



Human Authentication Using Ear Biometrics

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Abstract— Ear recognition has emerged as a robust biometric technique, prized for its immunity to facial expressions and minimal physical interaction requirements. Study unveils a pioneering algorithm harnessing deep convolutional neural networks (CNNs) for ear recognition, shedding light on the network's acquired features. The ear's consistent facial location, notably in profile views, bolsters its suitability as a biometric identifier, with proven efficacy even in distinguishing identical twins. Furthermore, ear segmentation from facial images presents fewer challenges than facial recognition, benefiting from a predictable background. The integration of support vector machine (SVM) classifiers with CNNs has significantly bolstered the robustness and accuracy of ear recognition models by adeptly managing high-dimensional feature spaces. Renowned for their capacity to find optimal hyperplanes for class separation and maximize margin, SVM classifiers enhance generalization and noise resilience, especially on unseen data. With the versatility to handle both linear and non-linear classification tasks through diverse kernel functions, SVMs effectively capture intricate decision boundaries. The successful applications span text classification, image classification, and pattern recognition domains, attributed to their adaptability to diverse data distributions and high-dimensional data handling capabilities.

I. INTRODUCTION

Ear biometrics-based authentication harnesses the distinctive anatomical features of an individual's ear to fortify security measures, providing a robust mechanism for identity verification. The integration of Convolutional Neural Networks (CNNs) within the authentication framework significantly enhances its efficacy and resilience, serving as the linchpin for discerning intricate patterns and features embedded within ear images. CNN

technology empowers meticulous image interpretation, even amidst lighting variations, by extracting hierarchical representations that encapsulate both low-level and high-level features. Pre-trained CNN models serve as adept feature extractors, transforming raw pixel values into informative feature vectors. The synergistic interplay between CNNs and Support Vector Machines (SVMs)

facilitates precise decision-making, with CNNs extracting discriminative features and SVMs delineating decision boundaries

for accurate predictions. This harmonious fusion underscores adaptability and resilience, offering a potent solution for fortifying biometric security and ensuring impregnable access to digital resources in diverse and challenging authentication scenarios.

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II. LITERATURE REVIEW

T. Ebanesar, A.D. Bibin, J. Jalaja et al. [1] proposes the biometric-based authentication, particularly utilizing the ear as a distinguishing feature, offers a promising solution. This approach leverages Convolutional Neural Networks (CNN) for accurate recognition, representing a nonintrusive and widely accepted method of human identification. The ear, with its unique attributes, emerges as a reliable biometric characteristic, forming the cornerstone of an integrated biometric security system encompassing both detection and recognition modules.

S.Anila; N.Devarajan et al., [2] talks about the trickiest preprocessing technique for adjusting illumination to address a common issue with ear images that arises from fluctuations in the actual capture system. Difference of Gaussian (DOG) filtering, contrast equalization, and gamma correction are among the stages.

P. Swapnil; Devesh Narayan; Sipi Dubey et al. [3] introduces the utilization of ear structure as a biometric feature is a subject of extensive research, and it has garnered recognition for its high reliability in human identification. This paper contributes to the growing body of work in the field of ear biometrics. The identification process is detailed, encompassing critical steps such as pre-processing, edge detection employing the Canny edge detection method, and the subsequent extraction of farthest boundary points forming a maxline.

Shruti Nikose; Hemant Kumar Meena et al. [4] introduces and underscores the growing significance of biometric technology in various applications, ranging from border control to workforce management. However, it also acknowledges the limitations of current biometrics, such as susceptibility to factors like aging, facial changes, or occlusion due to accessories. The paper proposes the ear as a promising alternative, emphasizing its stability over time, minimal sensitivity to external factors, and uniqueness.

Xuebin Xu; Yibiao Liu; Shuxin Cao; Longbin Lu et al. [5] proposes an Early human ear recognition method that relied on handcrafted features. However, their performance suffered when applied to unconstrained datasets due to variations in image quality. The advent of deep learning has significantly advanced ear recognition.

Yanmin Lei; Junru Qian; Dong Pan; Tingfa Xu et al. [6] discusses the biometric recognition has experienced rapid advancements in recent years, utilizing various common individual characteristics for accurate identification. Techniques such as iris, face, fingerprint, gait, electrocardiogram (ECG), electroencephalogram (EEG), and voice recognition have become prevalent in this domain. Among these, human ear recognition offers unique advantages over other biometric techniques.

Ramar Ahila Priyadharshini; Selvaraj Arivazhagan; Madakannu Arun et al. [7] discusses the Automatic person identification from ear images is an active field of research within the biometric community. Similar to other biometrics such as face, iris and fingerprints, ear also has a large amount of specific and unique features that allow for person identification. In this current worldwide outbreak of COVID-19 situation, most of the face identification systems fail due to the mask wearing scenario.

Joel Markus Vaz; S. Balaji et al., [8] discusses about Convolutional Neural Networks (CNNs) which have emerged as a powerful tool for extracting meaningful information from diverse datasets, revolutionizing various subfields of biological research. Notably, in pharmacogenomics, CNNs have addressed longstanding challenges encountered by traditional computational methods, ushering in a new era of accurate data interpretation.

Ranjita Chowdhury; Dalia Ghosh; Puja Agarwal; Samir KumaBandyopadhyay et al. [9] discusses about Ear biometrics which has witnessed significant progress in recent years, paving the way for further advancements in authentication processes. This paper introduces an innovative matching technique based on correlation, representing a pivotal parameter in ear authentication.

Aimee Booyens; Serestina Viriri et al. [10] discusses the face, ear, iris, fingerprint, and handprint are examples of physiological biometric features; voice, signatures, gait patterns, and keystrokes are examples of behavioral biometrics. To differentiate biometric features used in various applications, including security systems

and forensic investigations, numerous systems have been developed.

III.PROPOSED SYSTEM

The proposed system integrates Convolutional Neural Networks (CNNs) with a Support Vector Machine (SVM) classifier for human authentication using ear biometrics. CNNs are adept at extracting intricate features from images, while SVM serves as a robust classification tool, enhancing the system's authentication capabilities. The system workflow initiates with the acquisition of ear images, followed by preprocessing steps to enhance their analysis suitability. These may include noise reduction, resizing, and contrast adjustment for dataset consistency and clarity. Subsequently, the preprocessed ear images undergo feature extraction via a CNN model. The CNN employs convolutional layers to discern patterns at varying abstraction levels. Through subsequent fully connected layers, the model learns intricate data relationships and performs classification, thereby determining the ear image's authenticity.

During the training phase, the CNN-SVM hybrid model learns to discriminate between genuine and impostor ear images via backpropagation, minimizing prediction errors between actual and predicted labels within the training dataset.

Post-training, the CNN-SVM model is deployed for authentication tasks. When presented with a new ear image, the model processes it through its layers, extracting features and making an authenticity prediction.

This hybrid approach effectively addresses challenges inherent in ear biometrics, such as lighting variations, occlusions, and diverse acquisition angles. Leveraging CNNs enables the system to adapt and learn from these variations, bolstering robustness and accuracy.

In summary, the proposed CNN-SVM hybrid system offers a potent solution for human authentication using ear biometrics. By amalgamating preprocessing techniques, deep learning, and SVM classification, the system accurately identifies individuals based on their distinctive ear patterns, thus presenting a promising avenue for secure authentication systems.

Convolutional Neural Networks:

An especially developed class of deep learning models called Convolutional Neural Networks (CNNs) is used to process grid-like data, like pictures and videos. They have completely changed the field of computer vision and are now widely employed in a wide range of tasks that go beyond vision, such as natural language processing, image recognition, and object detection.

Types of layers:

- Convolutional layer (CONV): The convolution layer (CONV) scans the input I in terms of its dimensions by using filters that carry out convolution operations. Filter size F and stride S are two of its hyperparameters. Feature map or activation map is the term used to describe the final output O.
- Pooling (POOL) - The pooling layer (POOL) performs some spatial invariance and is a down sampling operation that is usually applied after a convolution layer. Specifically, the maximum and average pooling are specific types of pooling in which the respective maximum and average value is taken.
- Fully Connected (FC) – The fully connected layer (FC) operates on a flattened input where each input is connected to all neurons. If present, FC layers are usually found towards the end of CNN architectures and can be used to optimize objectives such as class scores.

	Max pooling	Average pooling
Purpose	Each pooling operation selects the maximum value of the current view	Each pooling operation averages the values of the current view
Illustration		
Comments	- Preserves detected features - Most commonly used	- Downsamples feature map - Used in LeNet

Fig1.Types of Polling Layers used in CNN

Filter hyperparameters:

The convolution layer contains filters for which it is important to know the meaning behind its hyperparameters.

- Filter dimensions: An $F \times F$ filter applied to an input with C channels is a $F \times F \times C$ volume that convolutionally processes an $I \times I \times C$ input and generates an $O \times O \times 1$ feature map (also known as an activation map) as an output.
- Stride: The number of pixels that the window moves after each operation, for either a convolutional or pooling operation, is indicated by the stride S.

- Zero-padding: This technique involves adding P zeroes to either side of the input's boundaries. One of the three modes described below can be used to set this value automatically or manually:

	Valid	Same	Full
Value	$P = 0$	$P_{start} = \left\lfloor \frac{S \left\lfloor \frac{I}{S} \right\rfloor - I + F - S}{2} \right\rfloor$ $P_{end} = \left\lceil \frac{S \left\lfloor \frac{I}{S} \right\rfloor - I + F - S}{2} \right\rceil$	$P_{start} \in [0, F - 1]$ $P_{end} = F - 1$
Illustration			
Purpose	- No padding - Drops last convolution if dimensions do not match	- Padding such that feature map size has size $\left\lfloor \frac{I}{S} \right\rfloor$ - Output size is mathematically convenient - Also called 'half' padding	- Maximum padding such that end convolutions are applied on the limits of the input - Filter 'sees' the input end-to-end

Fig2. Zero Padding used in CNN

IV. EXPERIMENTAL RESULTS

Data Preprocessing and Data Augmentation

In the realm of ear biometrics using Convolutional Neural Networks (CNNs), data augmentation and preprocessing play pivotal roles in enhancing the performance and robustness of the system. Data augmentation is a technique used to artificially expand the size of the training dataset by applying various transformations to the existing images. The transformations may include rotations, translations, scaling, and changes in lighting conditions. Preprocessing, on the other hand, involves a series of operations applied to the raw ear images before feeding them into the CNN. The step is essential for improving the quality and suitability of the data for training.

In combination, data augmentation and preprocessing significantly contribute to the effectiveness of CNN-based ear biometric systems. They enable the model to learn robust features from a diverse range of ear images, making it adept at recognizing ears under various conditions. By ensuring that the training data is representative of realworld scenarios, these techniques bolster the model's generalization capabilities, ultimately leading to a more accurate and reliable authentication system.

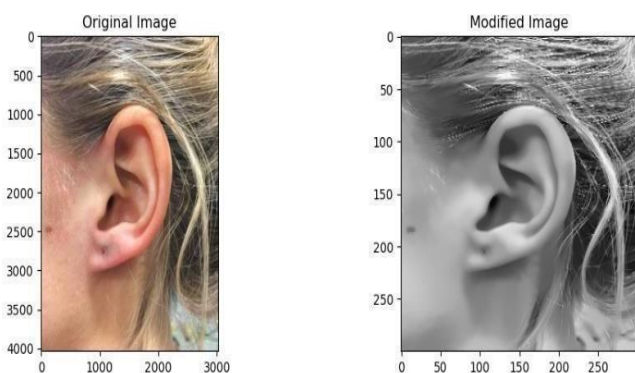


Fig 3.The Original Ear Image and The Modified Ear Image after Data Augmentation.

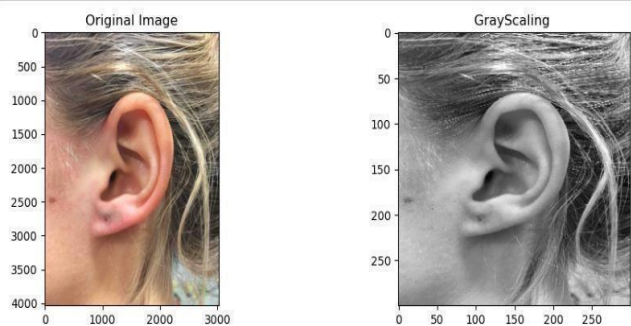


Fig4.The Original Ear Image and The Gray Scaled Ear Image.

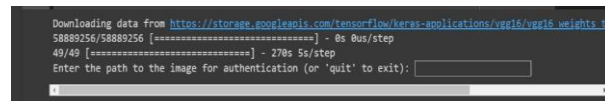


Fig 4. The Ear Image of the Person that need to be authenticated has to be chosen.

The procedure of entering the image path for authentication plays a pivotal role in the proposed system, serving as the initial step for initiating the authentication process. Upon receiving user input specifying the file path to the image, the system proceeds to load and preprocess the provided image for analysis. Subsequently, the preprocessed image is subjected to feature extraction and classification using the CNN-SVM hybrid model. The accuracy and effectiveness of the authentication process hinge on the correctness of the entered image path, emphasizing the importance of precise user input for reliable authentication outcomes

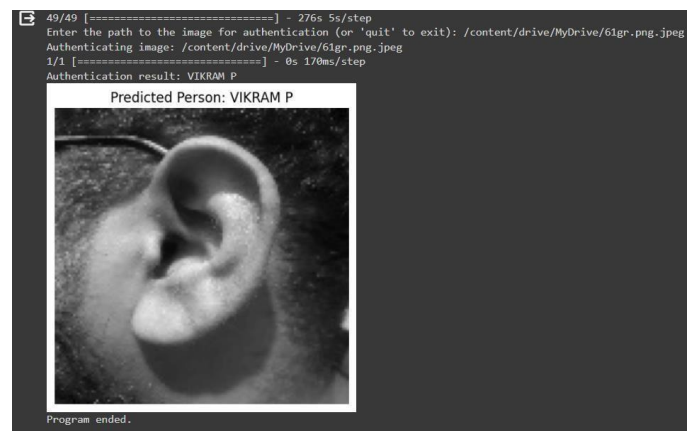


Fig 5. Authentication of the Ear Images

In the envisioned scenario, the authentication process has confirmed the identity of the individual based on the distinctive features extracted from the ear image. The CNN-SVM hybrid model utilized in the system has effectively recognized the unique anatomical characteristics, thereby granting access to the authenticated user. The seamless authentication experience highlights the robustness and reliability of the proposed CNN SVM hybrid approach, ensuring secure access to authorized Individuals.

V. CONCLUSION

The integration of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) in Ear Biometrics represents a significant advancement in biometric authentication. The hybrid model combines CNNs' deep learning capabilities with SVMs' robust classification prowess, demonstrating remarkable efficacy in accurately identifying individuals based on unique ear characteristics. The integrated approach holds substantial potential across various domains, addressing inherent challenges in conventional authentication methods. CNNs excel in feature extraction, analyzing intricate patterns within ear images, while SVMs discern genuine from impostor ear images based on these extracted features. Together, they offer a dependable solution for scenarios requiring precise identification, while also exhibiting resilience against variations in facial expressions and lighting conditions. The adaptability and performance of this hybrid model further enhance its utility, allowing for seamless integration into diverse datasets and real-world environments. With applications spanning security, healthcare, and beyond, CNN-SVM-based Ear Biometrics emerges as a cutting-edge authentication solution poised to revolutionize identification methods.

[10]Aimee Booyens, Serestina Viriri“Exploration of Ear Biometrics Using Efficient Net” (2018).

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