted inputs to a subsequent layer of receiving nodes, or in some cases, one receiving node. The YOLOv3 architecture extracts data from an input image using a number of neural layers, and then forecasts bounding boxes and class probabilities for each object in the image. The architecture employs a prediction module to enhance object detection outcomes and a feature pyramid network to detect things at various scales. Because of its speed and precision, YOLOv3 is a well-liked option for many applications, including robots, surveillance systems, and self-driving cars.

The classic object identification models that use region proposal methods, including R-CNN and its derivatives, are computationally expensive and slow, which is why the YOLOv3 architecture is required. These models are inappropriate for real-time applications because object detection requires numerous passes of the picture or video, which can take a long time [3]. Also to determine the bounding boxes and class probabilities of objects in an image or video, YOLOv3 employs a single neural network. It is substantially quicker thanks to this method than conventional object detection models, enabling real-time object detection.

A convolutional neural network (CNN) is used by YOLOv3 to find objects in pictures. Three sections make up the network: a backbone, a neck, and a head. Convolutional layers that extract features from the input image make up the backbone. To enhance object detection, the neck mixes features from several scales. Each object in the image is predicted to be in its expected location and class by the head, which is made up of fully connected layers.

B. Contour Detection

Contour detection involves a series of steps to accurately extract the ear contours from an image [4]. The process begins with preprocessing, where the input image is converted to grayscale and then smoothed using Gaussian blur. This blurring helps to reduce noise and create a smoother image for subsequent analysis. Next, Canny edge detection is applied to the blurred grayscale image. The Canny algorithm identifies significant changes in intensity, highlighting the edges of the ear [5]. Finally, contour detection is performed on the edge-detected image. Contour detection attempts to extract curves which represent the required boundaries of the ear, and can be used for further analysis.

Fig 2: Input Ear Image

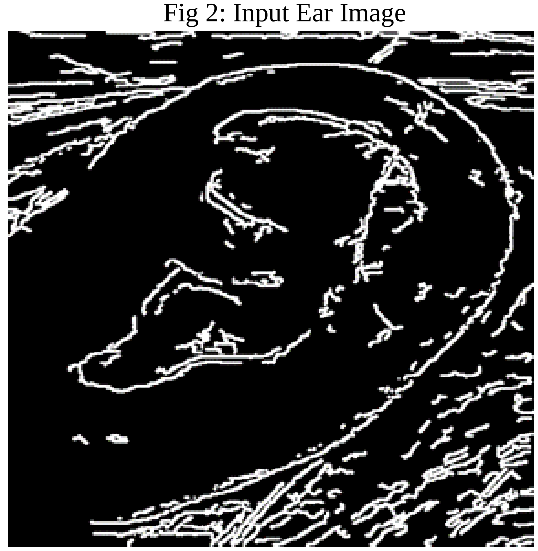


Fig 3: Identified Prominent Contours

C. Feature Extraction and Normalisation

The Discrete Radon Transform on ear contours can capture shape information from different orientations and provide a compact representation of the contour. It is commonly used in ear biometrics or shape analysis tasks where shape-based features are important for identification or recognition purposes. Once the ear contour is obtained, it needs to be discretized to represent it in a digital form suitable for further processing. This involves sampling points along the contour and representing them as a set of discrete coordinates. The discrete Radon transform is computed by projecting the discretized contour onto a set of predefined lines or angles. These lines traverse the image space and intersect the contour, calculating the line integral along each projection line. The line integrals obtained from the Radon transform are accumulated and stored in a matrix or a set of vectors. Each element in the matrix or vector represents the sum of the line integrals for a particular angle of projection line. The accumulated Radon transform matrix or vector can be considered as a feature representation of the ear contour. Depending on the application, further processing or analysis can be performed on these features, such as dimensionality reduction or classification algorithms [6]. The extraction of deep features from ear images have been investigated more recently. A number of deep learning techniques have been proposed. Dodge, Mounsef and Karam [7] [8] used deep neural networks for the explicit purpose of feature extraction.

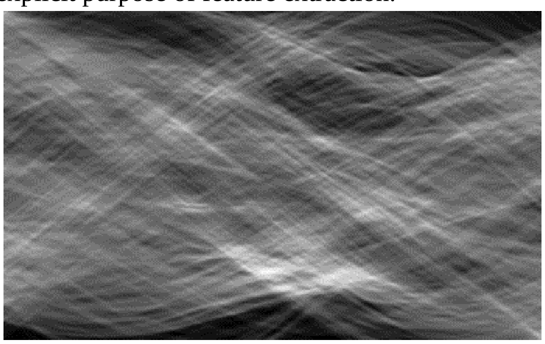


Fig 4: DRT Image

D. *Feature Matching and Verification*

The Euclidean distance is calculated between the corresponding normalized feature vectors of the questioned ear and ear images in the database. The Euclidean distance measures the straight-line distance between two points in a multidimensional space [8]. The questioned ear is compared to ear images belonging to other individuals. The dissimilarities between the questioned ear and ear of individuals are placed in a list. The dissimilarities are ranked in ascending order, with the smallest dissimilarity at the top (most similar) and the largest dissimilarity at the bottom (least similar). The verification is based on the relative position (ranking) of the dissimilarity associated with the reference ear in the list. If the dissimilarity associated with the reference ear is at or near the top of the list, it suggests that the questioned sample is likely to belong to the claimed individual. Conversely, if the dissimilarity associated with the reference ear is towards the bottom of the list, it indicates a lower likelihood of the questioned sample belonging to the claimed individual.

III. RESULTS

The implemented biometric authentication system, designed as a web application, successfully captures ear images from users during the registration process. Along with personal details such as name, email address, contact number, and username, the ear images are securely stored in a dedicated database. The subsequent steps of the system involve image segmentation, contour detection, feature extraction, and normalization.

By leveraging advanced image processing techniques, the system accurately isolates and identifies the ear region, achieving precise feature extraction. The extracted features, which represent the unique attributes of each user's ear, are then organized and stored within a specialized feature database.

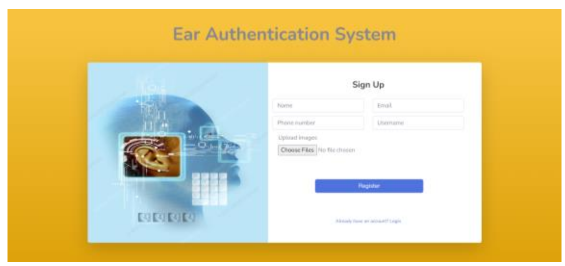
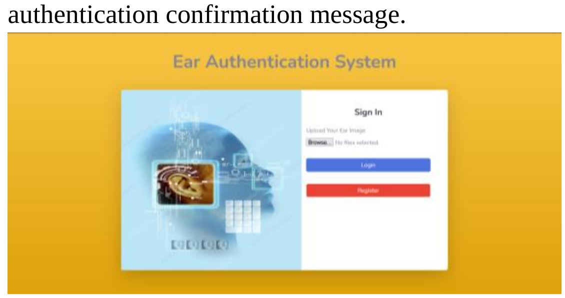


Fig 4: User Registration page

During the login process, users provide an ear image for authentication. The inputted image undergoes segmentation, contour detection, and feature vector extraction procedures. The resulting feature vectors are compared against the entire feature database, aiming to find a match. A successful authentication is considered when a match is found, and the system displays the name of the registered user associated with the matching ear image, along with an authentication confirmation message.



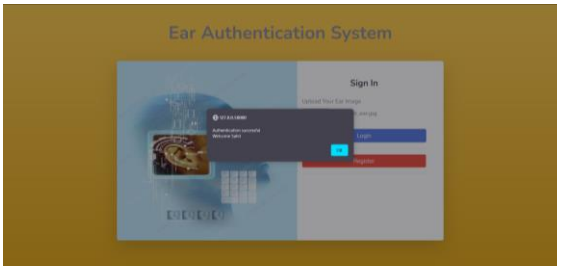


Fig 5(a) User Authentication page, 5(b) An example of User Authentication

IV. CONCLUSION

In conclusion, this research paper explored the development and implementation of a web application for a biometric authentication system utilizing the human ear. By leveraging the unique characteristics of the ear, such as its shape, contours, and landmarks, an efficient and secure method of user identification and authentication has been achieved. The study demonstrated that the proposed system offers several advantages over traditional authentication methods. Firstly, the ear-based biometric system is highly reliable and accurate, as the ear's structure remains relatively stable throughout a person's lifetime. This stability ensures consistency in identification, reducing the chances of false positives or negatives. However, it is essential to acknowledge some potential limitations of the proposed system. Environmental factors, such as lighting conditions and background noise, could influence the accuracy of ear recognition. Additionally, individual variations in ear anatomy may pose challenges in certain cases, requiring further refinement and optimization of the system. Nevertheless, the system's ability to provide reliable, accessible, and user-friendly authentication makes it an attractive solution for enhancing security measures in various domains.

V. FUTURE WORK

Some of the future modifications that can be implemented on our proposed system includes expanding the dataset, improving feature extraction techniques, exploring privacy-preserving methods, developing anti-spoofing techniques, investigating multimodal fusion with other biometric modalities, implementing real-time systems, assessing usability and user acceptance, establishing standardized evaluation metrics, and benchmarking. Addressing these areas can enhance the system's accuracy, security, usability, and practicality, promoting wider adoption in various applications.

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