EXPLORING THE EFFICACY OF EAR IMAGES FOR BIOMETRICS IDENTIFICATION

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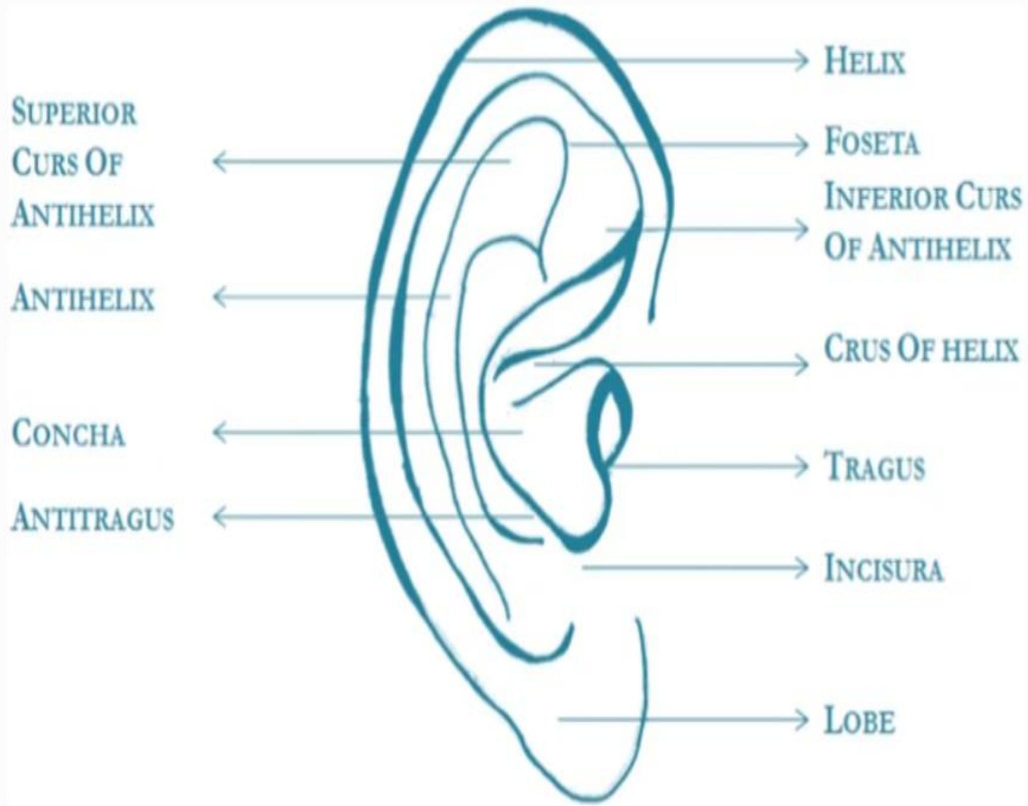
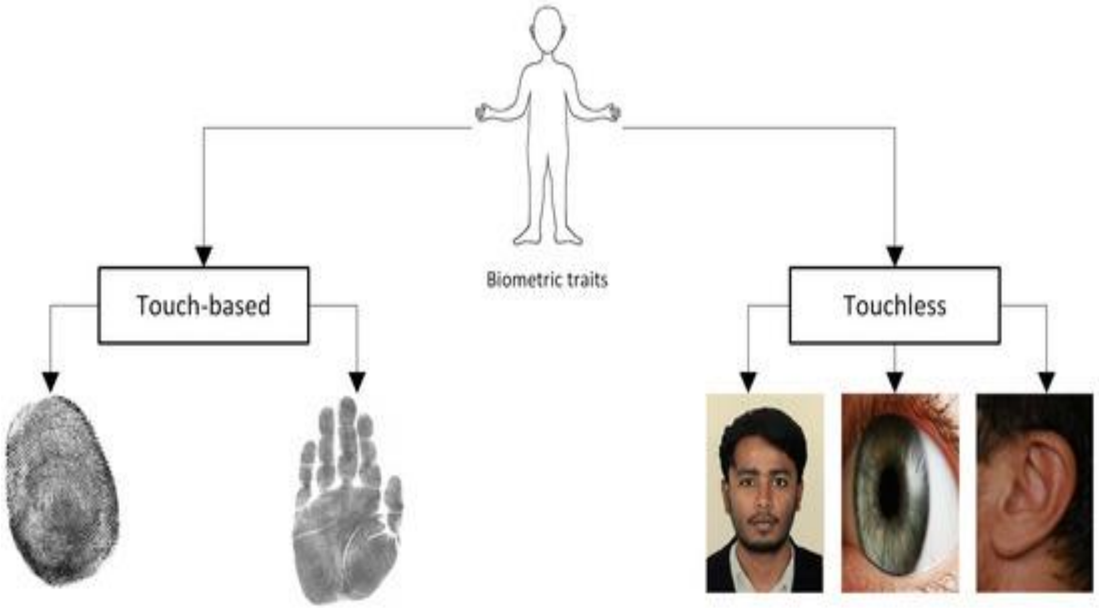
Research Problem

- Automatic person identification from ear images is an active field of research within the biometric community.
- Like other biometrics such as face, iris and fingerprints, ear also has a large amount of **specific and unique features** that allow for person identification.
- Three important factors for person identification are **temporal consistency**, ease of **acquisition**, and **uniqueness** to everyone.



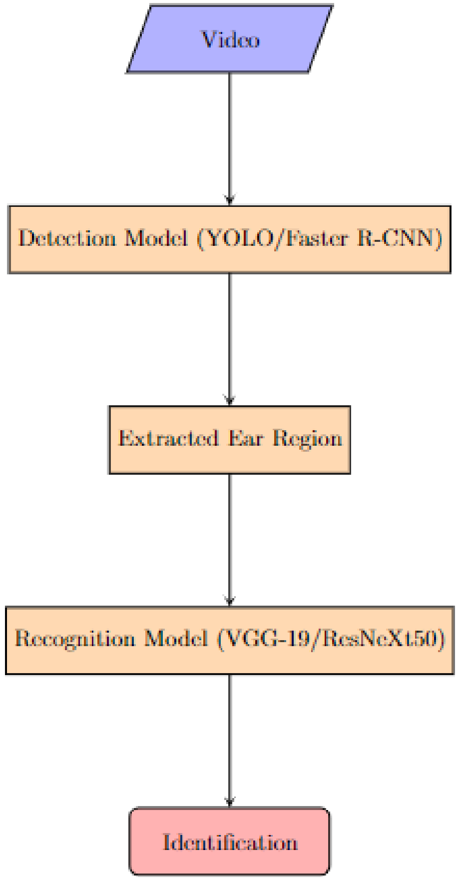
Advantages

- In the worldwide outbreak of COVID-19 situation, most of the face identification systems fail due to the mask wearing scenario.
- The human ear is a perfect source of data for **passive person identification** as it does not involve the cooperativeness of the human whom we are trying to recognize.
- Additionally, the ear can be acquired in a **contactless** and **nonintrusive** manner.



Approach

- The workflow begins with an input in the form of a video capture, which is obtained using OpenCV.
- This video feed is processed by the YOLOv8 model, which extracts the region of the ear.
- The extracted ear region is then used as input to a trained CNN (VGG-11) model for identification.



Novelty

- Evaluation of the performance of ear biometric system using video feed input.
- Using state of the art YOLOv8 (You Only Look Once) model for ear detection. YOLO popular object detection algorithm that can detect objects in real-time is the YOLO model. This method is quicker and more effective than conventional object detection techniques.
- Small custom dataset was created of annotated ear images for detection training and evaluation.

Related Works

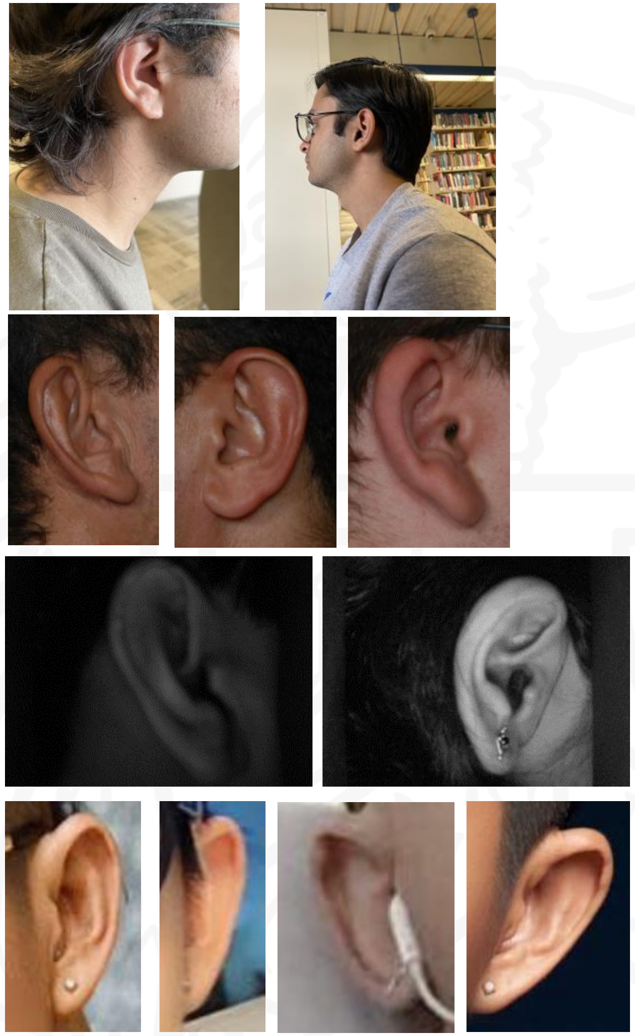
- Raveane, W.; Galdámez, P.L.; González Arrieta, M.A. Ear Detection and Localization with Convolutional Neural Networks in Natural Images and Videos. *Processes* **2019**, *7*, 457. https://doi.org/10.3390/pr7070457
- Ahila Priyadharshini, R., Arivazhagan, S. & Arun, M. A deep learning approach for person identification using ear biometrics. *Appl Intell* **51**, 2161–2172 (2021). https://doi.org/10.1007/s10489-020-01995-8

Table 1. Summary of the available ear databases in literature.

Datasets	Country	Number of peoples	Number of images	Image size
IIT Delhi-I [1]	India	121	471	272×204
USTB Ear [3]	China	77	308	varied
AWE [2]	Slovenia	100	1000	varied
AWE extend [8]	Slovenia	346	4104	varied
AMI [6]	Spain	106	700	492×702
WPUT [5]	Poland	501	2071	varied
UERC [7]	Slovenia	3706	11,804	varied
EarVN1.0	Vietnam	164	28,412	varied and low resolution

Dataset

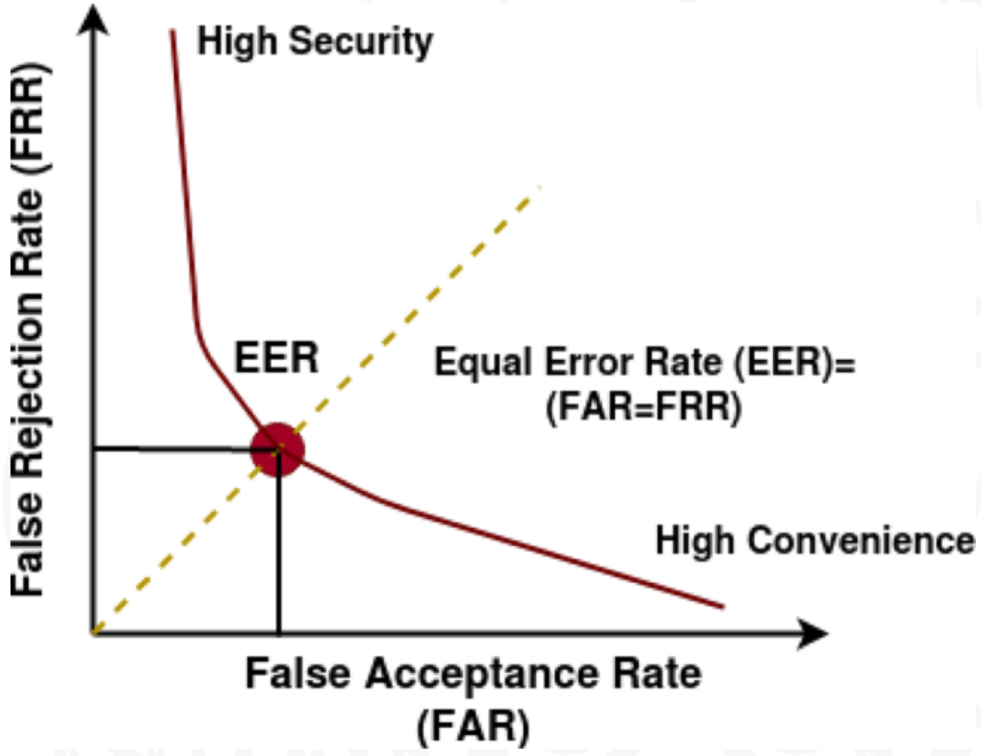
- Custom dataset for detection
  - 2 subjects, 31 images
- AMI dataset
  - 100 subjects, 492 * 702 pixels, 700 images
- IIT Delhi Ear Database version 1.0
  - 125 subjects, 493 images, 272 * 204 pixels
- EarVN1.0: A new large-scale ear images dataset in the wild
  - 164 Asian Individuals (98 males, 66 females)
  - 28,412 Color Images
  - Unconstrained conditions



Evaluation Protocol

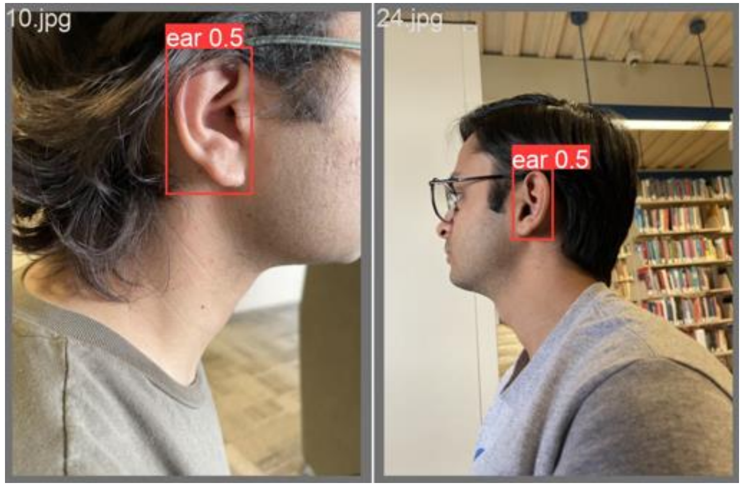
Some common metrics we will be using in our biometric identification systems include:

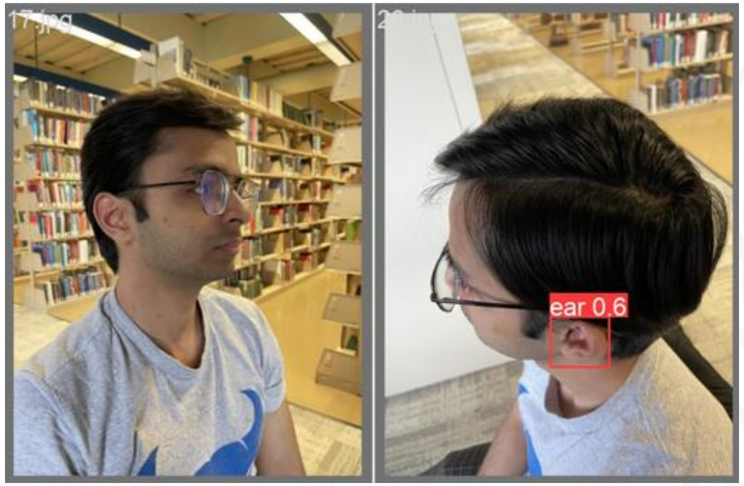
- **True Accept Rate (TAR)**: The percentage of genuine matches that are correctly identified by the system.
- **False Accept Rate (FAR)**: The percentage of impostor matches that are incorrectly identified as genuine by the system.
- **True Reject Rate (TRR)**: The percentage of impostor matches that are correctly rejected by the system.
- **False Reject Rate (FRR)**: The percentage of genuine matches that are incorrectly rejected by the system.
- **Equal Error Rate (EER)**: The point at which the FAR and FRR are equal.

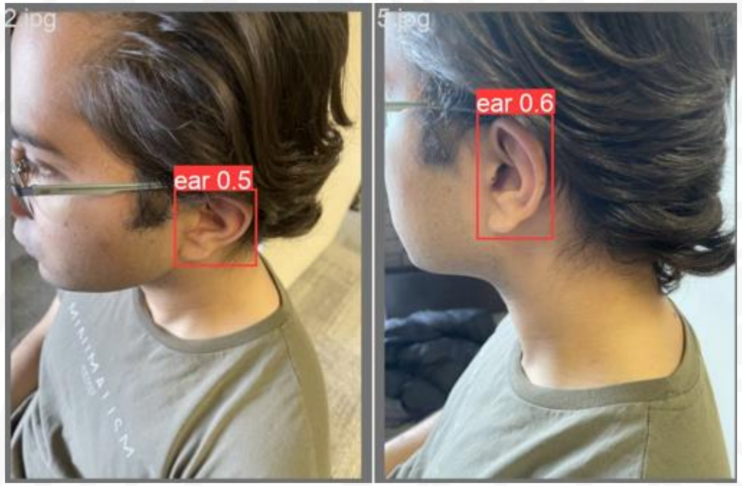


These metrics used to evaluate the performance of an ear biometric identification system and to compare its performance with other biometric identification systems.

Interim Result Analysis - Detection







Interim Result Analysis - Recognition

- VGG-11
  - Trainable params: 132,863,336
  - Training Accuracy: 63.9%
  - Validation Accuracy: 63.3%
- ResNeXt50 (Yet to test)
  - Ear Images Classification Based on Data Augmentation and ResNeXt50
  - 93% for a 70:30 ratio and 90% for a 60:40 ratio

Future Work and Improvements

- Detection
  - Improve the detection performance.
    - Provide more diverse dataset of ear images, including images with varying skin tones, ear shapes, and occlusions, and train a bigger YOLO model (try Faster R-CNN).
    - Multiple ear detection evaluation has not been done yet. Current approach assumes the model will detect single ear per frame.
- Recognition
  - Improvement of recognition accuracy.
  - Use of open set identification

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Questions?