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Review

A Systematic Literature Review on Human Ear Biometrics: Approaches, Algorithms, and Trend in the Last Decade

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Abstract: Biometric technology is fast gaining pace as a veritable developmental tool. So far, biometric procedures have been predominantly used to ensure identity and ear recognition techniques continue to provide very robust research prospects. This paper proposes to identify and review present techniques for ear biometrics using certain parameters: machine learning methods, and procedures and provide directions for future research. Ten databases were accessed, including ACM, Wiley, IEEE, Springer, Emerald, Elsevier, Sage, MIT, Taylor & Francis, and Science Direct, and 1121 publications were retrieved. In order to obtain relevant materials, some articles were excused using certain criteria such as abstract eligibility, duplicity, and uncertainty (indeterminate method). As a result, 73 papers were selected for in-depth assessment and significance. A quantitative analysis was carried out on the identified works using search strategies: source, technique, datasets, status, and architecture. A Quantitative Analysis (QA) of feature extraction methods was carried out on the selected studies with a geometric approach indicating the highest value at 36%, followed by the local method at 27%. Several architectures, such as Convolutional Neural Network, restricted Boltzmann machine, auto-encoder, deep belief network, and other unspecified architectures, showed 38%, 28%, 21%, 5%, and 4%, respectively. Essentially, this survey also provides the various status of existing methods used in classifying related studies. A taxonomy of the current methodologies of ear recognition system was presented along with a publicly available occlussion and pose sensitive black ear image dataset of 970 images. The study concludes with the need for researchers to consider improvements in the speed and security of available feature extraction algorithms.

Keywords: biometric technology; ear recognition systems; feature extraction; classification methods; convolutional neural network; restricted Boltzmann machine

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Citation: Oyebiyi, O.G.; Abayomi-Alli, A.; Arogundade, O.'T.; Qazi, A.; Imoize, A.L.; Awotunde, J.B. A Systematic Literature Review on Human Ear Biometrics: Approaches, Algorithms, and Trend in the Last Decade. *Information* **2023**, *14*, 192. https://doi.org/10.3390/info14030192

Academic Editors: Jose de Vasconcelos, Hugo Barbosa, Carla Cordeiro and Alessandra Lumini

Received: 19 December 2022
Revised: 13 March 2023
Accepted: 15 March 2023
Published: 17 March 2023

1. Introduction

Globally, over 1.5 billion people are without proper identification proof [1]. Establishing a person's identity, together with connected privileges, is an increasing source of concern for governments all over the world, as it constitutes a major requirement for the attainment of Sustainable Development Goals (SDG).

A formal means of personal identity verification is a primary requirement in modern societies. The inability to establish one's identity can significantly hamper access to basic rights, government, and other essential services. The task of effectively identifying an individual involves the use of biometrics technology. Biometric recognition involves using specialized devices to capture the image of an individual's feature and computer software to extract, encrypt, store, and match these features [2]. It typically involves the use of unique features such as the face, ear signature, gait, voice, fingerprint, etc., for automatic computerized identification systems.

A biometric system is principally a pattern recognition system that obtains biometric data from an individual, mines a feature set from the data acquired, and compares this feature set against the stored template in the database [3].

Computer-based biometric systems have become available primarily due to increasing technological sophistication and computing capabilities. The face is a prominent example of an innate human biometric used for identification [4]. It is a major feature for identification due to its uniqueness [5]. However, an upward surge in the global population coupled with cultural diversities makes effective identification more profound, particularly as traditional identification such as passwords, locks and pin codes are gradually becoming vulnerable to theft, sabotage, or loss hence the need for more reliable traits like the ear [6]. The recent global pandemic caused by the novel corona virus (COVID-19) has led to the compulsory use of face masks in public [7]. Consequently, this new dressing standard poses a serious challenge to facial recognition in public [8]. Further still, the challenge is further emphasized in the performance of recognition systems, particularly in surveillance scenarios, because the masks have occluded a large portion of the face [9] and have made the attention to ear recognition research even more important. Although strategies for ear recognition systems (ERS) were long conceived, actual implementation did not occur until much later [10]. Ear images are a promising feature that has been lately advanced as a biometric resource [11]. For instance, the human ears have an immediately foreseeable background, and scholarly work on the symmetric features of the human ear has continued to generate new interest [12]. For instance, structural features of the human ear abound, thereby making it readily suitable for robust processing and applications. Not only does the ear represent an unchanged biometric trait over time, but it also possesses characteristics applicable to every individual, such as distinctiveness, collectability, universality, and permanence [13].

The advantages of the external ear as a biometric feature include:

1. Fewer inconsistencies in ear structure due to advancement in age compared with a face.
2. Reliable ear outline throughout an individual life cycle.
3. The distinctiveness of the external ear shape is not affected by moods, emotions, other expressions, etc.
4. Restricted surface ear surface area leads to faster processing compared with a face.
5. It is easier to capture the human ear even at a distance.
6. The procedure is non-invasive. Beards, spectacles, and makeup cannot alter the appearance of the ear.

In summary, this study aims to conduct a Systematic Literature Review (SLR) on human ear biometric and recognition systems. The emphasis is on the contributions of deep learning to improving and enhancing ear recognition system performance vis-a-vis traditional machine learning methods. Subsequent sections of this paper are organized as follows: Section 2 highlights the sequence, search methods, and other strategies used in this study. Results obtained are presented in Section 3, with a follow-up discussion in Section 4. Lastly, Section 5 highlights the research outcomes and challenges and presents a current taxonomy of the ear recognition system.

2. Research Method

Research studies on human ear biometrics abound. These studies, mostly digital, were scientifically analyzed using quantitative methods to highlight significant trends and developments in ear recognition systems. The search procedure used in [1] was adopted and used for this study to provide answers to the following research questions:

RQ1: What is state of the art in ear recognition research?

RQ2: What has deep learning contributed to ear recognition in the last decade?

RQ3: Is there sufficient publicly available data for ear recognition research?

The research questions though intertwined motivates conducting this SLR.

2.1. Search Attributes

The methods of human ear recognition can be roughly divided into traditional and methods based on deep learning, [14] with studies particularly more inclined towards the latter.

Biometrics has, over time, evolved to include deep learning of artificial neural networks (ANN), [15]. Deep Convolutional Neural Networks are mathematical models that simulate the functional attributes of human biological neural networks [16]. They represent multiple data layers with multiple abstraction stages through learning to generate precise models autonomously [17]. Research into ear recognition using neural networks with varying performances has been in existence for a while. Several variants of ANN, such as the convolutional neural network (CNN) are applicable in advancing various biometric modalities. Studies suggest that approaches applying CNN epitomize state-of-the-art performance in object detection, segmentation, and image classification, particularly in unconstrained settings [18].

One of the initial efforts at the neural network for ear recognition was described by [19], which employed local binary patterns and CNN with a recognition accuracy of 93.3%. Recent advances in CNN for developing verification and identification systems have considerably pushed the development of image classification and object detection [20]. It combines a large set of parameters than traditional neural networks, thereby generating improved performance [16].

2.2. Search Queries

In other to obtain a robust and comprehensive collection of related articles that have significantly contributed to ERS, the following search criteria were used:

1. Boolean operators of "OR or "AND" to retrieve data.
2. Keywords generated from the research question as search parameters.
3. Restriction to some publication types and publishers.
4. Identifiers from related work.

Search results displayed outcomes with keywords and Boolean combinations such as (human ear) AND (deep convolutionary network (OR) biometrics), (Identification (OR) recognition (OR) deep-learning (OR) feature extraction). A logical procedure of review of the contributions of neural networks to ERS was conducted through a numerical assessment to identify innovative patterns, methods, and techniques in the ear recognition domain. Table 1 indicates the number of articles downloaded from respective indexed databases.

Table 1. Articles downloaded from indexed database.

S/n	Digital Library	No. Articles	Percentage (%)
1	Taylor & Francis	89	7.9
2	Science Direct	157	14
3	IEEE	255	22.7
4	Emerald	48	4.2
5	ACM	73	6.5
6	Sage	55	4.9
7	Springer	201	17.9
8	Elsevier	137	12.2
9	Wiley	45	4.0
10	MIT	61	5.4
	Total	1121	100

Search Stage 1 (Information Extraction): an in-depth search of seven electronic databases showed an initial total article count of 1121 and was further subjected to a careful selection process.

Search Stage 2 (Screening): after the removal of 784 duplicate and 245 irrelevant articles/works of literature, a residual quantity of 92 was obtained for onward analysis.

Search Stage 3 (Eligibility Determination): in obtaining appropriate articles relevant to the study, 92 articles were shortlisted. Subsequently, 18 articles were dropped for lack of clear-cut methodology.

Search Stage 4 (Inclusion): in-line with the research aim, the Authors conducted a quality check for the residual articles and concluded on 74 for further systematic review.

The summary of the search procedure from stage 1 (information extraction), stage 2 (screening), stage 3 (eligibility determination) to stage 4 (inclusion) are represented in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flowchart in Figure 1. Preliminary results from search criteria were obtained from Google Scholar, Scopus, Springer, Science Direct, ACM, Emerald, and IEEE explore databases using a search criterion of publications not later than ten (10) years.

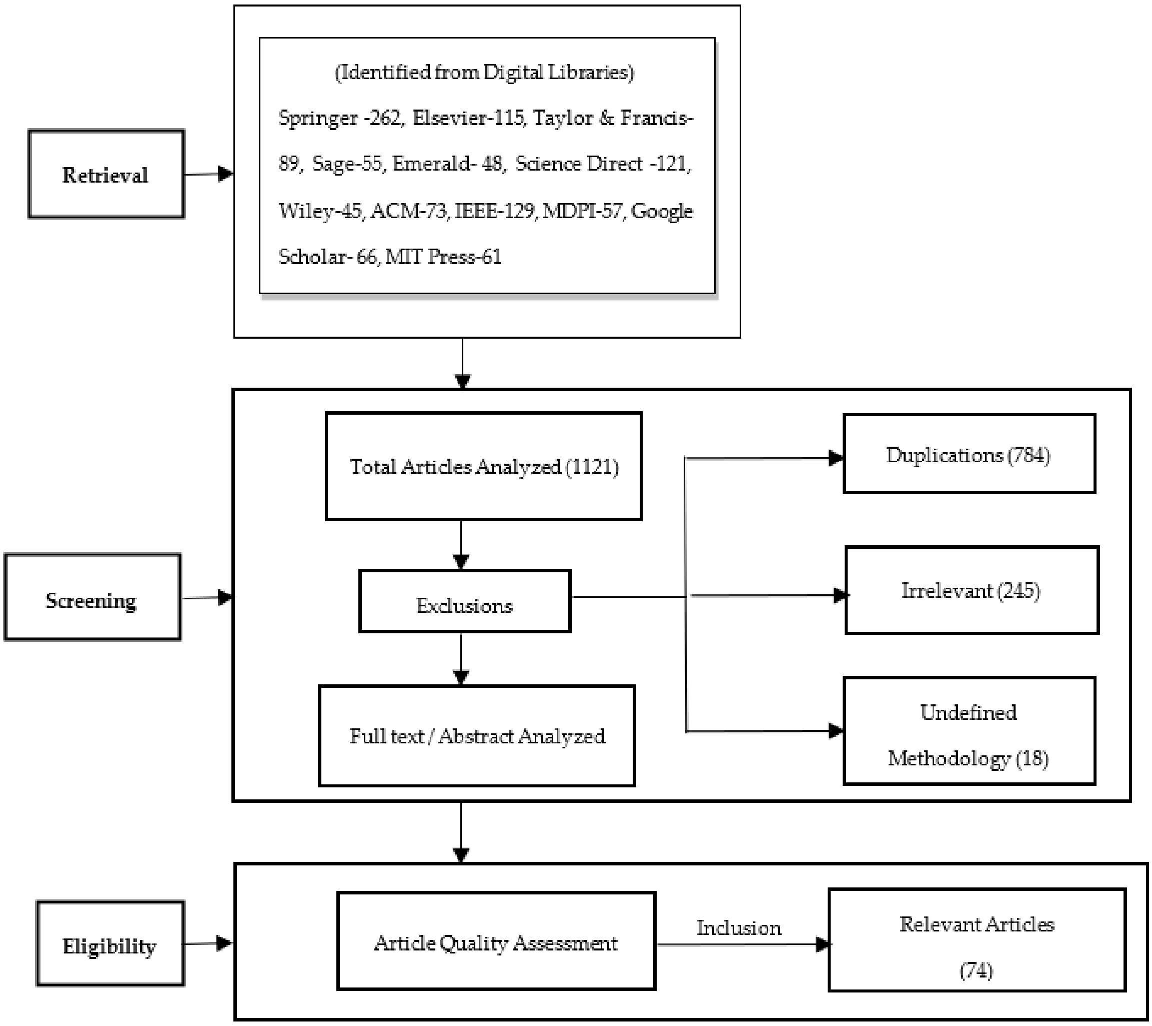

Figure 1. PRISMA flow chart for the search procedure.

2.3. Search Strategy

After a preliminary assessment of requirements suitable for answering the research questions, a predominance of varied knowledge repositories ranging from journal articles, online blogs, and bulletins to book chapters were returned. Five (5) main sources which include journals, conferences, workshops, book chapters and original thesis were selected for the review. A total of 74 articles were carefully selected based on relevance with 52 journal articles, 9 conference proceedings, 5 workshop reports, 5 theses and 3 book chapters.

2.4. Article Source (AS)

Ten (10) electronic databases, including Taylor & Francis, Springer, Elsevier, Emerald, Wiley, Science Direct, IEEE, ACM, Sage, and MIT, provided data for extraction using keywords and related terms in the study. The sources include workshops, conference proceedings, journal publications, original thesis, and book chapters.

2.5. Ear Databases

This section presents a review of databases used in ear detection and recognition. Ear databases are crucial in developing and evaluating ERS and algorithms. Existing databases are in different sizes with varied factors of influence ranging from illumination to the angle of the pose. A summary of existing databases used in ear recognition research studies is presented in Table 2. A number of these databases are either publicly available or can be acquired under license.

Table 2. Existing ear recognition research databases.

S/n	Catalogue	Year	Total Images	Sides	Volunteers	Description	Available
1	VGGFace-Ear	2022	234651	both	660	Iner and intra subject variations in pose, age, illumination and ethnicity.	Free
2	UERC	2019	11000	Both	3690	Three image datasets to train and test images under varied parameters	Free
3	EarVN1.0	2018	28412	N/A	164	Images captured under varied pose, illumination, and occlusion conditions	Free
4	USTB-HELLOEAR (A)	2017	336572	Both	104	Pose variations	Free
5	USTB-HELLOEAR (B)	2017	275909	Both	466	Left and right images captured in uncontrolled conditions	Free
6	WebEars	2017	1000	N/A	N/A	Images captured under varied conditions	Free
7	HelloEars	2017	610000	Both	1570	Images captured in a controlled environment	Free
8	AWE	2016	1000	Both	100	Images captured in the wild in an uncontrolled environment	Free
9	UND	2014	NA	Both	N/A	Different image collections with varied images captured in 3D.	Free
10	XM2VTS	2014	4 Footages	Both	295	32 khz 16-bit audio/video files	Not Free
11	UMIST	2014	564	Both	20	Head rotation from the left-hand side to the frontal view	Free
12	UBEAR	2011	4497	Both	127	Images captured in an uncontrolled environment with different poses and occlusion	Free
13	WPUT	2010	2071	Both	501	Varied illumination	Free
14	YSU	2009	2590		259	Angle images between 0 and 90	Free
15	IIT Delhi	2007	493	Right	125	3 Images taken indoor	Free
16	WVU	2006	460	Both	402	2 min audio-visual from both sides	Free
17	USTB (4)	2005	8500	Both	500	15-degree differences using 17 cameras	Free

Table 2. *Cont.*

S/n	Catalogue	Year	Total Images	Sides	Volunteers	Description	Available
18	USTB (3)	2004	1738	Right	79	Dual images at 5-degree variation till 60.	Free
19	USTB (2)	2003	308	Right	77	Varying degrees of illumination at +30 and −30 degrees	Free
20	USTB (1)	2002	180	Right	60	Different illumination conditions at a trivial angle	Free
21	UND (E)	2002	942	Both	302	Both 2D and 3D pictures	Free
22	UND (F)	2003	464	Side	114	Side profile appearance	Free
23	UND (G)	2005	738	Side	235	2D and 3D pictures	Free
24	UND (J2)	2005	1800	Both	415	2D and 3D pictures	Free
25	IITD	2007	663	Right	121	Greyscale images with slight angle variations.	Free
26	PERPINAN	1995	102	Left	17	Images with minor pose variations captured in a controlled environment	Free
27	AMI	NA	700	Both	100	Fixed Illumination	Free
28	NCKU	N/A	330	Both	90	37 images for each respondent	Free

2.6. Methods of Classification

The techniques of ear recognition can be grouped into four broad categories: hybrid, geometric, holistic, and local methods [10].

2.6.1. Geometric Approach

Research on geometric tendencies of the human ear dates to early 1890, when a French researcher, Alphonse Bertillon, suggested the potential of the human ear in identifying subjects [21]. Additional improvements using geometric features promoted the development of a Voronoi illustration with adjacency graphs [22].

The geometric method involves the extraction and analysis of geometric features of the human ear. These ranges from canny edge detection and contours to statistical features [23]. Ear image edges are computed after noise reduction using a Gaussian filter in canny edge detection. Edges are then connected to generate a pattern [24]. The contours of the ear start and end points are also useful information sources applicable in generating ear features and recognizable patterns [25]. Other feature-based statistical methods present ear images using parameters such as ear height, width, and angles between ear portions [26]. The work [27] presents a detailed taxonomy of ear features used for recognition by both machines and humans, such as texture, structure, and details. Typical texture-related features include ear type, skin colour; ear size, and shape, all extractable using linear discriminant analysis and principal component analysis algorithms. Ear features also use more prominent methods like local binary pattern [28], SIFT [29], and Gabor filters [30], on ear structures such as lobes, contours, and folds of the ear to represent the distinctiveness of the ear.

However, distortion invariant methods in ear geometry make only the required details available, thereby making this approach over-dependent on edge detectors such that only geometric ear information is considered with little emphasis on texture information.

2.6.2. Holistic Approach

In the holistic method, the overall stance of the ear is used to calculate input representations. It provides reasonable performance, particularly for suitably processed images. Hence, the approach requires normalization procedures before the extraction of desired features to ensure quality performance.

In this study, several studies on holistic techniques were reviewed. Ref. [31] conducted preliminary research on Force Field Transformation (FFT) for automatic ear recognition and returned a recognition rate of 99% on about 252 images in the XM2VTS database. Ref. [32] furthered the application of FFT with the underlying principle of Newton's law of gravitation to consider symmetric image pixels.

Experiments on the USTB IV database by [33] registered a comparatively low recognition rate of 72.2%. Gabor filters are also capable of identifying detailed texture data. When fused, its recognition accuracy varies between 92.06% and 95.93% [32]. Dimensionality reduction techniques such as PCA [31,34], ICA [35] and matrix factorization [36], feed higher-dimension vectors into lower dimensions while retaining their distinct features. Selected wavelet coefficients were used by [37] in repeated steps to represent features of ear images from the IITK database with a stated recognition accuracy of 96% [38] in their experiment on the UND and FEUD databases identified the suitability of sparse representations in changing degrees of illumination and pose.

In [39], numerical methods were used in composing six varied feature vectors that serve as feedback for a back propagation neural network for classifying moment invariant feature sets.

2.6.3. Local Approach

The local method depends on local areas of certain locations in an image to the extent of encoding texture details such that the region of interest does not automatically match structurally significant parts. Studies such as [40] present SIFT as a robust algorithm suitable for feature extraction under changing conditions. For instance, SIFT can accommodate variants in the pose for about 20 degrees [32]. Generally, assigning landmarks to ear images before training ensures proper filtering and matching operations in the local technique. Though SIFT landmarks have been very high such that obtaining an exact assignment is experimentally impossible, [41] attained a recognition rate of 91.5% with the XM2VTS database with possibilities for further improvements to 96%. Subsequent studies by [42] decomposed ear images into distinct colour segments with a reduced error margin that identifies and calculate unique identifiers for each key point detected. Unlike other approaches, local descriptors have varying degrees of complexity and are often combined with hybrid techniques to provide further reliable results in ear recognition [43].

2.6.4. Hybrid Approach

The hybrid technique involves the use of multiple parameters to improve the performance of recognition systems [5]. Edge models are initially generated from training images before adjustments into actual edges, as shown in [44]. Similarly, a fusion of Tchebichef moment descriptors and the triangle ratio method was experimentally determined in [45], while [46] achieved a recognition accurate of 99.2% in the USTB II database.

The study of [47] famously combined PCA and wavelets, while [39] opted for a fusion of Haar wavelet and LBP. The sparse representation algorithm by [48] was used on gray-level positioning features before initial dimension reduction procedures with LDA by [49]. In wavelet transforms, coefficient thresholds are required to obtain feature vectors that are particularly useful in the recognition and identification systems [50].

2.7. Ear Recognition Stages

In ear recognition systems, ear images are captured using a specific device. The images are then subjected to a preliminary stage of determining potential regions of interest using algorithms before being processed by a classifier, where details are enhanced before further procedures [51]. Essentially, the stages required in ear recognition are highlighted below:

2.7.1. Pre-Processing

This is the first step in ensuring the usability of acquired images. It involves the removal of unwanted background information (noise) before further processing. The techniques used are divided into intensity and filter methods.

Intensity Method: Analysing coloured images for edge and feature detection can be very complex [23]. Hence, a 3-conduit (RGB) image is often reduced to a single pathway (grayscale) to minimize complexity [52]. A method of spreading image intensity across a histogram, known as histogram equalization, is also sometimes applicable.

Filter method: In the filter method, noise reduction and feature enhancements are achieved using fuzzy technology [24]. Mean or median and Gaussian and Gabor filters are prominent examples of achieving a similar purpose.

2.7.2. Feature Extraction

The task of reducing the dimensions of an image for proper identification is known as feature extraction [53]. The features of an image must be precisely and correctly extracted using certain constituents of ear images, such as texture, colour, and shape. Subsequently, research parameters have been established to further determine the performance of recognition systems [9].

2.7.3. Classification

The classification or authentication stage is the final stage in the recognition process, where the feature set of the probe image is compared with a database image using various authentication techniques [23]. Many studies have been conducted on the stages involved in recognition of ear patterns. A summary of the common methods used by researchers for developing efficient and effective ERS is presented in Table 3.

Table 3. Summary of common methods in different stages of human ear recognition.

Pre-Processing	Feature Extraction	Decision-Making and Classification
Filter Method Log Gabor Filter [54] Gaussian filter [55] Middle filter [55,56] Fuzzy filter [24] Intensity Method Histogram equalization [53,57] RBG—grayscale [25,55]	Geometric Method Numerical technique [58] Ear contour [25] Detection of the edge [59] Appearance Based Method Descriptors of features [60] Reduction of Dimension [61] Force field Transformations [62] Wavelet Method [63]	Neural networks [64] Normalized cross-correlation [53] SVM classifier [64,65], K-Nearest Neighbours [28] Minimum Distance Classifier [50]

2.8. Deep Learning Approaches in Ear Recognition

In this study, a relationship between the most crucial stage (feature extraction) and classification techniques in relation to the volume of Authors is established.

Although deep-based schemes are often data-hungry, requiring significant processing time, several light, computationally fast variants have recently evolved [66,67].

In deep learning, more prominent feature extraction techniques include Gabor Mean [54], ANN Classifier, Haar wavelet ([50], Linear Discriminant Analysis (LDA) [68,69], Back Propagation Neural Network [70], FFT [23], Principal Component Analysis (PCA), [71], Edge-based method [12] and Voronoi diagrams [20].

Over time, the field of ear recognition has naturally developed along traditional machine learning methods, with few of its methods showing resilience to unconstrained conditions, including lightning and pose variations [69], hence inhibiting the overall performance of traditional systems.

Traditional ear detection and feature extraction methods typically rely on physiological attributes of the ear for normalization, feature extraction and classification [69,72]. For instance, in [73], training of various geometrical attributes of the ear was conducted with neural classifiers before the appearance of the inner and outer ear was suggested by [74]. Similarly, a combination of ear shape, average, centroid, and distance between pixels has been used to extract features using contour algorithms [75] geometrically. The work [58] extracted features using exterior ear edge and other local geometric features. Though these procedures appear straightforward, the performance level is often significantly low due to other salient processes involved [23].

Techniques involving subspace learning such as PCA, LDA and ICA, sometimes referred to as "Eigenears" have been experimentally determined suitably in local ear contour feature extraction [23]. More recently, The work [61] used a combination of multi-discriminative attributes and dimension reduction techniques to locally extract features of the ear. Such fusion techniques are referred to as hybrid and are usually more computationally expensive but with higher recognition performance over individual local, holistic, and geometric methods [76].

Nevertheless, traditional learning methods in ear recognition are severely hampered by more complex realities [72]. Even more interesting is the recent research focus which involves obtaining ear images in unrestrained conditions, generally referred to as in the wild. Traditional approaches to human ear recognition often rely on the preliminary processing of images, complex feature extraction, and determination of suitable classifiers [70]. These challenges have opened a new landscape as the research focus has gradually shifted to the automation of biometric identification [77].

3. Results Analysis

This section presents a discussion of search strategy outcomes to provide answers to research questions. Subsequently, different subsections are structured to highlight interpretations of the findings.

3.1. Search Strategy 1: Source

RQ1: What is state of the art in ear recognition research?

In the initial phase, a categorized search was used to identify similar articles on ERS and Neural Networks using paper titles and related keywords before developing a concluding search technique. The search for similar works was conducted for articles between 2010 and 2020 from the following sources: Springer, Elsevier, ACM, IEEE, Sage, Wiley, MIT Press, Taylor & Francis, Emerald and Science Direct. Figure 1 shows the number of relevant articles from selected sources, thus addressing RQ1.

3.2. Relevance of Publication

The 74 selected publications show that IEEE had the highest number with 15 relevant articles, followed by Springer having 12 relevant articles, Elsevier published 11, while Science Direct published 9 relevant articles. Taylor & Francis, Emerald, ACM, and Sage had 8, 8, 7 and 3 articles, respectively, while Wiley and MIT had one relevant publication each.

Ear recognition technique remains an active area of research that continues to generate diverse interest. The total number of relevant publications and the corresponding levels of citation from 2011 to 2020 is 2, 3, 5, 5, 4, 8, 7, 12, 10, and 13, respectively. Thus, confirming the steady rise in neural network techniques with the year 2020 having the highest number of relevant articles within the decade.

Although diverse methods of pre-processing, feature extraction and classification exist in the recognition process, there is an upward surge in the use of neural network methods for classification in ear recognition systems. Reasons for this might be inferred from the increasing demand for more fool proof biometric identification systems requiring large datasets and the ability of neural networks to train very large data sets autonomously.

3.3. Search Strategy 3: (Method)

Ear recognition techniques vary. Overtime, several Authors, have experimentally determined the performance of ERS using single or combined approaches on a wide array of datasets. Table 4 presents a summary of identified works containing metrics used in ear recognition.

Table 4. Summary of Performance metrics used in Traditional and Deep learning techniques in selected articles.

Traditional Learning Technique			
True Acceptance Rate [6,78–83]	Template capacity [5,84–86]	False Acceptance Rate [4,6,21,23,83,87–91]	Equal Error Rate [92–94]
Matching Speed [3,95]	Recognition Accuracy [14,15,24,28,68,85,96–105]	Recall [106–108]	Precision [40,95,102,109–111]
Deep Learning Techniques			
True Acceptance Rate [110–114]	Template capacity [115]	False Acceptance Rate [110–114].	Equal Error Rate [72,114]
Matching Speed [61,115–117]	Recognition Accuracy [70,118–121]	Recall [57,77,122–125]	Precision [126,127]

Previous studies have highlighted the numerous methods applied in the process of ear recognition, including local, holistic, geometric, and hybrid. The study on 74 existing related literature carefully selected from several works of literature [7–180] revealed that 65%, 20%, 12% and 8% of the studies employed local, hybrid, holistic, and geometric methods, respectively. Although several works of literature on ear biometrics abound, a concise summary of some existing ear recognition approaches from the list is presented in Table 5. A summary of the Pros and Cons of different sub-areas in Ear Recognition Stages is given in Table 6 in Section 4.

Table 5. Comparative summary of ear recognition approaches.

Reference.	**Year**	**Method**	**Type**	**Dataset**	**Performance (%)**
[7]	2010	PCA and NN	Holistic	UBEAR	96
[18]	2022	Deep Learning	CNN	VGGFace	NA
[23]	2019	NA	NA	NA	NA
[27]	2016	Geometric features	Geometric features	CP	88
[31]	2003	Force field transform	Holistic	Own	NA
[31]	2003	PCA	Holistic	UND(E)	71.6
[35]	2005	Matrix factorization	Holistic	USTB II	91
[38]	2008	Sparse representation	Holistic	UND	96.9
[39]	2010	Moment invariant method	Holistic	Own	91.8
[40]	2010	SIFT	Local	XM2VTS	96
[41]	2007	Combination of pre-filtered points and SIFT	Local	XM2VTS	91.5
[47]	2007	PCA and wavelet transformation	Hybrid	USTB II, CP	90.5
[47]	2007	Inpainting techniques, neural networks	CNN, Traditional learning	UERC	75
[48]	2013	SIFT	Local	CP	78.8
[49]	2014	Hybrid-based on SURF LDA AND NN	Hybrid	Own	97

Table 5. *Cont.*

Reference.	Year	Method	Type	Dataset	Performance (%)
[41]	2007	Combination of pre-filtered points and SIFT	Local	XM2VTS	91.5
[47]	2007	PCA and wavelet transformation	Hybrid	USTB II, CP	90.5
[47]	2007	Inpainting techniques, neural networks	CNN, Traditional learning	UERC	75
[48]	2013	SIFT	Local	CP	78.8
[49]	2014	Hybrid-based on SURF LDA AND NN	Hybrid	Own	97
[49]	2014	Neural networks	Deep CNN	UERC	99.7
[72]	2019	Neural Networks	CNN	AMI	75.6
[73]	1999	Orthogonal log-Gabor filter pairs	Local	IITD II	95.9
[75]	2005	Ear framework geometry	Geometric	Own	86.2
[81]	2013	Not Applicable (NA)	NA	NA	NA
[85]	2019	NA	NA	NA	NA
[87]	2019	Neural networks	CNN	-	-
[92]	2020	Deep learning	CNN	NA	97
[98]	2014	Edge image dimension	Geometric	USTB II	85
[107]	2016	CNN	Local	Avila Police School & Bisite Video	80.5 & 79.2
[107]	2013	Deep neural network	CNN	Avila Police School	84
[108]	2017	Traditional Machine Learning	YOLO, Multilayer perceptron	Own	82
[117]	2018	Maximum and minimum height lines	Geometric	USTDB&IIT Delhi	98.3 & 99.6
[119]	2018	Deep Learning	CNN	Open image dataset	85
[123]	2023	Neural networks	CNN	AMI, UND, Video Dataset, UBEAR	98
[128]	2010	PCA	Holistic	Own	40
[129]	2002	ICA	Holistic	Own	94.1
[130]	2014	Log-Gabor wavelets	Local	UND	90
[131]	2007	Multi-Matcher	Hybrid	UND(E)	80
[132]	2007	Log-Gabor filters	Local	XM2VTS	85.7
[133]	2008	LBP and Haar Wavelet transformation	Hybrid	USTB III	92.4
[134]	2008	Improved locally linear embedding	Holistic	USTB III	90
[135]	2008	Null Kernel discriminant analysis	Holistic	USTB I	97.7
[136]	2008	Gabor filters	Local	UND(E)	84
[137]	2009	Block portioning and Gabor transformation	Local	USTB II	100

Table 5. *Cont.*

Reference.	Year	Method	Type	Dataset	Performance (%)
[138]	2009	2D quadrature filter	Local	IITD I	96.5
[140]	2013	Sparse representation classification	Holistic	USTB III	90
[141]	2019	Multi-level fusion	Hybrid	USTB II	99.2
[142]	2014	Enhanced SURF with NN	Local	IITK 1	2.8
[143]	2014	Non-linear curvelet features	Local	IITD II	96.2
[144]	2014	BSIF	Local	IITD II	97.3
[145]	2014	LPQ	Local	Several	93.1
[146]	2014	LPQ, BSIF, LBP, HOG with LDA	Hybrid	UND-J2, AMI, IITK	98.7
[147]	2014	Weighted wavelet transforms and DCT	Hybrid	Own	98.1
[148]	2015	Haar wavelet and LBP	Hybrid	IITD	94.5
[149]	2016	BSIF	Local	IITD I, IITD II	96.7 & 97.3
[150]	2015	Multi-bags-of-features histogram	Local	IITD I	6.3
[151]	2015	Gabor filters	Local	IITD II	92.4
[153]	2017	Modular neural network	Hybrid	USTB	99
[154]	2018	Biased normalized cut and morphological operations	Deep Neural Network	Own	95
[155]	2018	Traditional machine learning	Local	NA	NA
[156]	2020	Deep learning	CNN	Own	95
[157]	2020	Traditional Machine Learning	Sparse Representation	USTB III	NA
[158]	2022	Traditional Machine Learning	Hybrid	IITDelhi	NA
[159]	2022	Deep Learning	SIFT and ANN	IITDelhi	NA
[180]	2022	Global and local ear prints	Hybrid	FEARID	91.3

In this study, the authors of selected articles were divided into five groups. These categories represent the level of the ERS implementation in the article in terms of if the study was based on:

1. an **assessment** of existing algorithms on a given dataset (A);
2. a **proposed** or yet-to-be-evaluated techniques (S);
3. a **designed** templates using existing procedures (D);
4. **planning and assessment** with studies based on established procedures (PA);
5. newly **proposed** and **executed** techniques (PE).

The results showed A, S, D, PA and PE returned 26, 19, 8, 9, 13 articles respectively. The details of the articles in each category is in Table 7 (see Section 4).

Results show that 25.33% of the methods used in the selected articles were suggested (proposed) and not implemented. This might not be unconnected with the availability of limited ear databases collected in unrestrained situations for experimental studies.

RQ2: What are the contributions of deep learning to ear recognition in the last decade?

At present, acceptance of deep learning techniques is increasing as it combines the traditional steps in the recognition process into single connecting models [72]. Deep learning algorithms have overcome many of the challenges associated with machine learning algorithms, particularly those associated with feature extraction techniques, while also having the ability for biometric image transformations. Consequently, attempts at ear detection using neural networks though initially limited are rapidly gaining pace. Early attempts by [160] focused on multi-class projection extreme learning machine methods to augment performance. In [10], a concise and detailed review of advances in ear detection using machine learning was presented. Geometric morphometric and Neural Networks were suggested in [57] to compare non-automated instances. Ref. [87] developed a neural network model to authenticate responses originating from the human ear with a 7.56% and 13.3% increase in identification and verification tasks, respectively.

However, variants of the neural network such as Convolutional Neural Networks (CNN) have shown remarkable performance against conventional systems [161]. The CNN design originates from [162], it is majorly a multi-layer network with capabilities to handle several invariants [169]. Subsequent experimental studies have gradually adapted its use to the recognition of specific human biometric traits. It eliminates cumbersome pre-processing procedures associated with traditional methods [163,164] and its robustness against texture and shape makes it dominant over traditional approaches [20,24].

Experimental studies by [72] compared the performance of some traditional ear recognition approaches to a variant of CNN with results above 22% of the initial descriptors. Nonetheless, ear recognition using deep neural networks is still significantly hampered by limited ear recognition databases and few experimental images leading to data augmentation [18].

RQ3: Is there sufficient publicly available data for ear recognition research?

A summary of findings from Table 2 indicates a predominance of free publicly available ear databases. This research identifies 27 publicly available datasets. Findings studies suggest the existence of publicly available ear databases since 1995, however, ear databases have grown to further accommodate different poses, angles, occlusion, and modes of collection.

Ear biometrics represents an active field of research. Nevertheless, ear image databases are very rare and usually strongly limited [165]. Further still, an absence of a unified large-scale publicly available ear database still represents a major challenge in the overall objective evaluation of ear recognition systems.

For instance, as of 2017, the reported performance of ear-recognition techniques has surpassed the rank-1 recognition rate of 90% on most available datasets [10]. This fact suggests that though technology has reached a level of maturity that easily handles images captured in laboratory-like settings, presently available ear databases are inadequate. Consequently, more challenging datasets are needed to identify open problems and provide room for further advancements.

3.4. Comparison with Related Surveys

ERS is not so popular compared to other biometric systems like fingerprints, faces, Veins, iris etc, [113]. Data augmentation of images in neural networks is often a challenging factor. Hence [166] suggested a learning method using limited datasets to train the network in ear image recognition. Similarly, Ref. [69] proposed a means of ear identification using transfer learning. Ref. [10] also recommended a mean method to improve the performance of datasets and suggested various architectures and controlled learning on previously trained datasets to develop a widely accessible CNN-based ear recognition method. In order to improve upon factors that affect image acquisition techniques such as contrast, position, and light intensity, a framework for ear localization using a histogram of oriented gradient (HOG) and support vector machine (SVM) was developed by [116] before subsequent CNN classification. A discriminant method was suggested by [61] to extract ear features in a pecking order, while [21] introduced dual images using SVM to tackle the challenge of limited images per subject. In exploring hand-crafted options, Ref. [167] combined CNN and handcrafted features to augment deep learning techniques, thus suggesting that deep learning can be complemented with other techniques.

This survey extended the review from [23], whose focus was mainly on the three core phases of ear biometric research: pre-processing, feature extraction and authentication. Consequently, a comprehensive overview of the contributions of prior research efforts is further amplified with particular emphasis on methods used for feature extraction and classification process. Despite previous reviews, this study focuses on qualitative and quantitative analysis of prevailing techniques through diverse search strategies as done in [11]. To the best of our knowledge, this study is the first to provide an in-depth novel synopsis and grouping of research approaches in ear biometric using different categories: existing approaches and methods.

Table 7 in Section 4 shows shows the predominantly used ear databases amongst several researchers from the list of reviewed articles.

A careful review of selected publications revealed some factors highlighted below as major determinants of the challenge raised in R3.

1. Poor feature selection: the application of feature selection is very diverse as it aims to reduce factors that can affect the performance of classifiers. Many images are acquired with several inherent background noises. Invariably, poor feature selection results in poor classification.
2. Hardware Dependence: A common drawback identified from selected works of literature is the resource-intensive tendencies of neural networks and other associated costs. They often require large volumes of data for training, placing heavy computational demand on processors.
3. Gaps between industry, implementation, research, and deployment: studies from reviewed articles revealed a missing link between the industries, researchers, and other stakeholders such that the majority of the related experimental studies were performed for purely academic purposes, hence limiting the potential to fine-tune existing technologies to suit user requirements.

Consequently, a need for merging research with actual deployment at user-ends is crucial in assessing the strengths and weaknesses of recognition systems and in providing relevant state-of-the-art systems capable of mitigating emerging vulnerabilities.

3.5. State of the Art in Ear Biometrics over the Last Decade

In the past few years, ear biometrics have been very prominent in achieving state of the art status applicable within the fields of human verification and identification [173]. Although poor quality images have often been a demerit, improved methods have since been developed to tackle it. Research from various authors, Refs. [181,182] have consistently explored novel approaches targeted at optimal performance of ear biometric systems. Typically, concentration on ear biometrics have been largely focused on the approaches of ear detection. This is seen from the study in [183–189]. The fundamental goal of researchers for years has been and continues to be developing ear recognition model that can overcome all detection challenges [183], but ear detection remains an image segmentation problem. In [184], deep CNN and contextual information was applied for ear detection in the 2D side of the face image. A single stage architecture was used to perform detection and classification with scale invariance. A context-provider in Context-aware Ear Detection Network (ContexedNet) developed in [190], extracts probability maps from the input image corresponding to facial element locations, and a model specifically designed to segment ears that incorporates the probability maps into a context-aware segmentation-based ear recognition algorithm. Extensive tests were conducted on the AWE and UBEAR datasets to evaluate ContexedNet, and the results were very encouraging when compared to other state-of-the-art methods. In [185], a deep learning object detector called Faster R-CNN was developed based on CNN, PCA and genetic algorithm (GA) for feature extraction, dimensionality reduction and selection, respectively. The work [186] went further to propose a deep network for segmenting and normalising ear print patterns, the model was trained using the IITD dataset.

Furthermore, the authors in [113] proposed a method for ear detection based on Faster Region-based Convolutional Neural Networks (Faster R-CNNs). On the UBEAR and UND dataset, the model was demonstrated to assure highly competitive outcomes by building on advancements in the general object detection area. El-Naggar et al. later presented a theoretically related method in [191], which once more showed the effectiveness of the Faster R-CNN architecture for ear identification. A geometric deep learning-based method for ear recognition was reported [76]. The suggested model uses Gaussian mixture models to define convolutional filters and permits the use of CNNs on graphs (GMMs). Based on this idea, the authors develop a framework for competitive detection that is both highly rotation-resistant (i.e., rotation equivariant) and has other advantageous features. Using a multi-path model topology and detection grouping, the authors [123] proposed a CNN-based method for ear detection that locates ear regions in the images. This method's core idea is to search for ears at various scales, like contextual modules seen in contemporary object identification frameworks like [192,193], to enhance detection the authors in [190] employed general object detection models with contextual modules for the job of ear detection, exploring a related approach.

The work in [187], studied ear landmarks detection while utilising the image contract, Laplace filter and Gaussian blurring techniques. Sobel Edge detector and modified adaptive search window was applied for highlighting ear edges and detecting region while [188] automatically identified the primary anatomical contour features in depth map pictures to detect the auricular elements of the ear. Ear Mask Extraction (EME) network, normalization algorithm and a novel Siamese-based CNN (CG-ERNet) was used to segment, align, and extract deep ear features, respectively in [189]. Curvature Gabor filters were used by CG-ERNet to take advantage of domain-specific information while triplet loss, triplet selection, and adaptive margin were adopted for better loss convergence.

Recent technological advancements in the field of artificial intelligence and particularly convolutional neural networks have inspired improved computer visions leading to improved detection, recognition, regression, and classification issues in ear biometrics. Some of these innovations are highlighted in [189] to include object detection methods such as F-RCNN, Mask-RCNN, SSD, VGG. Though these methods often have several non-linear layers, a myriad of parameters may be used in further training the ear recognition databases.

The work [194] employed a deep unsupervised active learning (DUAL) model to learn new features on the ear images while testing without any feedback or correction. Using conditional Deep Convolutional Generative Adversarial Networks (DCGAN) and Convolutional Neural Network (CNN) models, a framework that includes a generative model for colouring dark and grayscale images as well as a classification model was proposed in this [195]. When tested on the limited AMI and the unconstrained AWE ear datasets, the model displayed encouraging results. A quick CNN-like network (TR-ICANet) was suggested for ear print recognition in [67]. While PCA was used to geometrically normalize scale and posture, CNN was employed to detect the ear landmarks and convolutional filters were learned through an unsupervised learning method utilizing Independent Component Analysis (ICA).

Selecting and weighting characteristics has an impact on most ear identification techniques; this is a difficult problem in ERS and other pattern recognition applications [196]. The authors presented a deep CNN feature learning Mahalanobis distance metric technique. Discriminant correlation analysis was used to reduce dimensionality, Mahalanobis distance was learned based on LogDet divergence metric, and K-nearest neighbour was implemented for ear detection, various deep features are retrieved by adopting VGG and ResNet pre-trained models. In [197], unrestricted ear recognition was examined using a transformer neural network dubbed Vision transformer (ViT) and data-efficient image transformers (DeiTs). The recognition accuracy of the ViT-Ear and DeiT-Ear models was at par with previous CNN-based techniques and other deep learning algorithms. Without data augmentation procedures, ViT and DeiTs models was shown to outperform ResNets. The authors in [198], utilized Deep Residual Networks (ResNet) to create ear recognition models that acts as feature extractors in feeding an SVM classifier. ResNet was trained and improved utilizing a training corpus of various ear datasets. To improve the performance of the entire system, ensembles of networks with different depths were deployed.

A six layer deep convolutional neural network design was proposed in [199] to supplement the other biometric systems in a pandemic scenario. When deployed in conjunction with an appropriate surveillance system, the method was found to be very effective at identifying people in huge crowds in uncontrolled environments. The Particle Swarm Optimization (PSO)-based ERS was presented in [200] and evaluated with 50 photos and 150 images using the AMI EAR database. The recognition accuracy was 98% and 96.6%, respectively, which is superior to other benchmark approaches like PCA and Scale Invariant Feature Transform (SIFT).

Despite the advances in deep learning, ear recognition approaches have since grown to include bi and multi-modal methods. For instance, the works [201,202] underscores the accuracy of multimodal biometric systems in uncontrolled scenarios by integrating ear and face profile. Each biometrics' texture characteristics were extracted using a histogram-based local descriptor, local directional patterns, binarized statistical picture features, and local phase quantization. At the feature and score levels, the local descriptors from both modalities were combined to create the KNN classifier for human identification [201]. In [202], a high-dimensional feature vector was utilized to independently represent the ear and face modalities in the frequency and spatial domains utilizing local phase quantization (LPQ) and local directional patterns (LDP). To create more non-linear and discriminative characteristics for the kNN classifier's use in identifying persons, the feature set was merged with kernel discriminative common vector (KDCV). Experimental results on two benchmark datasets demonstrated that the suggested strategy outperforms individual modalities and other cutting-edge techniques in terms of performance.

3.6. Threats to Validity

Considering the related threats to the review procedures and possibly inaccurate data extraction, the highlighted papers in this review were selected based on the earlier described process. The details in Figure 1 reflects some of the answers raised in the research questions. There are numerous articles that no doubt may extend beyond the search parameters used; hence the possibility of exclusion of one or more vital but related articles remains likely. Consequently, a reference check was carried out at the initial stage to prevent any omission of such articles. The final article selection was based on parameters such as precision of the information, quality assessment and clear methodology. Also, the articles were further evaluated by comparing results published by various Authors to avoid overestimation.

4. Discussions, Limitations, and Taxonomy

This study underscores the contributions of deep learning to ear recognition systems while also highlighting a summary of contemporary techniques discussed in other studies. Security is paramount and accurate recognition of target elements from pre-processing to classification is critical in ensuring the integrity of any biometric system. The contributions of deep learning are multifaceted and far-reaching. Studies reviewed affirm the enormous work done in ERS using minimum distance and support vector machines.

However, newer methods capable of autonomously training large sets of data remain under explored. Based on the articles selected, the advantages and disadvantages of the various sub-units in ear recognition stages are indicated in Table 6. A small number of novel classification approaches exist for ERS. The work [168] highlighted a few bio-inspired algorithms, such as cuckoo search, particle swarm optimization, etc. Although some of the listed algorithms have widespread application domains, their significance is primarily for unraveling the optimization challenge in the location search. Consequently, in-depth knowledge of deep learning in pre-processing and feature extraction stages of ear recognition systems is required in subsequent research.

Table 6. Summary of the Pros and Cons of different sub-areas in Ear Recognition Stages.

Stage	Sub-Area	Pros	Cons
Pre-processing	Filter method	No need for object segmentation	Aligned ears are at a disadvantage
		Graceful degradation is a major boost	Some details may be lost
		Suitable for non-aligned images	Limited bandwidth is a drawback
	Intensity method	Reduced computational difficulty	Distorted uniform images are concealed
		Spin and reflection invariant	Poor performance against scaling
		Limited false matches	Copy and paste regions of an image cannot be detected
Feature Extraction	Geometric method	Suitable for obtaining a non-varying feature	Increased computation requirements
		Methods are easy to implement	Results can sometimes be inaccurate
		Image orientations are detected	Susceptible to noise
	Appearance Method	Very robust, particularly in 2-dimensional space	Performance decreases with size
		Any image characteristics is extracted as a feature	Average accuracy is less compared with other methods
		Minimized false matches	Cannot handle certain compressions
		It can be used with a few selected features	Illumination is a significant factor
		Recognition accuracy is high	Good-quality images are required
Classification	Neural Networks	Non-linear problems are easily resolved	Inability to model a few numbers of training datasets
	Support Vector	Increased performance with gap in classes	Large datasets are unsuitable in SVM
		Improved memory utilization	Noise is not effectively controlled
		Improved memory utilization	Limited explanation for classification

4.1. Limitations

In line with the study research questions, a thorough review of research articles on the contributions of deep learning to ERS was conducted, with 74 publications eventually identified as sufficient to achieve the research objectives. However, most of the papers listed were published between 2015 to 2022. Therefore, we cannot categorically state that all available studies in this research domain have been exhausted, considering the rate and volume of published research articles. Also, non-English articles were not considered during the article search.

4.2. Specific Contributions

Presently, the need to develop a black ear-pose invariant ear recognition database is motivated by the following:

1. This study identifies a need to evaluate the performance of ear recognition systems with ear images of different races before they are deployed in real-world scenarios. However, existing ear recognition databases contain mostly Caucasian ear images, while other minority ethnic groups such as blacks, Asians, and Arabs are ignored [169].

2. The black race form 18.2% of the total world population, however, previous research endeavors toward black ear recognition have not been established, and there is no publicly available dataset dedicated to black ear recognition in the works of literature reviewed.
3. This study observed that ear recognition images are often partially or fully occluded by hair, dress, headphone, hat/cap, scarf, rings, and other obstacles [170]. Such occlusions and viewpoints may cause a significant decline in the performance of the ear recognition algorithm (ERA) during identification or verification tasks [171]. Therefore, reliable ear recognition should be equipped with automated detection of occlusion to avoid misclassification due to occluded samples [51].

Therefore, the ear image samples were collected from 152 African (black-skinned) individuals from a public university in Nigeria. The dataset contains left and right ear images of the volunteers in varying pose angles of 0°, 30°, and 60°, respectively, with the ear images containing head scarfs, earrings, ear plugs, etc., thus, making the dataset pose and occlusion invariant. The corpus is published and publicly available to researchers at [203] with a total of 907 black ear images. Figure 2 shows the pose angles of the left and right ear images as captured for each volunteer.

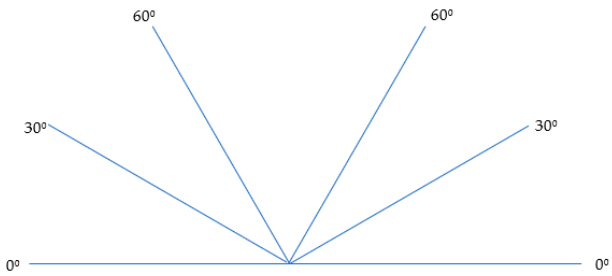

Figure 2. Pose of angles of the left and right ear images.

Also, this study classified current state-of-the-art techniques to reflect the contributions of the highlighted works under three core categories: approaches, performance parameters, and trait selection [204]. Figure 3 provides an explicit description of this taxonomy. The complete classification results of the articles is presented in Table 7.

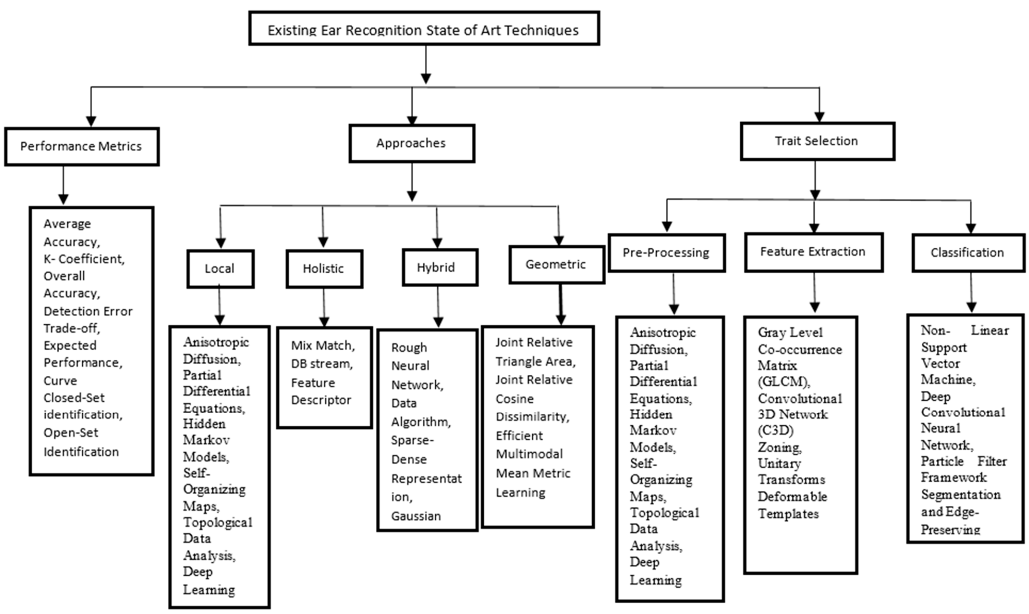

Figure 3. A Taxonomy showing ear recognition state of the art methodology.

Table 7. Article classification result.

			Approaches				Methods		Architecture			Status				
Year	**Authors**	**Dataset**	**Holistic**	**Local**	**Geometric**	**Hybrid**	**TL**	**DL**	**CNN**	**Others**	**Unspecified**	**Assessment (A)**	**Proposed (S)**	**Designed (D)**	**Planned & Assessed (P&A)**	**Proposed & Executed (P&E)**
2016	[3]							x	x							x
2017	[5]							x		x						
2019	[6]	x						x	x			x				
2010	[7]						x				x					
2017b	[10]	x				x	x				x					
2019	[12]	x					x							x		
2016	[16]	x						x	x						x	
2018	[17]	x						x	x						x	
2022	[18]	x						x	x							
2018	[20]	x						x	x					x		
2017	[24]	x						x	x							
2012	[25]	x				x	x				x	x				
2012	[28]	x					x			x		x				
2016	[29]	x						x	x							
2018	[34]	x						x	x			x				
2010	[39]	x						x			x		x			
2010	[40]	x		x			x						x			
2018	[43]				x		x				x	x				
2013	[46]	x		x			x			x		x				
2013	[48]	x				x	x				x				x	
2014	[49]	x		x			x				x	x				
2015	[50]	x		x			x				x	x				
2021	[51]	x						x								
2016	[52]			x			x				x	x				
2016	[53]	x						x	x							
2011	[55]	x		x			x				x			x		
2015	[56]	x			x		x				x	x				
2016	[57]	x			x		x		x							x
2014	[58]								x			x				
2018	[59]	x						x	x							x
2018	[60]	x						x	x			x				
2016	[61]	x			x		x						x			
2016	[64]	x		x			x									

Table 7. *Cont.*

			Approaches				Methods		Architecture			Status				
Year	**Authors**	**Dataset**	**Holistic**	**Local**	**Geometric**	**Hybrid**	**TL**	**DL**	**CNN**	**Others**	**Unspecified**	**Assessment (A)**	**Proposed (S)**	**Designed (D)**	**Planned & Assessed (P&A)**	**Proposed & Executed (P&E)**
2015	[65]	x		x			x				x	x				
2022	[66]	x						x	x							x
2018	[69]	x						x		x					x	
2019	[72]	x						x	x							x
2019	[76]	x						x	x					x		
2020	[77]	x														x
2018	[78]	x						x			x	x				
2014	[79]	x				x	x				x					
2011	[80]	x												x		
2013	[81]	x		x			x									x
2020	[83]						x		x			x				
2019	[87]	x				x	x				x	x				
2020	[88]	x					x			x					x	
2010	[91]	x		x			x			x		x				
2020	[92]	x						x	x						x	
2017	[93]							x	x							
2018	[94]	x						x	x				x			
2016	[95]	x		x			x						x			
2014	[98]	x		x			x		x							
2018	[99]	x		x			x				x					
2014	[100]						x				x				x	
2019	[101]	x						x	x			x				
2018	[102]	x			x		x				x					
2017	[104]						x				x					
2013	[106]	x		x			x							x		
2016	[107]	x						x					x			
2020	[108]	x					x				x					
2017	[109]	x			x		x				x					
2017	[110]	x						x	x			x				
2020	[111]						x			x						
2020	[112]							x	x						x	
2017	[113]	x						x					x			
2019	[116]	x						x	x				x			

Table 7. *Cont.*

			Approaches				Methods		Architecture			Status				
Year	**Authors**	**Dataset**	**Holistic**	**Local**	**Geometric**	**Hybrid**	**TL**	**DL**	**CNN**	**Others**	**Unspecified**	**Assessment (A)**	**Proposed (S)**	**Designed (D)**	**Planned & Assessed (P&A)**	**Proposed & Executed (P&E)**
2018	[119]	x						x	x							
2020	[121]	x						x	x			x				
2019	[123]	x						x	x							x
2014	[124]	x		x			x			x		x				
2016	[126]	x						x	x							x
2010	[127]	x		x			x				x	x				
2013	[140]	x					x		x							
2013	[141]	x		x			x			x			x			
2014	[142]	x		x			x			x			x			
2014	[143]	x						x		x		x				
2015	[150]	x				x	x						x			
2020	[156]	x						x	x						x	
2020	[157]	x						x	x			x				
2019	[166]	x						x	x			x				
2018	[167]	x						x	x					x		
2010	[179]	x		x			x				x	x				
2020	[183]	x						x	x				x			
2021	[184]	x														
2021	[185]	x						x	x				x			
2021	[186]	x						x						x		
2021	[187]	x					x						x			
2021	[188]						x						x			
2021	[189]	x						x		x						x
2021	[190]	x				x	x						x			
2021	[194]							x		x						x
2021	[195]	x						x	x				x			
2021	[196]	x						x	x							x
2021	[198]	x						x		x						x
2021	[199]	x						x	x				x			
2022	[202]	x		x			x						x			

5. Conclusions and Future Direction

Although a high volume of research is geared toward improving the recognition accuracy of biometric systems, none of these techniques has shown 100% accuracy. In this study, an SLR showing the current contributions of deep learning to ear recognition in different stages is presented. Before the screening, a total number of 1121 articles was returned during a preliminary search followed by a thorough analysis of existing contributions of deep learning, research questions, and the various methods used in the recognition process. In the end, 74 articles were deemed relevant to the study and were selected for further analysis.

In terms of the number of publications per year, results indicate that significant contributions were made to ear recognition in 2018, as it had 18 relevant articles, closely followed by 2016 with 16 articles. Results based on contributions from Deep learning obtained from Table 7 showed CNN, other architectures and non- unspecified architectures had 51.95%, 18.18%, and 29.87%, contributions, respectively. Similarly, local, geometric and hybrid feature extraction approaches had 60.61%, 18.18% and 21.21%, respectively. For studies that employed existing or developed image databases, the analysis revealed that 85.42% (82) articles used one database or another in their studies, while 14 did not use any database.

Contrastingly, results from analyzing the status of articles showed gap between proposed methods (S) and proposed & executed works (P&E) which accounted for 25.33% and 17.33%, respectively. Articles that assessed existing algorithms (A), designed a templates (D) or planned and assessed using established procedures (PA) had 34.67%, 10.67%, and 12.0%, respectively.

Traditional machine learning methods was used in 45 (48.91%) of the articles while 47 (51.09%) employed deep learning methods. This is due to increase in the ER datasets sizes.

Further still, an examination of selected performance metrics of recognition accuracy, template capacity, true acceptance rate, false acceptance rate, false rejection rate, equal error rate, precision, recall, and matching speed used by the Authors of selected articles was systematically determined. Interestingly, most studies on ear recognition system are assessment of existing algorithms on a given dataset followed by newly proposed or yet to be evaluated techniques.

In real-life applications, speed is of great essence. Future works should investigate various enhancement techniques to improve the speed of feature extraction algorithms in ERS. Although ear biometric technology is renowned for its long history of use, particularly in developed countries, it is still enjoying rapid growth and potential with increasingly dynamic but secure classification procedures. Establishing an efficient and foolproof ear biometric recognition system is not only a growing concern but also an opportunity to explore the inherent gaps in feature extraction and classification procedures targeted at accurate authentication or identification tasks.

Author Contributions: The manuscript was written through the contributions of all authors. O.G.O., was responsible for the conceptualization of the topic; article gathering and sorting were carried out by O.G.O., A.A.-A., O.'T.A. and A.Q.; manuscript writing and original drafting and formal analysis were carried out by O.G.O., A.A.-A., O.'T.A., A.Q., A.L.I. and J.B.A.; writing of reviews and editing were carried out by A.A.-A., O.'T.A., A.Q., A.L.I., J.B.A. and A.A.-A. led the overall research activity. All authors have read and agreed to the published version of the manuscript.

Funding: The work of Agbotiname Lucky Imoize is supported by the Nigerian Petroleum Technology Development Fund (PTDF) and the German Academic Exchange Service (DAAD) through the Nigerian-German Postgraduate Program under grant 57473408.

Data Availability Statement: The black ear recognition dataset is publicly available. Other data that supports the findings in this paper are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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