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Human Recognition Using Ear Features: A Review

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ABSTRACT

Over the past few years, ear biometrics has attracted a lot of attention. It is a trusted biometric for the identification and recognition of humans due to its consistent shape and rich texture variation. The ear presents an attractive solution since it is visible, ear images are easily captured, and the ear structure remains relatively stable over time. In this paper, a comprehensive review of prior research was conducted to establish the efficacy of utilizing ear features for individual identification through the employment of both manually-crafted features and deep-learning approaches. The objective of this model is to present the accuracy rate of person identification systems based on either manually-crafted features such as DCT, DWT, DFT, PCA, LBP, SURF, SIFT, etc., or deep learning techniques such as CNN, DNN, Alex Net CNN, VGG-16, SVM, Squeeze Net, Google Net, MobileNetV2, etc. The effort will make it easier for researchers, especially those who are new to the field, to have a brief understanding of the trend of employing deep learning in a trustworthy biometric for the identification and recognition of human identification.

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1. Introduction

A biometric system refers to a type of pattern recognition system that serves to authenticate the identity of a user by confirming the genuineness of a specific physiological or behavioral characteristic inherent to that user. The efficacy of biometric systems in verifying human identity has been widely acknowledged due to their unparalleled accuracy and security features [1], [2]. Physiological biometric modalities include various physical traits such as facial features, ear structure, iris patterns, hand geometry, fingerprints, palm prints, and hand vein geometry. In contrast, behavioral biometric modalities incorporate characteristics such as voice patterns, signature dynamics, motion recognition, and keystroke dynamics [3], [4]. Numerous biometric systems have been developed based on the aforementioned biometric modalities and tested in real-world scenarios [5]. Ear-based biometrics has been identified as a dependable physiological characteristic for the recognition and identification of individuals. The ear is regarded as a unique and distinguishable trait that can be used to confirm or verify a person's identification, and it remains a stable anatomical

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feature that undergoes minimal changes throughout an individual's life. Additionally, ear-based biometric authentication methods have the advantage of being non-intrusive. While this area of research is relatively new, traditional ear-based biometric systems previously relied on hand-crafted feature extraction methods, whereas modern systems have employed neural networks to learn deep features [6]. In recent years, the prominence of ear biometrics has increased due to [7]:

1. The ear is characterized by a consistent shape and uniform color distribution.
2. The shape of the ear remains constant from 8 to 70 years of age and is unaffected by variations in facial emotions.
3. The fixed placement of the ear in the middle of the side face makes it easier to handle the background.
4. Ear image capture requires minimal cooperation from the individual.

The subsequent sections of this manuscript are organized as follows: Section Two elaborates on the structural aspects of ear images, Section Three offers a summary of related works, Section Four addresses a discussion of the manuscript, and Section Five gives the paper's concluding remarks.

2. Ear Image Structure

The human ear is fully formed during the early stages of pregnancy and is integral to the sense of hearing. Its characteristic structure is mostly shared by all people. The ear's exterior appearance is most well-defined by structural components such as the tragus, antitragus, helix, antihelix, incisura, and lobe, as depicted in Fig. 1. Variations in the shape, appearance, and relative positions of these anatomical cartilage formations between individuals make them exploitable for identity recognition. Although there are differences between left and right ears, they are sufficiently similar to enable automatic techniques to match them with a very high grade of accuracy [8], [9].

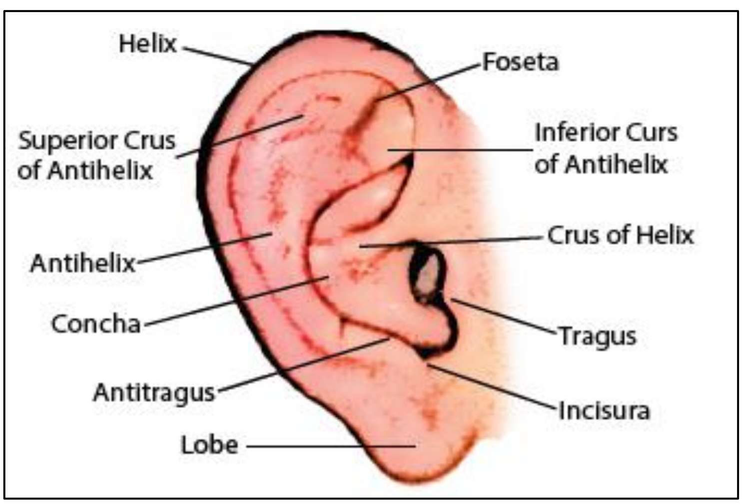

Fig. 1 - Ear structure [5]

3. Related Works

During the early days of human ear recognition, researchers relied mainly on manually-crafted features to recognize individuals. However, presently, researchers predominantly depend on deep learning features. In this study, prior research works were reviewed to ascertain the identity of individuals using ear features based on both manually-crafted features and deep-learning features as mentioned in the subsections below:

3.1. Handcrafted Features

Various algorithms have been suggested to extract distinguishing characteristics from ear images. Handcrafted features extracted from these images are typically classified into three kinds: geometrical features, local appearance-based features, and global features. Many techniques have been devised to extract and recognize ear characteristics from photographs, as described below [10]:

- Tian et al. [11] proposed a novel approach to ear recognition based on converting the pictures of the human ear to a two-dimensional discrete wavelet transform, which is then followed by a block discrete cosine transform on the wavelet transform's low-frequency and weighted high-frequency components. The extractions of the image's DCT coefficients as well as the creation of feature vectors are the outcomes of this operation. The nearest neighbor classifier and weighted distance are combined to perform classification and recognition. The maximum recognition rate achieved through this approach is 98%.

- Basit et al. [12] proposed a technique for ear recognition, predicated upon the employment of the curvelet transform. With the use of the wrapping approach, this methodology involves computing ear characteristics using the Fast Discrete Curvelet Transform. Each image's feature vector contains the second-coarsest level curvelet coefficients at eight distinct angles as well as the approximation curvelet coefficient. Classification is carried out using the k-NN (k-nearest neighbor) classifier. In order to appraise the efficacy of this method, an experiment was conducted on two ear databases from IIT Delhi. The outcomes of this study indicate that the proposed approach yields impressive performance, with outcomes achieved on a publicly accessible ear database demonstrating an accuracy rate of up to 97.77%.

- K. Annapurani et al. [13]) proposed a novel approach for the extraction of the tragus feature of the ear. The methodology used an improved edge detection technology to increase the tragus detection process' accuracy. A line connecting the maximum coordinate, midpoint, and minimum coordinate was used to identify the mid-region of the line as the tragus of the ear. The tragus feature was selected due to its relatively low likelihood of occlusion, making it a desirable feature for the development of an efficient ear authentication system. To further enhance the authentication system, feature-level fusion was utilized, where the shape of the ear was also extracted and combined with the tragus feature to form a fused template. The effectiveness of the identification system was evaluated using the Hamming distance and Euclidean distance methods. Experimental results were obtained from two ear databases, namely, the IIT Delhi ear database and the Mathematical Analysis of Images (AMI) ear database, both of which included occlusion. Results showed that the accuracy was 100% when using the Hamming distance method with all three features. For the Euclidean distance method, the accuracy was found to be better for the fused template compared to the individual features and equal to 99.8%. Overall, the proposed approach offers a promising solution for the development of an effective ear authentication system.

- Lamis et al. [14] proposed a hybridized approach named DWT-SIFT for extracting features from the ear. Wavelets and SIFT, two local and global approaches, are combined in the strategy. The suggested technique has been established on the USTB 2 and IIT Delhi ear biometric databases. Several metrics were computed, including the false rejection rate (FRR), the false acceptance rate (FAR), accuracy, and the time required for ear authentication. According to test findings, when compared to SIFT and wavelets techniques, the suggested approach provides greater accuracy and requires less time. Overall, the findings of this study suggest that the DWT-SIFT approach has the potential to enhance the performance of ear biometric feature extraction, which may have practical implications for the development of efficient and reliable ear authentication systems. The accuracy rate achieved is 94.2%.

- Ibrahim et al. [15] proposed a new geometric feature extraction technique to overcome the challenges associated with ear recognition. The proposed method focuses on identifying and utilizing the minimum Ear Height Line (EHL) to effectively describe the outer helix shape. Additionally, combining the maximal and minimal EHL has been shown to improve recognition performance. The proposed method also extracts three properties that are resistant to size changes, resulting in a six-dimensional feature space. This approach proves to be efficient for real-time ear recognition. The results conducted on USTB1 and IIT Delhi databases demonstrate that the suggested method can produce hopeful recognition results of 98.33% and 99.60%, respectively.

- Asmaa et al. [16] proposed a novel algorithm that is dependent on (SIFT) features to recognize ear images. It involves extracting SIFT features from the ear image and creating an augmented vector of those characteristics for matches. The preprocessing stage is included, which consists of converting the image to a gray level, smoothing the image with a median filter, and cropping the ear part from the image using edge detection. The SIFT features are subsequently extracted from the ear image and then classified using a minimum distance classifier. Importantly, the proposed approach is resistant to scale, translation, and rotation. Results on the IIT Delphi and AMI databases demonstrate that the proposed approach achieves an accuracy of nearly 95.2% and 100%, respectively.

- Ali et al. [17] proposed a novel methodology for human recognition through the use of ear images. The approach involved two primary stages, namely ear segmentation and ear recognition. Ear segmentation is achieved through the application of the Likelihood skin detector to identify skin areas in side-face images, followed by morphological operations to delineate the ear region. The ear region is then extracted through image processing techniques. For ear recognition, segmented ear images serve as inputs, and a hybrid PCA_Wavelet algorithm is employed to extract relevant ear features. The feature vectors are subsequently used to train a feed-forwarding back-propagation neural network. The system's efficacy was evaluated through tests involving 460 images, captured over four months and under varying illumination and pose conditions. Results indicated an accuracy rate of 96.73% for ear extraction and 98.9% for ear recognition.

- MATTHEW et al. [18] presented a novel method for ear recognition, called the 2D Wavelet based Multi-Band PCA (2D-WMBPCA) technique. Inspired by PCA-based methods for multispectral and hyperspectral images, the proposed method involves a 2D non-decimated wavelet transform applied to the input image, resulting in wavelet subbands. The segmentation of each subband into frames is determined based on the coefficients' values by applying equal-size or greedy hill-climbing techniques to define frame boundaries. Subsequently, traditional (PCA) is employed for each frame in the subband, generating eigenvectors utilized for matching. According to the test results, the accuracy rate achieved is 97.32%.

- Muthukumar et al. [19] proposed an ear recognition algorithm that employs a band-limited phase-only correlation (BLPOC) based local block matching technique for improved efficiency. The discrete wavelet transform (DWT) is used to extract the phase information over the frequency domain of the ear image, decomposing it into a set of basis functions. The BLPOC technique is found to be robust to noise and variations in scaling, consequently improving the ear recognition system's efficacy for biometric applications. The proposed algorithm utilizes phase matching between the registered and query images and is capable of handling local image deformation during local block matching. Experimental analysis is conducted using the IIT Delhi Ear database. The accuracy rate achieved is 88.0%.

- Rizhin et al. [20] proposed a novel technique for ear-based recognition of individuals from profile facial images, a task that can be complicated due to partial occlusion caused by hair and/or earrings. The proposed approach employs a two-stage process: first, a cascaded classifier-based ear detection technique that utilizes Haar-like features is employed to locate ears in profile images. Then, a Shape Context descriptor-based ear recognition technique is applied to the detected ear regions. Standard datasets were used to assess the effectiveness of the suggested approach. Specifically, the proposed technique achieved 100% recognition accuracy on non-occluded ear images and 57% accuracy on occluded ear images caused by both hair and earrings.

- Salman et al. [21] proposed an algorithm that integrates both texture and geometric features to facilitate the recognition of human ears. The objective of the research is to extract Local Binary Patterns features and Laplacian filters from raw images to identify the region of interest in the ear images. The AMI ear database was used to conduct the experiments, wherein the ear images were separated into four quarters and analyzed individually. The fusion of texture and geometric features was performed, and further experiments were achieved to assess the efficacy of the fused features. The suggested algorithm achieves an accuracy rate of 80%.

- Aishna et al. [22] focused on extracting the area of the ear image. It involves the application of a series of image processing techniques to a database of ear images. First, the images in the database are resized to 128 x 256 pixels and converted into grayscale images. Then, various transforms such as Discrete Cosine

Transform, Discrete Fourier Transform, and Discrete Wavelet Transform are employed to extract relevant features from the images. The extracted coefficients of the test image are compared with those of the registered database image, and the Euclidean distance classifier is used to recognize the test image from the database. The database used in the study comprises 25 subjects, with six images per person. The first four images are used for training the model, while the remaining two are reserved for testing purposes. The outputs of different transforms were compared, and it was found that the most optimal accuracy rate of 86% was achieved using DWT. The best accuracy achieved is 86%.

- Abbas et al. [23] proposed a novel approach utilizing machine learning techniques for developing a system for human ear recognition. The proposed system comprises four primary phases: ear detection, ear feature extraction, ear recognition, and confirmation. The central idea behind the proposed approach is to partition the ear image into the skin and non-skin pixels using a likelihood skin detector, followed by processing the likelihood image through morphological operations to complete the ear regions. Fixed features of the ear are extracted using the (SIFT) technique. Ear recognition is performed in two modes, namely identification and verification modes. A new image and the first image in the database are compared using the Euclidean Distance Measure (EDM). The obtained accuracy rate is 92%.

- Abdulkareem et al. [24] proposed a novel approach for enhancing ear recognition accuracy which involves modifying the AdaBoost algorithm to optimize adaptive learning. In order to mitigate the impact of image illumination, occlusion, and registration problems, the SIFT technique was employed for feature extraction. The proposed method involves several phases, including image acquisition, preprocessing, filtering, smoothing, and feature extraction, which are conducted sequentially to improve classification accuracy. The performance of the proposed system was evaluated by comparing the classification accuracy using various classifiers, including Naïve Bayesian, KNN, J48, and SVM. The outcomes demonstrated that the suggested approach achieved a range of identification accuracy between 93.8% and 97.8% for all processed databases, indicating its effectiveness in enhancing ear recognition accuracy.

- N Sathisha et al. [25] proposed an automated ear recognition system that utilizes the (SIFT) technique and an Artificial Neural Network (ANN). The proposed system includes a pre-processing stage where the input images are converted to grayscale and the ear edge is detected using the canny algorithm. Subsequently, the SIFT method is employed to extract the crucial ear features from the pre-processed sample, and the obtained characteristics are classified using ANN. The outcomes indicate that the suggested approach outperforms existing methods and achieves an accuracy of 94%.

3.2. Deep Learning Features

Deep learning is an artificial intelligence (AI) paradigm that employs multiple layers to gradually comprehend the underlying data. Recently, there has been a surge of interest in exploring the application of deep feature extraction to ear images. Notably, deep learning methodologies have been rapidly evolving and have become a popular approach for data-driven learning across diverse computer vision tasks. These techniques integrate traditional procedures by incorporating feature extraction and classification into an end-to-end model. A prominent example of a deep learning model for feature learning is Convolutional Neural Networks (CNNs). Additionally, various techniques have been proposed to further enhance deep learning, which are detailed below:

- Ibrahim et al. [26] proposed an innovative approach for human ear identification, which entails the combination of hierarchical deep features. First, the work uses a (CNN) pre-trained on a sizable dataset to extract hierarchical deep features from images of ears. Discriminant correlation analysis (DCA) is used to combine deep features from several layers, which further improves feature representation and lowers high dimensionality. The authors compose paired samples and use a pairwise (SVM) to solve the ear identification problem in order to convert it to binary classification due to the limited amount of ear images per participant. The suggested method is evaluated on four publicly available databases: USTB1, USTB2, IIT Delhi1, and IIT Delhi2. The best accuracy rate is 99.5% with IIT Delhi I .

- Nursuriati et al. [27] presented a novel methodology for gathering ear images under varying levels of uniform illumination, measured in lumens or lux, ranging from 2 lux to 10,700 lux. In total, 1,100 images of both left and right ears from 55 participants were taken using natural lighting. In order to generate a sufficient quantity of data for (CNN) training, the ear images were rotated at 5-degree intervals, resulting in 25,300 images. Each participant's dataset was divided such that 50 images were allocated for validation and testing purposes, while training was done with the remaining pictures. The suggested CNN model was then trained from scratch, and the results of the validation and testing showed that the recognition accuracy was 97%.

- Samuel et al. [28] presented a method that uses deep neural networks (DNNs) and transfer learning to recognize unconstrained ears. The approach involves using existing DNNs as feature extractors to generate effective ear recognition features, which are then utilized by a shallow classifier. To improve performance, small image transformations are introduced to augment the training dataset. The research also discusses the problem of over-fitting because of the small dataset size and compares feature-extraction models' effectiveness with modified networks' performance. In order to reduce the impact of over-fitting, a deep learning-based averaging ensemble is presented. The AWE, CVLE, and combined AWE + CVLE datasets are used to evaluate the proposed technique. Thus, the accuracy obtained for all three datasets is 85.00%, 99.69%, and 93.48%, respectively.

- Ali et al. [29] proposed a transfer learning was applied to the widely-used Alex Net (CNN) to recognize human individuals based on ear images. The Alex Net CNN was customized and refined to address the specific problem domain, including the substitution of the final fully connected layer to enable the recognition of 10 classes instead of the original 1000 classes. An additional Rectified Linear Unit (ReLU) layer was also incorporated to improve the network's non-linear problem-solving capabilities. The refined network was trained using a dataset of 250 ear images obtained from 10 subjects for training, while 50 ear images were used for validation and testing. The results indicate that the proposed refined network achieved exceptional performance in the target application, with a validation accuracy of 100%.

- Fevziye et al. [30] explored the challenge of unconstrained ear recognition, focusing on the crucial role of domain adaptation when using deep CNN models. To facilitate domain adaptation, created a novel ear dataset, called the Multi-PIE ear dataset, by leveraging the Multi-PIE face dataset. Moreover, to enhance the classification performance, integrated various DCNN models. A comprehensive analysis was conducted to investigate the impact of different factors, such as illumination and aspect ratio, on the quality of ear image recognition. Furthermore, we addressed the issue of dataset bias in ear recognition by conducting experiments on the UERC dataset. The results reveal that domain adaptation leads to a significant improvement in performance. Specifically, applying domain adaptation to the VGG-16 model led to a notable increase of approximately 10%, and combining various deep convolutional neural network models further enhanced the accuracy by 4%. Additionally, the experiments demonstrate that image quality significantly influences the results. Notably, our investigation of dataset bias revealed that could classify the dataset from which an ear image originated with 99.71% accuracy.

- William et al. [31] proposed a novel ear detection system that utilizes multiple CNN and a detection grouping algorithm to identify ear presence and location in input images. The performance of the proposed system has been evaluated against other existing methods using clean and purpose-shot photographs. The outcomes indicate that the suggested approach outperforms existing methods, achieving a comparable accuracy of upwards of 98%. These findings suggest that the proposed ear detection system may be a promising approach for ear detection tasks in various practical applications.

- Harsh et al. [32] proposed a novel deep learning-based solution for ear localization and recognition. The suggested system comprises Histograms of Oriented Gradients (HOG) for ear localization, SVMs for ear recognition, and CNNs for ear classification. The suggested method overcomes difficulties, including fluctuations in illumination, contrast, rotation, scale, and position by combining feature extraction and recognition tasks into a single network, on the USTB III database, where CNNs technology produced an average recognition accuracy of 97.9%. These results indicate that the proposed approach holds promise for biometric recognition applications.

- Arkadiusz et al. [33] proposed a technique in geometric deep learning (GDL) that extends (CNNs) to non-Euclidean domains. The proposed approach specifies convolutional filters using the Gaussian mixture model (GMM) in continuous space, allowing for easy rotation without additional interpolation, resulting in systems with rotation equivariance properties. The effectiveness of this approach is demonstrated through the problem of ear detection, an important task in biometric human identification. The study shows a relatively simple model with reduced information on image content, in comparison to classic CNNs. Thus, the best accuracy obtained is 98.22 %.

- Hammam et al. [34] proposed an innovative method to recognize individuals based on ear images using deep convolutional neural networks (CNNs), which make use of network architectures similar to the Visual Geometry Group (VGG) for feature extraction from ear images. The suggested system is created by using random weight initialization to train multiple networks with increasing depth on images of ears. Also, pre-trained models are tested for their capacity to extract features before being fine-tuned on ear pictures. To further enhance recognition performance, ensembles are created using top-performing models. Using ear images collected from controlled and uncontrolled situations across several datasets, including the recently introduced AMI cropped (AMIC) dataset is carried out to assess the proposed method. The results demonstrate that the achieving significantly higher accuracy rate is 99.29%.

- Susan et al. [35] proposed a system of human recognition from ear pictures. looked specifically for a suitable convolutional neural network architecture for the task of ear recognition. In order to do this, the performance of four different network architectures Alex Net, Squeeze Net, Google Net, and MobileNetV2 was studied. Using transfer learning, data augmentation, and domain adaptation strategies improves learning given the scarcity of training data. Overall, this study offers a significant understanding of the applicability of various convolutional neural network architectures for ear detection and illuminates the difficulties involved in identifying ears in various positions. The findings show that Mobile NetV2 has a 95.67% accuracy rate, which is a noticeably higher rate.

- Ramar et al. [36] proposed a brand-new six-layer deep convolutional neural network architecture for ear recognition. The IITD-II and AMI ear datasets are used to assess the effectiveness of the proposed deep network. With these datasets, the recognition rates are attained by the deep network model of 97.36% and 96.99%, respectively. Additionally, the AMI Ear dataset is used to evaluate the proposed system's robustness in an uncontrolled setting. When used in conjunction with an adequate surveillance system, this approach can have substantial practical consequences for locating specific people among a huge crowd.

- Ahmed et al. [37] proposed a Faster Region-based Convolutional Neural Network (Faster R-CNN), a deep learning object detection framework, for the detection of ears. Feature extraction was accomplished via the utilization of a Convolutional Neural Network (CNN). Subsequently, feature reduction was achieved through (PCA), while feature selection was achieved via the employment of a genetic algorithm. Finally, a fully connected (ANN) was used as a matcher. The results of the testing phase indicate a recognition rate obtained is 97.8%.

- Yanmin et al. [38] proposed a block diagram for recognizing the ear of a human based on a pre-trained deep learning model utilizing migration learning methodology. Specifically, the study aimed to address challenges associated with multi-posture variations, changes in contrast, translation and rotation motions, and occlusion. To achieve this, simulation trials using the CCU-DE small sample database and multiple deep learning models, including YOLOv3, YOLOv4, YOLOv5, Faster R-CNN, and SSD. The best recognition rate obtained is 98%.

- Maha et al. [39] proposed two distinct approaches for the classification of ear images. In the first method, features were taken from the discrete curvelet transform and sent to a classifier using a traditional machine-learning strategy. Image preprocessing methods were used for picture improvement and segmentation before feature extraction. In particular, the segmented ear images were wrapped with the curvelet transform after the ear region had been first picked from the background. The coarse image was divided into blocks after investigating various curvelet transform levels. Each block's mean, variance, and entropy were determined, and the similar statistical properties derived from the sub-images at various levels were concatenated with them to create a feature vector. The ensemble classifier was the only classifier that could give results that were competitive after receiving the feature vector for ear recognition. In the second strategy, deep learning techniques were used to categorize photos of ears. To classify the ears, characteristics from various end-to-end networks were retrieved and then sent to a shallow classifier. The recognition rate achieved is 99.4%.

- Solange et al. [40] proposed a novel dataset by augmenting the pre-existing VGGFace dataset. Subsequently fine-tuned deep learning models that were pre-trained on this dataset, and investigated their sensitivity to various covariates present in the data. Additionally, explored the efficacy of a score-level fusion technique in enhancing the overall recognition performance of these models. To this end, conducted open-set and close-set experiments using both the proposed dataset and the challenging Unconstrained Environments for Recognition Challenge (UERC) dataset. The results of the analysis indicate a statistically significant improvement of approximately 9% in recognition performance when employing pre-trained face models compared to general image recognition models. Furthermore, the integration of scores from both types of models led to an additional 4% increase in recognition accuracy and reached 98.10%.

- T. Ebanesar et al. [41] proposed a novel and efficient method for ear-based recognition utilizing (CNN) technology. This non-intrusive approach capitalizes on the unique features of the person's ear, which is one of the most common biometric markers utilized for individual identification. The suggested system comprises two parts, namely ear detection and ear recognition (authentication and identification). The current investigation employs the AMI dataset, captured using a Nikon D100 camera. The pre-processing stage involves converting the two-dimensional images into a one-dimensional space, followed by classification, recognition, and detection using the (LBP) method. Histogram analysis is used to obtain more discriminatory features. This system employs a CNN-based model that enhances the security level of the ear biometric system. The results show an overall accuracy rate of 98.99%, signifying the potential of the proposed methodology in advancing biometric security.

- K. R. Resmi et al. [42] proposed a method to assess the impact of splitting left and right ear images and the influence of occlusion on recognition accuracy in the AWE dataset. Asymmetry between the left and right ear images of a person is common, hence warranting a systematic evaluation of each ear separately. The investigation employed a pre-trained ResNet50-based model to evaluate the recognition accuracy of the left and right ear images. The outcomes demonstrate a noteworthy improvement in accuracy when the left and right ear images are processed independently. Moreover, a novel data augmentation approach is proposed that incorporates occlusion, which was evaluated using the ResNet50-based model. The results reveal that the accuracy rate for the right ear is 80%, while that for the left ear is 77.33%. These findings provide evidence of the effectiveness of separating left and right ear images and the value of using occlusion in enhancing recognition accuracy in biometric identification systems. The accuracy rate for all dataset is 63.00%.

Table 1 shows the results obtained from previous studies in terms of the number of persons, the total number of ear images, the accuracy rate value, and the recognition rate value.

Table 1 - Summarized the results of previous research work.

References	Person No.	Total Ear Images	Accuracy%	CRR%
[11] (2014)	75	750	-	98%
[12] (2014)	125	493	97.77%	-
[13] (2015)	125	375	%100	-
[14] (2015)	77	308	94.2%	-
[15] (2016)	DB1= 60	DB1= 180	DB1= 98.33%	-
	DB2=125	DB2= 375	DB2= 99.60%	-

[16] (2016)	DB1= 125	DB1= 375	DB1= 95.2%	-
	DB2= 100	DB2= 700	DB2= 100%	-
[17] (2016)	55	460	-	98.9%
[18] (2016)	60	180	97.32%	-
[19] (2017)	125	375	88.0%	-
[20] (2018)	DB1= 501	DB1= 2071	DB1= 57%	-
	DB2= 90	DB2= 3330	DB2= 100%	-
[21] (2018)	100	700	80%	-
[22] (2019)	25	150	86 %	-
[23] (2021)	25	250	92%	-
[24] (2022)	166	2304	97.8%	-
[25] (2022)	125	375	94 %	-
[26] (2018)	125	375	99.5%	-
[27] (2018)	55	1100	97%	-
[28] (2018)	DB1= 100	DB1= 1000	DB1= 85.00%	-
	DB2= 16	DB2= 804	DB2= 99.69%	-
	DB3= 116	DB3= 1804	DB3= 93.48%	-
[29] (2018)	10	1000	100%	-
[30] (2018)	166	2304	99.71%	-
[31] (2019)	100	700	98%	-
[32] (2019)	79	785	97.9%	-
[33] (2019)	126	4429	98.22 %	-
[34] (2019)	100	700	99.29%	-
[35] (2019)	3706	11804	-	95.67%
[36] (2020)	DB1= 125	DB1= 375	-	DB1= 97.36%
	DB2= 100	DB2= 700	-	DB2= 96.99%
[37] (2021)	65	534	-	%97.8
[38] (2022)	80	330000	-	98%
[39] (2022)	100	700	-	99.4%
[40] (2022)	100	700	98.10%	-
[41] (2022)	100	600	98.99%	-
[42] (2023)	100	1000	63.00%	-

4. Discussion

The review of human recognition using ear features highlights the potential of ear biometrics as a reliable and accurate means of human identification. However, the field still faces several key issues that need to be addressed for its widespread adoption. In this discussion section, we will address these issues and suggest new directions for future studies in this field. One of the main issues that need to be addressed is the lack of standardization in ear feature extraction and recognition algorithms. There are currently many different algorithms being used, and this can lead to inconsistencies in results. To address this issue, future studies should focus on developing standardized algorithms that can be used across different datasets and applications. Additionally, efforts should be made to improve the accuracy and robustness of these algorithms, especially in challenging conditions, such as low-quality images or noisy environments.

Another issue that needs to be addressed is privacy concerns. With the growing use of biometric technologies, there is a need to ensure that individuals' privacy is protected. Future studies should focus on developing privacy-preserving ear recognition systems that do not store personal information or biometric data in centralized databases. Additionally, these systems should have robust security features to prevent unauthorized access or misuse of the data. Another area of concern is the lack of diversity in the datasets used to train and evaluate ear recognition algorithms. Most datasets currently available have limited diversity in terms of ethnicity, age, and gender. Future studies should focus on developing more diverse datasets to ensure that ear recognition algorithms are inclusive and do not lead to bias or discrimination.

Lastly, future studies should focus on exploring the potential of ear biometrics in real-world applications beyond security and law enforcement. For instance, ear recognition technology can be used in healthcare for patient identification, in retail for personalized marketing, or entertainment for customized user experiences. More research is needed to explore these potential applications and to develop specialized algorithms that can perform well in these contexts.

5. Conclusion

In conclusion, ear biometrics has great potential as a reliable and accurate means of human identification. However, several key issues need to be addressed to ensure its widespread adoption. Future studies should focus on standardization, privacy, and diversity, and explore potential applications beyond security and law enforcement. Addressing these issues will pave the way for a more inclusive and ethical use of ear biometrics in various domains. In particular, the present study provides a comprehensive survey of various approaches for identifying individuals through ear-based features, highlighting opportunities for further advancement despite the existence of several established methods for ear image recognition. Thus, the process of identifying humans based on ear features is done by using manually-crafted features such as DCT, DWT, DFT, PCA, LBP, SURF, SIFT, etc., and deep-learning approaches such as CNN, DNN, Alex Net CNN, VGG-16, SVM, Squeeze Net, Google Net, Mobile NetV2, etc.

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