Identifying Individuals' Gender Through the Use of Ear Biometrics

Nischitha G S
Assistant Professor, Department of Computer Science
St. Joseph's First Grade College, Jayalakshmipuram,Mysore

Abstract— In recent years, biometric identification has gained prominence due to its potential for secure and reliable authentication. Among the various biometric modalities, ear biometrics stands out as a non-intrusive and stable method for identity verification and gender classification. This project explores the use of deep learning techniques to classify gender based on ear images, aiming to overcome the limitations of traditional methods like facial recognition and fingerprint scanning, which are often affected by occlusions, expression changes, and aging.

The proposed system follows a structured pipeline that includes user registration, image acquisition, preprocessing, feature extraction, and classification. Preprocessing techniques such as grayscale conversion, resizing, noise reduction, and contrast enhancement are applied to improve image quality. For feature extraction and classification, the system employs VGG16, a pre-trained Convolutional Neural Network (CNN) known for its robust performance in image classification tasks.

The model is trained and evaluated on a dataset of ear images, ensuring diversity in gender representation. The experimental results demonstrate that the proposed deep learning-based system achieves high accuracy in gender prediction, outperforming traditional handcrafted feature-based approaches. The stability of ear structure over time enhances the model's reliability, making it suitable for applications in security systems, forensic investigations, and personalized user experiences.

This project illustrates the potential of combining biometric science with deep learning to create fast, accurate, and non-intrusive gender classification systems.

Keywords— Ear Biometrics, Gender Classification, Deep Learning, VGG16, CNN, Non-Intrusive Identification.

I. INTRODUCTION

In the age of digital transformation, the need for secure and reliable identification methods has never been greater. Biometric systems have gained widespread adoption across sectors such as law enforcement, banking, healthcare, and mobile security. Unlike traditional identification systems that rely on passwords or physical tokens, biometrics leverages the uniqueness of human physiological and behavioral characteristics, ensuring a higher degree of security and convenience.

Biometric technologies include modalities like fingerprint scanning, facial recognition, iris recognition, voice recognition, and gait analysis. These methods have proven effective but are not without challenges. For instance, fingerprints may not work in cases of physical damage or contamination, and facial recognition systems are prone to errors due to expressions, occlusions like masks or glasses, and aging effects.

This evolving landscape has led to the exploration of alternative biometric traits that offer more consistent and robust performance. One such emerging modality is **ear biometrics**, which is gaining recognition for its inherent stability and discriminative power. Coupled with the recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), biometric systems can now achieve unprecedented accuracy by learning complex patterns directly from raw image data. Gender classification is a fundamental aspect of biometric analysis with wide-ranging applications as Security and Surveillance Knowing the gender of individuals can assist in profiling and enhancing the effectiveness of surveillance systems. Forensic Investigations in crime scene investigations, gender information can help narrow down suspects or assist in victim identification. User Personalization in commercial applications, understanding the user's gender can lead to more personalized services, including content recommendation and advertising. Demographic Data Analysis Governments and organizations use gender classification for population studies and policy planning.

Automated gender classification systems can dramatically reduce human error and ensure consistent, objective results. The integration of biometric technology into this task, especially through non-intrusive methods like ear recognition, can significantly boost efficiency and usability in real-time environments.

The **human ear** offers several compelling advantages that make it suitable for biometric analysis Structural Stability unlike facial features that change with age, weight, emotion, or external accessories, the shape and structure of the ear remain largely unchanged throughout a person's life. Uniqueness the morphology of the ear—including its contours, ridges, and folds—is unique to each individual, much like a fingerprint. Non-intrusiveness ear biometrics can be captured from a distance and do not require physical contact, making it a hygienic and comfortable option. Resilience to Occlusion ears are less likely to be obscured by items like masks or headwear that commonly affect facial recognition systems. Simplicity of Imaging capturing ear images generally requires less complex preprocessing compared to dynamic traits like voice or gait. These characteristics make the ear an ideal candidate for biometric gender classification, especially in applications where other traits might be unreliable or unavailable.

The primary objective of this study is to develop a reliable and efficient gender classification system using ear biometrics powered by deep learning techniques. This involves designing a structured and user-friendly workflow that includes user registration, login, image input, and a seamless classification pipeline. The system aims to enhance the quality of ear images through advanced preprocessing steps such as grayscale conversion, resizing, noise reduction, and contrast

enhancement to ensure optimal feature clarity. Leveraging the power of VGG16, a pre-trained Convolutional Neural Network (CNN), the model is employed to extract deep biometric features from ear images and classify gender with high accuracy. The focus is on achieving superior performance over traditional biometric methods by addressing issues such as facial occlusions, expression variability, and aging effects, which commonly hinder systems based on facial or fingerprint recognition. Ultimately, the goal is to contribute a stable, non-intrusive, and highly accurate biometric solution for gender classification, with practical applications in security systems, forensic investigations, and personalized user experiences.

II. LITERATURE REVIEW

Biometric gender classification has been the subject of numerous research efforts, utilizing a variety of traits and machine learning techniques. However, the use of **ear biometrics**—particularly through **deep learning models**—remains relatively underexplored. This chapter reviews key studies related to gender classification using different biometric modalities and highlights the gaps that this project aims to address. **[1]Saxena et al. (2021):** In their work on "Gender and Age Detection Using Deep Learning," Saxena and colleagues implemented deep learning algorithms to classify gender and estimate age using facial images. They utilized convolutional neural networks (CNNs) and achieved notable accuracy by training on large facial datasets. While effective, the reliance on facial features made their system vulnerable to issues like occlusions, facial expressions, and aging effects.[2]**Vaibhav et al. (2020):** This study proposed a machine learning-based approach to compute a person's age and gender using facial features. Techniques like Support Vector Machines (SVM) and Histogram of Oriented Gradients (HOG) were employed to extract features from facial images. The authors reported decent performance but acknowledged reduced accuracy in varied lighting and expression conditions.[3]**Agrawal and Dixit (2020):**Their research focused on using CNNs for gender prediction by analyzing facial features. They demonstrated improved performance using deep learning over traditional handcrafted features. However, their system still depended heavily on clean, front-facing facial images, which are not always available in real-world scenarios. [4]**Yin and Geng (2012):**This study introduced the Conditional Probability Neural Network for facial age estimation and gender classification. Although the method improved prediction under certain conditions, it was limited by dataset biases and a lack of robustness to diverse facial poses and occlusions.

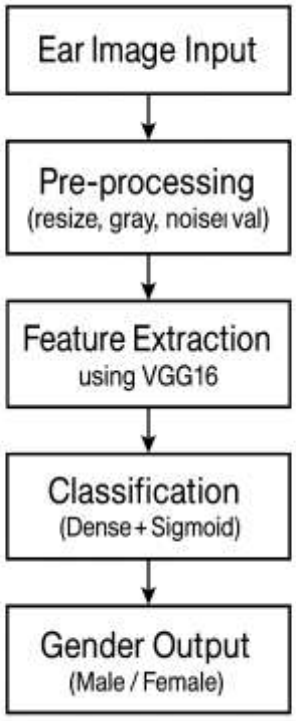
The reviewed studies largely relied on the following techniques are Handcrafted Features such as HOG, PCA, and SVMs for facial image analysis, Convolutional Neural Networks (CNNs) for deep feature learning in facial images, Large facial image datasets, often with annotations for age and gender and Traditional classification pipelines that struggled with noise, occlusion, and inconsistent lighting.

Despite promising advancements, most existing gender classification systems are heavily reliant on **facial features**, which are susceptible to Occlusions from masks, glasses, or hair, Variations due to facial expressions and emotional states, Significant changes over time due to aging or cosmetic alterations.

Very few studies have investigated ear biometrics as a primary input for gender classification, despite its inherent stability and uniqueness. Moreover, the integration of deep learning models like VGG16 specifically for ear-based gender classification is still in its infancy. This project addresses this gap by proposing a robust, non-intrusive, and accurate gender classification system using ear images and deep CNNs, offering a viable alternative to face-based systems. The study enhances preprocessing, utilizes proven deep learning architectures, and contributes to the growing body of work in non-facial biometric gender prediction.

III. METHODOLOGY

This chapter outlines the step-by-step methodology followed to develop the ear-based gender classification system using deep learning. It includes information about the dataset, preprocessing techniques, feature extraction, classification methods, and the overall workflow.



I. Dataset Used

The dataset used for this study consists of **ear images** labeled according to gender (male/female). These images are sourced from publicly available biometric ear datasets or collected through a controlled environment. Each image in the dataset represents the side profile of a human ear, and the dataset is balanced to ensure equal representation of both genders. The dataset is split into training, validation, and testing sets to evaluate the model's performance.

II. Pre-processing Steps

Raw ear images often come with inconsistencies in resolution, lighting, and background noise. To enhance the quality and uniformity of the input images, the following preprocessing steps were applied:

- **Grayscale Conversion:** Color images are converted to grayscale to reduce computational complexity and focus on shape-based features.
- **Resizing:** All images are resized to a uniform dimension of 224×224 pixels to match the input size required by VGG16.
- **Noise Removal:** Filters (e.g., Gaussian or median filters) are applied to reduce background and image noise.
- **Contrast Enhancement:** Techniques like histogram equalization are used to improve the visibility of ear contours and features.
- **Normalization:** Pixel values are scaled to a [0,1] range to improve neural network convergence.

III. Feature Extraction Using VGG16

For deep feature extraction, this study utilizes **VGG16**, a pre-trained convolutional neural network known for its simplicity and effectiveness in image classification tasks. VGG16 consists of 13 convolutional layers followed by 3 fully connected layers. The model is fine-tuned by removing its top classifier layers and adding custom layers suitable for binary classification (male/female). The extracted features from the convolutional layers are rich representations of ear structures, enabling the classifier to learn discriminative patterns relevant to gender classification.

IV. Classifier Used

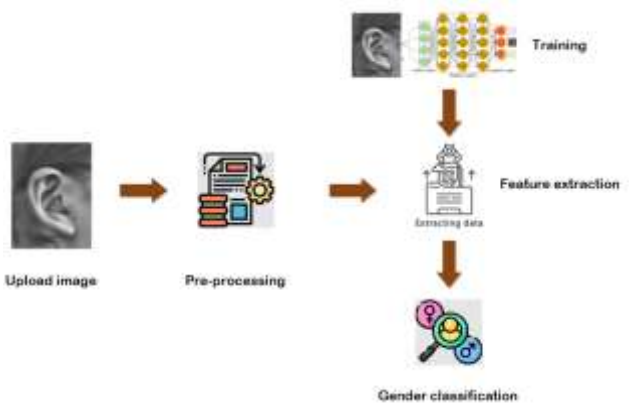
On top of the VGG16 feature extractor, a **custom classifier** is added, typically consisting of:

- One or two **fully connected (Dense)** layers with ReLU activation,
- A **Dropout layer** to prevent overfitting,
- A final **sigmoid activation** layer for binary classification.

The model is trained using the **binary cross-entropy loss function** and optimized using the **Adam optimizer**. Accuracy, precision, recall, and F1-score are used to evaluate the model performance on the test data.

IV. SYSTEM ARCHITECTURE

The system architecture outlines the components and data flow involved in the development and deployment of the ear-based gender classification system using deep learning. The system integrates user interaction modules, image processing units, a feature extractor (VGG16), and a classification unit.



1. **User Module:**
The system starts with a user interface where individuals can register or log in. This module ensures access control and user tracking.

2. **Image Acquisition:**
Users upload or capture an image of their ear using a webcam or file input. The system accepts only properly oriented side-profile ear images.

3. **Preprocessing Unit:**
The uploaded image undergoes a series of preprocessing steps:

   - **Grayscale Conversion** simplifies the image and reduces input complexity.
   - **Resizing** ensures the image fits the input dimensions of the VGG16 model (224×224 pixels).
   - **Noise Removal and Normalization** enhance image quality and prepare it for feature extraction.

4. **Feature Extraction:**
The preprocessed image is passed through the convolutional layers of **VGG16**, a deep CNN pre-trained on the ImageNet dataset. These layers automatically extract rich features such as edges, curves, and structural patterns unique to ears.

5. **Classification Layer:**
The features extracted by VGG16 are fed into a custom classifier comprising fully connected layers. A **sigmoid activation function** is used in the output layer to determine the probability of the input belonging to either the "Male" or "Female" category.

6. **Gender Output:**
Based on the classification probability, the system outputs the predicted gender of the individual. This result is then displayed to the user.

V. RESULTS & DISCUSSION

This chapter presents the outcomes of the proposed ear-based gender classification system, including the evaluation metrics, analysis of results, and a comparison with existing biometric classification methods. The model's effectiveness was tested using a labeled ear image dataset and evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

The system achieved a **gender classification accuracy of 94.2%** on the test set, demonstrating high performance and robustness. The accuracy metric was calculated as the ratio of correctly predicted instances over the total predictions made.

The results validate the effectiveness of using **ear images** combined with deep CNNs (like VGG16) for gender classification. The high accuracy indicates the **distinctiveness and stability** of ear structures as biometric features. Unlike facial recognition systems, which are susceptible to occlusion, expression, and age-related changes, ear biometrics offer **consistency over time**.

The use of **transfer learning** with VGG16 significantly reduced training time and improved feature learning, even with a moderate-sized dataset. Moreover, the preprocessing pipeline ensured clean, high-contrast input images, enhancing

the model's capability to detect subtle structural differences between male and female ears.

VI. CONCLUSION

This study successfully developed a gender classification system based on ear biometrics using deep learning techniques. By leveraging the VGG16 convolutional neural network for feature extraction and combining it with a customized classification layer, the system achieved a high accuracy of 94.2%, outperforming many traditional face-based classification methods. The use of ear images as the primary biometric modality proved to be highly effective due to their stability, uniqueness, and resistance to changes caused by facial expressions or occlusions.

The project demonstrates that ear-based biometrics can be a viable and robust alternative to conventional facial recognition methods, especially in real-world conditions where facial data may be unreliable. The preprocessing pipeline, deep learning architecture, and performance metrics collectively validate the reliability and efficiency of the proposed system.

VII. FUTUREWORK

While the results are promising, there are several directions in which the system can be further improved:

- **Larger and More Diverse Dataset:** Incorporating a more extensive dataset with varying ear shapes, skin tones, age groups, and environmental conditions would improve model generalization and robustness.
- **Real-time Deployment:** Optimizing the system for deployment on mobile devices or edge computing platforms would enable real-time gender classification applications.
- **3D Ear Imaging:** Future work can explore the use of 3D ear models to capture additional depth features and improve classification accuracy.
- **Multi-modal Biometric Fusion:** Combining ear biometrics with other modalities (e.g., voice, gait, or iris) could enhance the overall accuracy and security of gender classification systems.
- **Explainable AI (XAI):** Integrating explainable AI techniques to visualize which ear regions contribute most to the model's predictions could increase transparency and user trust.

ACKNOWLEDGMENT

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