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Comprehensive Survey of Machine Learning Techniques for Ear Recognition System

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---ABSTRACT---

Ear biometrics is non contacting and so it can be applied for identification of a human at a distance, making it a helpful supplement to facial recognition, law enforcement, crime investigation etc. Although ear detection and identification systems have rapidly improved to a certain extent, their success is still confined to specific circumstances such as an occlusion of hair. A major challenge for researchers nowadays is to recognize human based on ear with pose variations and occlusion.

This summarized survey aims at identifying the research gap which is helpful in proposing a novel machine learning approach as a pathway for budding researchers.

Most of the selected articles have common and a wide variety of preprocessing, feature extraction techniques such as SIFT, Gabor filter, shape features are gain. Performance of all surveyed methods is evaluated for comparison purposes using evaluation metrics such as Precision, Recall and Accuracy.

The challenges before an effective Ear recognition system are discuss. This comprehensive survey article will be useful for identifying research gaps as a pathway for the same researchers to get the idea regarding of Ear recognition system which further can be transformed into a marketable product. This article at the end presents the prototype model.

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1. INTRODUCTION

1.1 History and background of Ear Biometrics

In this world of uncertainty, reliability is a significant issue. The influence of biometrics in reliability has extended impetus due to its numerous advantages. In present day society, the biometric method based verification has become the most consistent and usually used method for automated individual identification in to variety of civilian applications. With the widespread usage of social media apps like Facebook, Google, Skype, WhatsApp, Instagram, Twitter, and Telegram on smart phones and the fact that most financial transactions are now done online (through online banking), it is crucial to establish a person's identification with accuracy. A trustworthy method of identifying persons is also needed for a number of law enforcement and military applications, for example decisive whether a person is a potential threat or a criminal suspect. Accomplishing higher recognition concerts in uncontrolled circumstances along the various biometric traits come to be a new class of biometrics due to their characteristics. In biometrics, various methods of identifying human beings are used: fingerprints, face, voice, iris, gait, etc. The reason for the particular interest in biometrics is the practicality for consumers and the difficulty of hacking compared to passwords and cards. The biometric systems categorized into two parts, active and passive. For example, face biometric is an active biometric technique. This biometric has poor identification performance because to shape and expression variance with time, as well as further difficult concerns like changing lighting, poor contrast, and user resistance. Several instances of forensic uses include Revolutionary identification, Criminal search, and mislaid person identification and on the other hand cyber commerce, law-enforcement agency, border crossing control, device access control, internet access, ATM security, driving license, social security, welfare disbursement, and everyday attendance are a number of emerging cases of civilian applications [1].

1.2 Significance of Ear as Biometric

Similar to how a facial image is easily acquired with a low resolution camera, ear images can also be obtained with little to no human input. The best emerging biometric method for human recognition has researchers' attention due to the ridiculousness of face recognition issues in comparison to a previous Ear shape. One of the most sophisticated and a unique use of human identification is Ear-based identification. The Ear has unique physiological and structural aspects. In surveillance systems, for example, it is

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easier to recognize and identify an Ear than an eye. As a person ages, their ear undergoes little modifications. More crucially, ear biometrics can be passive since the person is not required to actively participate in the entire process and may not even be aware that the form of identification is being used. Technology for ear recognition may also be useful in the biometric toolbox. Using investigation videotapes to evaluate defendants in gas station robberies who had covered their faces but not their ears, forensic investigators in the Netherlands, for instance, used the Ear biometric to identify the suspects [1]. When French criminologist and biometrics researcher Alphonse Bertillon proposed utilizing the form of an individual's ears to identify criminals in the 1890s, the concept of ear biometrics first emerged [2]. A human Ear finds a constant structure which quite change significantly as an outcome of aging and perhaps regarded as one of the best unique human biometric traits since it possesses all of the aforementioned characteristics of uniqueness, collectability permanence and universality [3]. Human ears are unaffected by changes in facial expression, have a uniform hue, and have a constant shape from the age of eight to seventy and this is in contrast to the face. [4].

1.3 Ear Structure

Maternity causes the human ear to develop early, and by the time of delivery, it is fully developed. A sensitive part of the human body is the ear [5]. Sound detection, transmission, and transduction are its key concerns. Another crucial task carried out by the human ear is maintaining balance, and it has the distinctive structure seen in Figure 1 to accomplish this task. There are numerous forms and sizes for the outer ear. This framework contributes to the distinctive appearance that each of us has. Technically, the auricle or pinna is the term used to describe the exterior ear. Skin and bones make up the outer ear. The tragus, helix, and lobule are the three separate components of the outer ear. Because they vary from person to person in terms of structure, appearance, and relative positions, these structural cartilage formations can be used for identity and recognition.

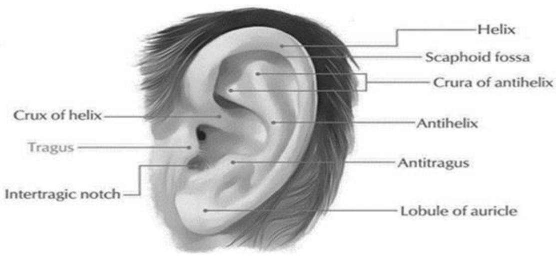

Figure 1. Ear Structure

1.4 Ear Recognition System

Figure 1 displays the block diagram for Ear identification system with different states. An appropriate camera is used to acquire images. Pre-processing is used to improve the image's quality. Preprocessing allows us to eliminate undesirable distortions and enhance certain qualities that are essential for the specific application we are developing. Those characteristics could vary according to the application. It will take less time to train models and take less time to infer models when image preprocessing is used. Decreasing the size of the input images will considerably decrease the amount of time it takes to train the model if the input images are extremely huge. Image segmentation is a technique for splitting up a digital image into different groupings of pixels called "Image Objects," which simplifies image analysis and decreases the complexity of the image. There are many image segmentation techniques available to isolate and classify a certain collection of pixels from the image. The most important process is feature extraction, which entails converting unprocessed data into numerical features that can be analyzed while maintaining the accuracy of the data in the original data collection. Compared to using machine learning on the raw data directly, it produced better outcomes. Classifiers classify data by analyzing the numerical properties of distinctive image features. Usually, classification algorithms have two processing stages: training and testing. However, it is fairly clear to examine the structure of the human ear before we attempt to understand various processing on the ear. The most important thing to process and analyze an image is to capture it. This is called Image Acquisition. The block diagram of common ear identification is shown in Figure 2.

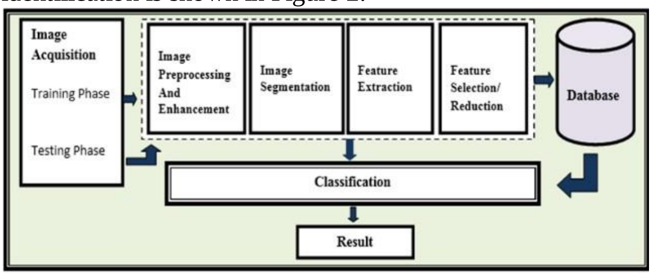

Figure 2. Ear Recognition System

1.5 Motivations

The rapid increase in popularity of biometric identification tools is largely due to how easily they solve the majority of concerns with standard identification methods. Ear biometric trait has various features such as unique structure, small shape compared to face, uniform color, and persistence over long period as well as higher user acceptance. That's why, eat biometric gains more attention by the research community. A remarkable progress has been reported in the related work over last two decades. However, major challenges of the ear biometrics include poor recognition performance due to illumination changes, low contrast, partial occlusion, and presence of noise.

1.6 Objectives

In this article, various feature extraction methods and machine learning algorithms are discussed with their accuracy. Basic preference of this article is to find out a proper machine learning algorithm for human ear identification and to extract significant features towards improving accuracy. Accuracy and performance of all surveyed approaches are highlighted for comparison purposes. This work is proposed to provide the research scholars a present status further scope of machine learning techniques in ear biometrics. In order to develop and implement new approaches and towards future research directions for accurate feature extraction methods, scholars will get the combined information of machine learning algorithms in this single article. This article will definitely be helpful to improve the accuracy with selecting modified feature extraction techniques and by improving the accuracy of classifiers with modified classification algorithms.

The specific objectives of this research work are as follows,

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- To summarized the technical performances of the latest articles on ERS using machine learning techniques.
- To discuss the parameters or factors affecting the performance of ERS.

1.7 Article selection strategy and organization of article

For this study we identified several key concerns regarding this work, which encompass

1. Selecting appropriate and latest articles for last few years
2. Identify common ground and parameters for evaluating and comparing performances.
3. Use common strategy to compare different techniques.

For this comprehensive survey, we have chosen 11 machine learning techniques for ear biometrics from the sources such as peer reviewed international journals and proceedings of international conferences, book chapters from indexed books and some official websites to discuss in this article. In all we have selected 11 research articles based on machine learning algorithms for automatic and semiautomatic classification and recognition of human ear. Enough care is taken to ensure that the research articles are covering the variety of dataset from various countries all over the world. This will allow the researcher to understand the changing trend of datasets and techniques so that a new robust technique can be developed to identify the human from any test dataset accurately.

The rest of the article is organized as follows. The databases used by all the authors in selected articles are described in Section 2. Section 3 takes an overview of wide variety of the selected articles covering machine learning techniques for ear recognition. Principal findings and observations noted from all the articles are mentioned in Section 4. Based on the gap identified in section 4, a new approach for ear recognition is proposed in Section 5 and Section 6 concludes this article.

2. AVAILABLE DATABASES

This section includes a number of databases that have been utilized in articles considered in this study research. The majority of these datasets can either be shared publicly or with a license.

WVU database [6]: The West Virginia University (WVU) ear dataset includes 60 multi-sequences and 460 video sequences for roughly 400 individual people. Every video starts with the subject's left profile and ends with their right profile. In this dataset, there are individuals who wear earrings, eyeglasses, and partially occluded ears.

USTB Databases [5]: For academic study, the University of Science and Technology Beijing (USTB) databases 5 are accessible [USTB 2005].USTB I: 180 pictures of the 60 volunteers. Three photographs were taken of each subject: (a) a regular ear image; (b) an image rotated by a modest amount; and (c) an image taken in a different lighting scenario. The dataset comprises of 308 photographs of 77 volunteers from USTB II. Using the definition of the profile view (0°) as the angle at which the CCD camera is at right angles to the ear, the following four images were captured for each subject: (A) the profile image; (B) two photographs taken at different angles of 30° and 30°; and (C) one image taken with varying lighting. 79 participants in USTB III, IV, and USTB A camera setup with 17 CCD cameras was used to take pictures of 500 volunteers' faces and ears from various angles. The cameras were spaced 15 apart around the subject.

UMIST Database [6]: 20 persons are depicted in 564 photographs from the UMIST Face database 8 gently turning their heads from the front to the profile. A modest database called UMIST is freely accessible to the general public [Graham and Allison 1998; UMIST 1998]. The UMIST database has only been utilized in investigations involving ear detection in the literature.

IIT Delhi ear image database [7]: A database of ear images gathered by IIT Delhi students and staff in New Delhi, India, can be establish in the IIT Delhi Ear Image Database. Using a straightforward imaging setup, this database was collected at the IIT Delhi campus between October 2006 and June 2007 (continuously). With the use of a straightforward imaging setup, all images are taken remotely (non-contact) and indoors. There are currently 121 different subjects in the database, with each subject having at least three pictures of her ears. The database only contains people between the ages of 14 and 58. All 471 images in the database are in the JPEG format and are sequentially numbered with an integer ID/number for each user. The ear database recently expanded to include 754 automatically cropped and standardized images of the ears from 212 individuals.

The University of Notre Dame (UND) databases 1 [8]: For face and ear modalities, the UND database contains numerous collections. Collection E contains 464 left face side profile (ear) images from 114 subjects; Collection F contains 907 right face side profile (ear) images from 286 subjects; Collection G contains 738 3D profile (ear) images from 235 human subjects; and Collection J2 contains 1800 3D profile (ear) images from 415 human subjects. All of these collections were taken between 2003 and 2005.

Annotated Web Ears (AWE) database [9]: 100 subject photos may be found in the AWE dataset. The AWE dataset was compiled from web photos of well-known people of all ages, genders, and ethnicities, including actors, musicians, and politicians. A tight crop was applied to 10 photos for each subject. Every image has annotations, which are likewise kept in JSON files with the images.

3. LITERATURE SURVEY

We studied a number of ear recognition systems in all of the articles under this survey. The short comprehensive summary of the few selected articles is presented as below.

Iannarelli's system, which was created for the first time in 1949 [3], is one of the earliest ear recognition systems. Using the Voronoi neighbourhood graph, they created a classification invariant under affine transformations. They illustrated the issue of hair occlusion and suggested using a thermogram image to detect an ear through surface heat. However, because they did not include a scheme evaluation, the study was not comprehensive.

Asmaa Sabet Anwar et al [8] described a novel method for ear detection based on the extraction of geometrical data such as shape, mean, centroid, and Euclidean distance between pixels. All photos were initially pre-processed with the same size, and the ear was then detected using the snake contour detection model. The photos were then converted to

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binary format after applying a median filter to reduce noise. After that, it made some picture enhancements using a clever edge detecting algorithm, computed the major boundary, and then created a distance matrix. Following this effort, the picture features were extracted. Last but not least, nearest neighbours by absolute error distance was used to classify the retrieved features. About 100 images as training, 50 images as testing from the IIT Delhi ear database, version 1.0, are used in the experiment. The author noticed in the related work that most scientists used their own databases rather than conventional databases due to accuracy. About 98% of the results from this investigation were obtained with greater accuracy. In order to evaluate the efficiency of this system in the future, it was planned to employ more datasets and increase the quantity of ear images. We will attempt to address issues like the ear's drop-down hair, which partially conceals them, in our future work.

M. Khamiss et.al. [10], Iterative Closest Point (ICP) and Stochastic Clustering Method (SCM) are combined to form the improved algorithm known as ICPSCM, which is recommended for ear recognition. These two strategies suggested reconstructing the ear surfaces from several scans, localizing locations, and using clustering techniques to achieve the best classification planning. The ICP algorithm and the SCM method are portable methodologies used in this study for feature extraction and pose variation in ear identification, respectively. The SURF Technique is used in this work to extract features. The proposed Multilayered Neural Network (MNN) strategy used in ear identification methods is used for ear classification and identification. The effectiveness of the analysis is defined by the criteria that were considered at various stages. The design of an ear identification system introduced a fully integrated sense of biometrics and integrative closest point based on an ear surface matching approach with features. The concept behind the ear identification technique blends the outcomes of ear matching using neural classifiers that focused on the outer ear points, data from the profile and shape of the ear, and density data generated from macro features. Integrative nearest points are used to start identifying the ear after the ear location has been extracted from the input image. This study makes use of the IITK, WPUTED, and USTB datasets. For this study, 500 images from each dataset are chosen. They draw their conclusions from the implementation phase's outcomes, including FAR and FRR. The experimental outcome in this work demonstrates 96.12% accuracy.

R. Dhivya et.al. [11], worked on Edge Detection and Feature Extraction for Ear Authentication. An enhanced technique for feature extraction, recognition, and ear edge detection is presented in this work. The accuracy of this work, which is carried out on the ear in a random orientation, is superior to that of the leading approaches at the moment. The accuracy of recognition is improved by eliminating noise from obtained ear shots and applying a novel new technique to work with online images. The Region of Interest used in this work is segmented using an active contour algorithm and a cunning edge detector, and the ear contours are then used for authentication. The entire procedure is carried out in Matlab. This method can be used to capture and handle the moving person's ear, and it can be drawn out more precisely than the current one. This software implementation for Ear Verification with the resulting steps of image acquisition, preprocessing, contour tracking, edge detection, feature extraction, and authentication is obtained in an efficient manner for the ROI. In this study, it can be expanded to match the inside curve of the ear and extract features from the inner part of the ear edge. For this investigation, the complete methodology was used on just one image. As a result, they did not find accuracy in this paper. Future implementation of any other method besides the clever edge detection method is within the purview of this study.

K. Mohanapriya et.al. [12], represented Ear Recognition by Feature Extraction using Force Field Transformation. This study identifies the use of an Ear Visual Biometric as a measure of identification for the Teaching Management System in Universities and Colleges. Teachers who use this study to instruct their pupils have a greatly reduced burden, and the system as a whole enhances the integrity and controllability of the data. For higher performance than existing edge detection algorithms, in this work, ear detection and recognition is carried out utilizing Feature Extraction techniques such Force Field Transformation and Chord Point Detection Algorithm. This technique was successful in taking advantage of the increase in test and attendance at lectures and exams. In this investigation, the force field method yields a classification accuracy rate of 99.2%.

Ahmed Kawther Hussein [13], analysed the performance of two classifiers for the detection of ears, one trained to execute HOG functions and the other to perform LBP functions. A dataset, the number of hidden neurons, and the activation function are all inputs in this study. In the first stage, the data is split into training and testing, and in the second stage, HOG and LBP are extracted. Afterwards in third step Normalize Train an ELM based on HOG, he call it ELM- HOG using Train and ELM based on LBP. The last step is to test an extreme learning machine - HOG using testing data and test extreme learning machine -LBP using testing data and then return testing accuracy. He used the dataset to include 180 images of 60 subjects, both students and teachers from USTB from 3 sessions in July and August 2002. The database includes images of the right ear from each subject. In this study to evaluate both HOG and LBP features, an ELM with a number of neurons equal to 10000 was created. The sigmoid function is used as an activation function. It was observed that the accuracy of HOG at 99.83% was superior to LBP with 99.87%. Future work is to examine the performance of other types of functions and use 3D images for the ears as input.

Bassam S. Ali et.al. [14], collected ear images from 100 test subjects, three right hand side using a 12- Megapixel digital camera under a steady lighting condition. In this work, an ear recognition system (ERS) with Match Region Localization (MRL) was applied. The MRL segmentation technique is used to pre-process and segment the captured ear pictures, which resulted in 96 sub images. The principle components analysis is applied to each segment individually in order to convert the segments into PCA spaces. Each segment is regarded as a unique image that represents a unique person according to the segments used. K-nearest

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Neighbour algorithms and Euclidean distance calculations were used to categorize the data. The effectiveness of this method can be assessed using the FRR, FAR, and Recognition Accuracy metrics. (RA). The resulting algorithm is tested on additional freely available ear databases if users agree to cross-database comparisons. The MRL Ear Recognition System with PCA Recognition Accuracy of 97.07% and the other algorithm produced by Adeolu and Ademiluyi, with Recognition accuracy of 72.46%, performed better in this test than the ERS developed by Adeolu and Ademiluyi (2016). It was established from the trial that the system can function effectively as an identification system. The approach, method, or solution must be tested on an increasing number of photos, maybe more images from various datasets, and images with (hair-like) impediments on the ear, in order to be practically relevant.

Mangayarkarasi N et.al. [15], in their contour detection algorithm select a gray image as input. Setting a threshold number for Ear detection allows for the initial design of the masks for the ear image. The segmented final mask, which is in binary format, was obtained by convolving the mask with the gray picture. After applying the final mask to the input image, the bounding box then drawn around the ear portion. The bounding box was then drawn around the section of the ear after the final mask had been applied to the input image. Using Perceptive's bounding box dimensions, the ear is cropped, stored for feature extraction, and then the SIFT technique is utilised to identify the SIFT feature vectors. These feature vectors are saved for the conclusion after being extracted from each person's image during the training phase. This input test image goes through the same procedures as training images. The subject is identified using the Euclidean distance measure approach by assessing the SIFT vectors from both the training and testing phases. The two vectors are comparable if the space between them is as little as possible and thus, every person is recognized by using this value. With the Snake model some drawbacks like it do not solve the complete problem of finding contours in humans, since the method needs knowledge of the desired contour shape beforehand. As a result, they created a mask with 1s values starting at a threshold of 150 and increasing until the picture reached its maximum size. After that, the mask was convoluted, and the binary output of the segmented ear image was created. The bounding box is drawn around the ear after a subsequent application to the original RGB image to identify only the ear part. The ear portion is finally segmented out on its own and saved after learning the size of the bounding box. Reducing the feature values for better recognition systems will be the focus of future study.

Pre-processing and Feature Extraction in Ear Biometrics research work presented by Bhavani Petchiammal C et.al [16]. In this study, the RLBP algorithm and KNN classifier were utilized in conjunction with a straightforward technique for extracting ear information called Radon feature extraction to recognize objects. Image segmentation is done after image pre-processing to remove extraneous information from ear pictures. In this study's related work, a three-step technique was used that included a typical combinatorial feature selection algorithm, K-means clustering to reduce duplication, and a RELIEF filter to reduce irrelevancy. The RELIEF filter will provide training features with relevant values while eliminating the irrelevant features. The IIT Delhi database was employed for this study, and from it, 3 to 6 photographs of the same person's right and left ears were obtained. The median filter is utilized in this study to filter out undesired noise. 100 images from the dataset are used in this study's training set, and all 100 images are trained using the necessary pre-processing and feature extraction techniques. The system's estimation is provided with the use of a testing database that contains 46 photos. A classifier based on the KNN classifier is created, and it is then tested using Euclidean distance, to identify the ear images in the test and estimate datasets. The Radon feature extraction method has a higher accuracy rate while compared to RILBP. In order to accurately recognize a person in the future, classifiers like SVM, multi-class classifiers, and classifiers from neural networks were used.

Samik Chakraborty et.al [17], investigated the usage of ear-based biometrics for human identification. In this ear recognition system investigation, 10 people were used, and a geometrical solution was used to address the jewellery occlusion issue. When wearing no jewellery, the geometrical relationship between the image's points can be seen and determined. The information obtained in this way is noticeably close together. This information used to project a point from the area of the image that the jewellery has obscured. Following the discovery of this point, features that are similar to those in the original image are discovered. The tiny dataset meant that this had a 100% success rate. However, more research is required utilizing a larger database with additional objects, such as the existence of ear buds or hair and with dissimilar illumination experience.

Debbrota Paul Chowdhury et al. provided semantic ear feature reduction for source camera detection task [18]. By determining the source camera of the ear biometric photos, a semantic strategy to lowering this feature vector is debated in this study. The 36 energy components are a key component that is employed in the described study. This study also confirms that the presence of many different camera models lowers source recognition precision. The mechanism succeeds in classifying only a few distinct camera sources, and it is visible that it is now processing three sources. Before the bi orthogonal tunable wavelet filter is applied to the complete ear image for feature extraction, the ear image is divided into six blocks and the wavelet filter is applied to each block. This is done because jewellery, hair, or glasses may obscure some of the ear picture. The energy from each block is mined and used to produce the merged feature vector for the entire ear picture. Due to the lack of easily accessible datasets for camera source identification, the author combined three ear databases to create this. Three ear databases—IITDI, AMI, and WPUT—serve as the study's camera models I, II, and III, respectively. True positive, false positive, precision, recall, F-measure, the area under the receiver operating characteristic (ROC) curve, the area under the precision-recall curve, and accuracy are the parameters utilized in this study to gauge how well the system performs when the feature size is reduced. They chose 36 characteristics with the following performance metrics: True Positive (%) 99.3; False Positive (%) 0.4; Precision (%) 99.3; Recall (%) 99.3; F Measure (%) 99.3;

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ROC Area (%) 100; PRC Area (%) 99.9; and Accuracy approximately 99.25%. The research is successful in identifying source cameras with significantly smaller feature sizes.

Abbas H. Hassin Alasadi et.al [19] proposed a machine learning approach for a human ear recognition system. The proposed system aims for use a probable skin detector to filter the ear image into skin and non-skin pixels. The static features of the ear are retrieved by using scale-invariant feature transform (SIFT). The initial image in the database and a new image are compared using the Euclidean Distance Measure (EDM). According to the three experiments presented in this research, the recognition rates for the various datasets when using the Gabor sampling filter method are 65%, 83% when using the Gabor mean feature extraction, and roughly 92% when using the SIFT feature approach in the proposed system. The enrolment phase and recognition phase are the two primary phases of the proposed system, which is a multistage procedure. Software called MATLAB is used to implement the suggested system. This study made use of the AMI ear database. In this study, the pre-processing algorithm is first used to an input side face image to produce an output ear color image. In the second iteration of the Morphological Operation algorithm closing operation. The third experiment tests a matching algorithm that determines if two provided data sets are similar or dissimilar. In the fourth experiment, the feature vector is used as the input for the identification mode algorithm, which is then used to verify the data. The accuracy rate of the proposed method decreases with an increase in number. In order to examine how ear print evidence is used in criminal investigations, the FearID research project was started in 2002 and ran until 2005. In this project, the usefulness of ear prints at crime scenes is investigated. In all 1229 donors were used in this project. From three different countries, three left and three right ear prints were obtained. The same error rate, which was 4% for lab-quality photos but increased to 9% for print versus mark comparisons, was employed for evaluation [28]. In Table 1, a summary of a few chosen articles from relevant work is listed.

4. PRINCIPAL FINDINGS

Basic preference of all selected research articles was to improve the performance on Ear Recognition, are analysed with the help of SIFT and machine learning techniques for the classification. During this study we came across different findings which are recorded for future research directions.

4.1 Challenges which are discussed

Many researchers have performed various automated systems for human ear identification with an additives technique and trying to increase the accuracy. The furthermost noticeable ones are in the data collection stage, where it is problematic to even crop an image containing an ear.

Table 1: Summary of some selected articles from related work

Referenc / Author	Preprocessing/ Segmentation	Feature Extraction Method	Classifier	Dataset	Performance metric, percentage
[24], Li Yuan, Zhichun Mu 2014	Preprocessing: ear detection using modified Adaboost algorithm and ear normalization Using Active Shape Model.	Gabor Feature Extraction	Full Space Kernel Discriminant Analysis	USTB dataset3 79 UND collection J2 150 subjects	96.46% 94.00%
[9],Asmaa Sabet Anwara et.al 2015	Preprocessing : Gaussian Filter, Median Filter, Global Threshold, Canny Edge detection	Geometrical Features	Naive classifier, nearest neighbor (distance type: Euclidean) and KNN (distance type: minimum absolute difference).	IIT 150	98.00%
[21], Lamis Ghoualmi et.al 2016	Artificial bees for ear image enhancement	scale in-variant feature transform (SIFT)	Euclidean Distance	IIT Delhi USTB USTB 2	99.6% 97.15% 94.79%
[15], Mangayarkarasi N,*, RaghuramanG, Nasreen A 2019	Preprocessing : resize the image and convert it into grayscale Segmentation : Contour Detection Algorithm	SIFT	Euclidean Distance	Own Dataset 545	96.00%
[19],Abbas H. Hassin Alasadi, Dheyaa Abbood Chyad 2021	Preprocessing : convert RGB to YCbCr, binary image conversion, Morphological Operation	SIFT	Matching algorithm	AMI 175	92.00%

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Selection of proper feature extraction techniques is one of the interesting, complex and long-lasting domains of research from last two decades due to:

- As the number of dimensions increases, the feature extraction method will not work effectively.
- There is no special standard rule for validating classification results.

The exact performance rates of the study on any given dataset are merely a proof-of-concept; they are only of secondary significance. The progress of ear recognition system research is utterly dependent on the availability of new and more difficult public databases. New datasets for benchmarking Ear Biometrics should be compiled and published in order to maintain research in the field. Such a dataset might, for example, include left and right ears from the same person from different angles, as well as higher demographic variances. In addition to accelerating the pace of ear biometrics research, new datasets also present an opportunity to advance associated systems. In addition to the requirement for more difficult datasets, there are a few notable concerns with ear biometrics that are rarely brought up.

Most pre-processing algorithms are created to work on a single reference image before being applied to all the other datasets, which results in poor results. These concerns must be taken into consideration while creating new pre-processing methods.
Feature extraction algorithms cannot work well if dimensionality rises hence, there must be proper trade-off between classification accuracy and number of features. Using this literature survey our future work will highlight on accuracy improvement by extracting the suitable features from the human Ear, feature selection and integration of different classification algorithms to advance the classification results and try to implement an accurate system for ear recognition.

4.2 Challenges which are not discussed

Following are some of the points which are not discussed in this article due to limitation on text length.

- Reliable milestone detection in occlusion- and pose-varying ear pictures. Particularly the detection and masking of occluded regions would be an important contribution for ear recognition in surveillance scenarios.

- Classification accuracy of different survey methods is varying, hence the need to design a more precise segmentation algorithm to classify Ear more accurately.

4.3 Gap identified

An active area of study within the biometric community is automatic identification recognition from ear images. Significant advancements have been achieved in the subject over the past few years; however there are still unresolved research issues and no system for commercial use has yet to be created. A major challenge in face biometrics was the discordance between form and expression, whereas in the case of ear biometrics, the shape and look are constant. Biometrics for human identification is sometimes required by forensic and criminal justice technology used in everyday life. Numerous techniques, including face and fingerprint identification, have shown to be highly effective in computer vision-based human recognition systems.

4. PROPOSED PROTOTYPE

The research gap identified in the Section 5 encouraged us to propose a new approach towards ear based human recognition system. The proposed system architecture depicted in Figure 5 provides a broad overview of all the system modules and the process flow from data gathering to classification. Initially, photographs of various people's ears were collected and stored in a database. Similar to this, various picture datasets of the human ear have been amassed online. This data set comprises of pictures of each person's right and left ears from three different angles: the front, the down, and the back. The suggested system's flow is depicted in the diagram below.

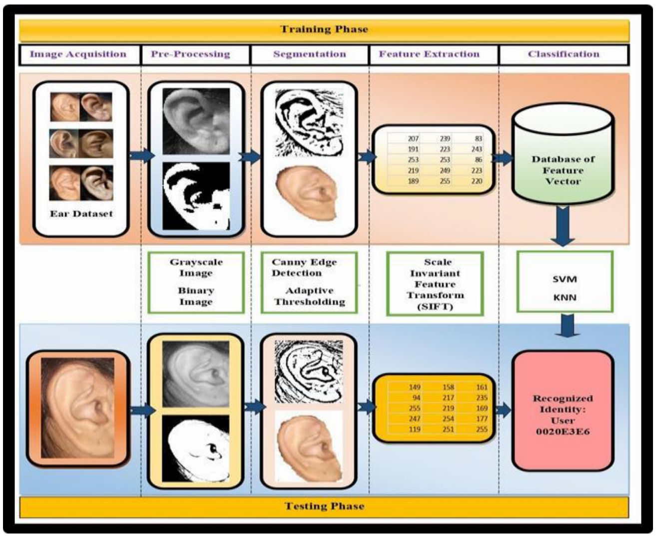

Figure 3.Proposed System architecture of Ear Recognition System

Step I: Image Acquisition

For the proposed method, a human ear dataset has been created. The basic idea of establishing this database was to simulate real scenes of real life. In this dataset the human ear image was taken at various angles of both right as well as left ear. The image acquisition step is the fundamental phase of every vision system. After the image has been captured, it is processed using a variety of ways to enhance its quality. Even by applying various image enhancing techniques, the proposed work might not be practical if the image was not

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acquired properly. All of the photos in this work are in the .jpg format and have a 450 x 689 pixel resolution.

Figure 4. Some samples from the dataset

Step II: Pre-processing

Pre-processing is the ear recognition system's initial stage, in essence. It improves the images and gets rid of unwanted effects. Pre-primary processing's objective is to improve the image's quality so that we can analyse it more effectively [18, 29]. They must be standardized and cleaned up before being fed to machine learning (ML) techniques. Since the form in which an image is taken must be taken into consideration while writing a unique approach, when we acquire an image we typically renovate it into a form that enables a universal way to solve it, as demonstrated in the proposed system architecture. Pre-processing allows us to improve some qualities that are essential for the specific application we're working on while also smoothing out unwanted distortions. Various applications may require different person characteristics. Pre-processing makes sure that the image's essential characteristics are highlighted and that extraneous details, such noise, are removed. The two main types of picture pre-processing techniques are intensity-based and filter-based approaches [7].

Algorithm (1): Preprocessing Algorithm

Input: Side Face image

Output: Ear Binarized Image

Step 1: Select image from the dataset.

Step 2: Crop Ear Image from the above step.

Step 3: Resize the image.

Step 4: Convert the Resized image to a grayscale image.

Step 5: Convert the image from the previous step to Binary Image.

Figure 5. Algorithm of Pre-processing of Ear Image

The filtering technique can be used to improve or alter an image. You can use a filter, for instance, to highlight some components of an image while deleting others. Mean and median filters are used in filtering to smooth and reduce noise during image processing activities. For the purpose of enhancing the image for further analysis, some sharpening and edge enhancement techniques are also applied. Applications for the Log-Gabor filter include texture generation, image denoising, speech analysis, contour recognition, and picture enhancement. The sample ear images while applying Gaussian and median filter are shown in Figure 6.

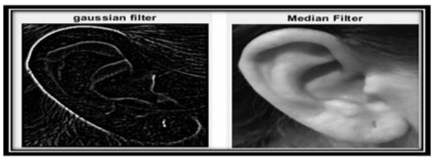

Figure 6. Ear image with Filter-based approach

Colour is not required in any of the ear biometrics articles we reviewed to recognize and understand an ear image. Grayscale can be suitable for identifying some objects. Due to the fact that colour images are more information-rich than black and white ones. The sample ear images while applying intensity-based approach are shown in Figure 7.

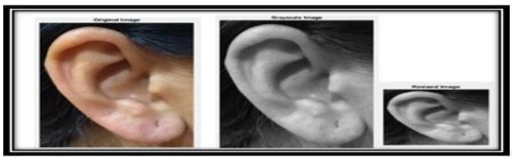

Figure 7. Ear image with Intensity-based approach

Histogram normalization is another intensity-based technique. A new architecture for ear biometrics was introduced by Lamis Ghoualmi et al. [22]. To show more realistic 2D ear images with higher-detail content and 97.15% accuracy, they used a method for enhancing the contrast of ear images based on gray-level mapping with the ABC algorithm.

Step III: Ear Segmentation

In automated ear identification algorithms, ear segmentation is crucial. Image segmentation's primary goal is to make the image simpler for easy examination [22]. Segmentation is the process of giving labels to pixels, to put it simply. The system for object identification that is suggested employs a boundary-based strategy. Algorithms like point detection, edge detection, line detection, and others use a boundary-based approach to recognize the edges of unique pixels and isolate them from the rest of the picture. Thanks to adaptive thresholding, which sets a threshold value for each fractional section of the image, each fractional portion of the image has a distinct threshold value. This method provides the highest level of accuracy and is best suited for the following action.

Step IV: Feature Extraction

A large matrix is just an image. Features are traits which are mathematically retrieved from this matrix to serve as the foundation for additional processing, analysis, or recognition. Feature extraction is the process of identifying an image's key characteristics that help identify it specifically. Because just a limited subset of features is utilized to represent the complete image, the goal of feature extraction is dimensionality reduction [30]. Shape, colour, texture, and other features of an image that can be taken into account during feature extraction. The bulk of review studies used the SIFT Algorithm to detect and analyse the picture local features, such as rotation, scale, and viewpoints in computer

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vision, based on their accuracy and processing complexity. Key characteristics are the output to identify the ear. For the purpose of recognition, it works better. The comparative analysis of reviewed articles is as follows.

Table 2. Comparative analysis of different Feature Extraction Techniques

Feature Extraction Techniques	**Accuracy**	**Computational Complexity**
Orthogonal log Gabor Filter	Moderate	Moderate
HOG and LBP	Average	Good
Geometrical Feature Extraction	good	Average
SIFT	Average	Average
Radon Feature Extraction and Texture based Feature	Moderate	Moderate

Step V: Storing Feature vector in a Database

In the database Feature vectors stored and then compared with testing phase outcome.

Step VI: Classification

The extracted features mentioned in Step V are applied to the machine learning algorithms for classification. In this research survey articles mostly used two machine learning algorithms known as SVM and KNN [31, 33]. The classification technique used as the last phase of the suggested methodology is a support vector machine (SVM) algorithm. The model was built faster using SVM, a well-known supervised machine learning method [23, 32].

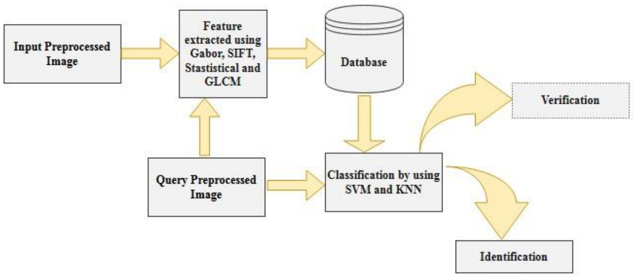

Figure 8. Ear feature extraction and classification

6. CONCLUSION

The primary objective of this comprehensive survey is to highlights challenges regarding design an automatic Ear Biometric System that can achieve better recognition performance in the uncontrolled scenarios. It can be used for real-time biometrics applications. In this paper we have taken the overview of a few selected research articles on ear recognition system using machine learning algorithms. The summary of the different techniques is enclosed in the table for better single view reading. The various classifiers are considered for comparison using a common ground of performance to the extent possible. The performance and accuracy of various methods enlisted may be useful for comparison and future direction purposes. The observations and lacunas found are enlisted properly. The research gap identified is then stated. Various methods proposed by researchers in literature reveal that there is still a research gap to design and develop a more accurate method of Machine Learning for Ear Biometric System by improving techniques of image processing pipe-line. At the end, the new approach for ear recognition system proposed with an altogether new dataset. The work on this proposed method to yield better classification accuracy is in progress.

In order to advance the accuracy of the classification, enhancement of the current classifier and selection of different classification techniques known like ensemble learning can be the future scope of research for the Ear Recognition System.

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