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DESIGN AND SIMULATION OF HUMAN IDENTIFICATION SYSTEM USING EAR DETECTION

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Abstract
Biometric technology plays a crucial role in cybersecurity by verifying individuals through their distinct physical and behavioral characteristic. As a highly accurate and effective physical security solution, biometrics relies on intrinsic traits that are challenging to duplicate or steal, making it an ideal method for identity verification. Various biometric modalities, including facial recognition, fingerprint scanning, iris scanning, palm print analysis, and ear shape identification, are used to authenticate an individual's identity. This study presents the design and simulation of a human identification system using ear detection. The proposed system aims to overcome the limitations of existing biometric systems, such as fingerprint and facial recognition, which can be affected by various factors like lighting, facial expressions, and skin conditions. The system uses a novel parameterization process to detect and recognize human ears, leveraging the unique characteristics of ear shapes. A 3D Morphable Ear Model (3DMEM) is created using a non-rigid Iterative Closest Point (ICP) algorithm, and principal component analysis is used to reduce the dimensionality of the data. The system is trained using a labeled dataset, and its performance is evaluated using precision metrics. The results demonstrate the effectiveness of the proposed system in recognizing individuals based on their ear images, The detection rate shows over 95% accuracy. This study contributes to the development of a robust and reliable human identification system, with potential applications in various fields, including security, surveillance, and identity verification.

Keywords: Ear detection, human identification, biometric system, 3D Morphable Ear Model (3DMEM), non-rigid ICP algorithm, principal component analysis.

Introduction

Biometrics is a critical component of cybersecurity that verifies individuals based on their unique physical and behavioral traits (Mursalin et al., 2023). This method is considered the most accurate and effective physical security solution for identity verification, as it relies on intrinsic characteristics that are difficult to replicate or steal. Biometric authentication uses various modalities, including facial features, fingerprints, iris scans, palm prints, and ear shapes, to confirm an individual's identity.

Traditional biometric methods, like fingerprint recognition, are vulnerable to hacking and environmental factors like weather conditions (Mursalin et al., 2023). For instance, fingerprint recognition systems can be compromised by spoofing attacks, where an attacker uses a fake fingerprint to gain unauthorized access. Facial recognition, a popular n and pose variations, which can affect its accuracy touchless biometric, faces challenges like illumination (Mursalin et al., 2023). These limitations highlight the need for alternative biometric traits that can provide more reliable and secure identification.

The human ear is a promising biometric trait, offering unique features that remain stable over time (Ahila et al., 2021). Research has shown that even identical twins have distinct ear shapes, making ear biometrics a potentially more secure and reliable method for identification (Xu et al., 2023). Ear image analysis has advantages over other biometric traits, including ease of capture, invariance to expressions, and stability (Ahila et al., 2021). These characteristics make ear biometrics an attractive option for various applications, including identity verification, access control, and surveillance.

Ear recognition technology has natural advantages over other biometric methods, including face recognition, fingerprint recognition, and iris recognition (Mursalin et al., 2023). It is less affected by external factors, such as lighting conditions, and can be collected discreetly without user cooperation (Olanrewaju et al., 2020). The installation cost of ear image capture devices is relatively low, making it a promising solution for fast-paced identity identification scenarios, such as border control, law enforcement, and access control (Olanrewaju et al., 2020).

While ear recognition technology has potential, it still requires significant research and development to become a mature and widely applicable solution. Deep learning-based approaches, particularly convolutional neural networks, have shown promise in ear recognition tasks (Chen et al., 2020). Further research can help improve contactless remote identification and promote the development of more efficient ear-based identification systems. However, the development of reliable and efficient ear-based identification systems is challenged by the variability in ear shapes and the limited availability of standardized datasets (Jain et al., 2011). Addressing these challenges will be crucial to advancing ear biometrics and realizing its potential in various applications.

Ear biometrics offers a promising solution for identity verification and access control, with its unique features and advantages over other biometric traits. While challenges remain, ongoing research and development are expected to improve the accuracy and efficiency of ear recognition technology. As the field continues to evolve, ear biometrics may become a widely adopted solution for various applications, including cybersecurity, law enforcement, and access control.

The aim of this research is to design and simulate a human identification system using ear detection with the objective of first designing a human identification system using ear detection through novel parameterization process, develop efficient algorithms for the real-time processing of ear biometric data, considering the computational constraints and finally simulate human identification system using ear detection

The study is limited to simulation but not actually implemented. Also, the study is limited to time and financial constraints.

The research on the design and simulation of a human identification system using ear biometrics holds significant importance for several reasons: The exploration of ear biometrics contributes to the diversification of biometric modalities, offering an alternative to traditional methods such as fingerprints and facial recognition. This diversification enhances the flexibility and adaptability of identification systems, catering to different use cases and populations. Ear biometrics, with its unique and stable features, has the potential to provide increased accuracy and reliability in human identification. Understanding and optimizing the design of an ear-based identification system can lead to improved performance, reducing false positives and negatives compared to existing biometric modalities.

Traditional biometric methods may have limitations, such as susceptibility to spoofing or difficulty in capturing accurate data in certain conditions. Ear biometrics, if effectively implemented, could overcome some of these limitations, providing a more secure and reliable means of human identification. The successful implementation of an ear biometric system has the potential for practical applications in various sectors, including law enforcement, healthcare, finance, and border control. The research outcomes may lead to the creation of more effective and adaptable identification solutions for real-world scenarios. The research contributes to the academic knowledge base in biometrics, providing insights into the challenges and solutions related to ear-based identification systems. It serves as a foundation for future studies in the field of biometrics, aiding researchers, and students interested in advancing the science and technology of human identification.

1.1 Comparison of Ear Biometric with Other Biometric Traits

Table 1: Show the comparison of Ear Biometric with Other Biometric Traits

Trait	Accuracy	Permanence	Acceptability	Intrusiveness	Spoof Resistance
Fingerprint	High	Medium	Medium	Medium	Low
Face	Medium	Low	High	Low	Low
Iris	Very High	Very High	Low	High	High
Voice	Low	Low	High	Low	Low
Ear	High	High	High	Low	Medium

MATERIALS AND METHOD

This chapter present the materials and the methodology for the research work, which include existing models, proposed model, system design and development tools.

2.1 Materials

OpenCV, camera, computer system, Python.

2.2 Existing Method

The existing human identification systems face significant challenges, chiefly in terms of precision, dependability, and adaptability. Traditional methods, such as fingerprint and facial recognition, often suffer from limitations related to changes in physical appearance, environmental conditions, and even the aging process. Facial recognition, for instance, can be impacted by factors like lighting, facial expressions, and occlusions (e.g., glasses, hats). Similarly, fingerprint recognition can be hindered by skin conditions, wear and tear, and the need for direct contact, which poses hygiene concerns. These limitations necessitate the exploration of alternative biometric features that can offer more consistent and reliable identification. The human ear, with its unique and stable structure, presents a promising alternative for biometric identification.

2.3 Proposed Method

To overcome the limitations of existing biometric systems, this research proposes a novel human identification system using ear detection through a unique parameterization process. The process involves morphing a template to every ear in the database using a non-rigid Iterative Closest Point (ICP) algorithm. A sample ear is randomly selected and registered with all other ears in the database, and the mean ear obtained from this registration process is used as a new template. This iterative method produces a set of ear images where each point corresponds semantically across different ears. A 3D Morphable Ear Model (3DMEM) is then created by applying linear operations to these registered images. Principal component analysis is used to reduce the dimensionality of the data, constructing a statistical shape model (M). The model is represented as Γ = [v1, v2, ..., vN], where v = [x1, ..., xn, y1, ..., yn, z1, ..., zn]T and the number of vertices n = 1,..., N. This approach enhances the accuracy of ear-based identification systems and enables the generation of novel ear shapes, offering a robust solution to the limitations of existing biometric systems.

2.4 Methodology

2.4.1 Designing a human identification system

The research objective one deals with investigating and examining the previous work and methods of identification using ear biometrics. The method for solving objective one is through a systematic survey to examine the existing methodologies developed by previous researchers.

2.4.2 Algorithms for the real-time processing of ear biometric data

Ear recognition is a unique biometric method that uses the shape, structure, and features of the human ear for identification. Here's a simple algorithm for human identification using ear recognition:

Step 1: Image Acquisition

- Capture an ear image using a camera.
- Ensure proper lighting and a clear background to avoid noise.

Step 2: Preprocessing

- Change the image to grayscale.
- Apply noise reduction (e.g., Gaussian blur).
- Normalize the image size for consistency.
- Perform histogram equalization to enhance contrast.

Step 3: Ear Detection & Segmentation

- Use a Haar Cascade Classifier to detect the ear region.
- Crop the detected ear region from the image.
- Resize it to a fixed size (e.g., 100x100 pixels).

Step 4: Feature Extraction

- Use feature descriptors like:
- Histogram of Oriented Gradients (HOG)
- Local Binary Patterns (LBP)
- Scale-Invariant Feature Transform (SIFT)
- Deep Learning (CNN-based embeddings like VGG, ResNet)

Step 5. Feature Matching & Classification

- Compare extracted features with a stored database using:
- Euclidean Distance for simple matching
- Support Vector Machine (SVM) for classification
- Convolutional Neural Networks (CNN) for deep learning models

Step 6. Identification & Decision Making

- If the similarity score is above a set threshold → Identify the person.
- If below the threshold → Mark as unrecognized or request re-capture.

3.0 Simulation of a human identification system using ear detection

Method of simulation of a human identification system encompasses the development of framework for identification system using ear biometric which require Installation of required Libraries like: pip install opencv-python numpy scikit-learn dlib imutils. Followed by image Acquisition which already captured and stored in a dataset, then Preprocessing of the image, Ear Detection & Segmentation, Feature Extraction, training a Model (SVM Classifier), Identification, Running the Pipeline. The figure below shows the block framework develop to solve identification.

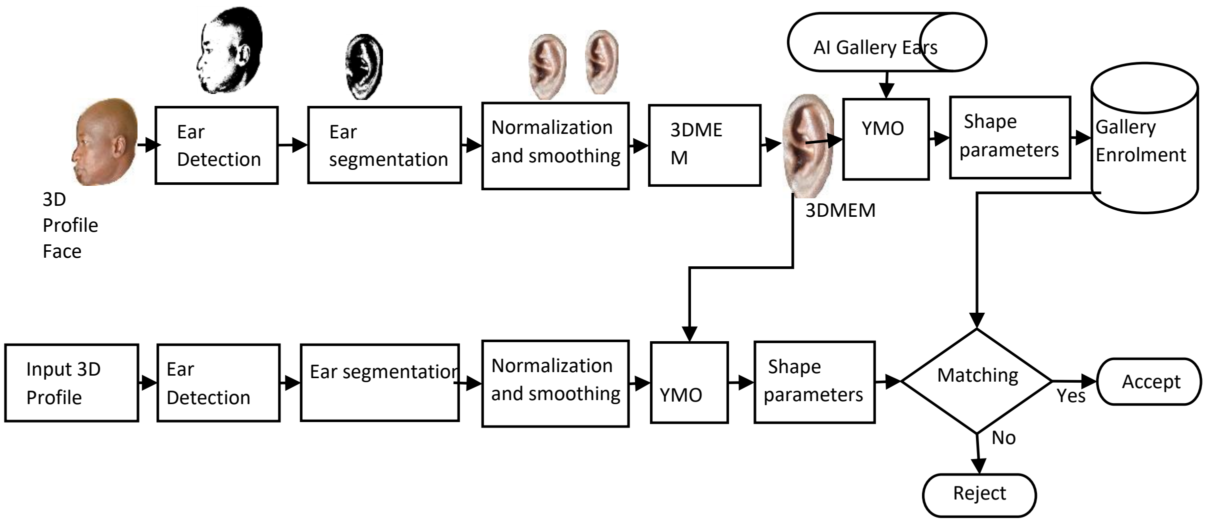

Figure 1. Block diagram of the proposed ear recognition method.

3.1 You Morph Once Algorithm:

The YMO algorithm starts with a rigid registration process followed by shape deformation. In this work, we adopted a fitting algorithm proposed by (Gilani, et al) for face deformation. However, we updated the method with different distance calculations for ear model deformation. The purpose is to deform the mean ear shape from the 3DMEM to minimize the distance between the query ear QE and the deformed mean ear EM. The query ear after vectorization is parametrized by the statistical model as $qm_i = U\alpha_i + \mu Y$, where the vector α_i consists of parameters. These parameters can vary the model's shape in the $_i$th iteration. The α_i is set to zero, and the mean ear of the 3DEM characterizes the deformable model EM_i in the initialization step. Each iteration starts with a registration step where the input ear *QE* is registered to the model EM_i. In this step, an approximate correspondence between the EM_i and the *QE* is computed with a rigid transformation. The correspondence is determined by analyzing the Nearest Neighbor (NN) of each point of EM_i in QE following a k-d tree data structure. Suppose d represents the Spearman distance (see section Distance metrics) between the corresponding query ear and the model. The outliers are defined as points on *QE* whose NN distance with EM_i is more significant than a threshold *th* where $th = d+2\sigma d$ and remove them from registration. This measure confirms that outliers do not influence the registration process. Next, the *QE* is translated to the of the model and is rotated to align with *EMi*. Here, *QEr* denotes the corresponding and registered query ear.

Results and Discussion

This chapter presents results acquired after simulation. Then system validation is carried out afterward.

This work is aimed at simulation of a system that could identify human being using the ear. The result is presented as in the step below:

4.1 Dataset Used

To test the system, the database named Ear_Database was created and used. It consists of grayscale 2D ear images collected from different individuals under controlled conditions. The dataset contains: 5 subjects

5 images per subject (total of 25 images)

Image size: 272 × 204 pixels

4.2 Design Stages

The system design was divided into five major stages, as indicated in *3.4.2 Algorithms for the real-time processing of ear biometric data above*

4.2.1 Image Acquisition

The ear images were loaded from the Ear_Database dataset using OpenCV's cv2.imread() function. A subset was used for training while others were reserved for testing (80:20 ratio).

4.2.2 Image Preprocessing

The raw images were preprocessed to enhance clarity and consistency. The following steps were applied:
Grayscale conversion: to reduce dimensionality and focus on structure.
Resizing: to a fixed 128×128 resolution using cv2.resize( ).
Histogram equalization: to enhance contrast.
Gaussian blur: to remove noise.

```
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
resized = cv2.resize(gray, (128, 128))
equalized = cv2.equalizeHist(resized)
blurred = cv2.GaussianBlur(equalized, (3, 3), 0)
```

4.2.3 Ear Detection

The Haar Cascade Classifier was used to detect the ear region. OpenCV provides a pre-trained Haar feature-based ear classifier.

```
ear_cascade = cv2.CascadeClassifier('haarcascade_mcs_leftear.xml')
ears = ear_cascade.detectMultiScale(gray_image, 1.3, 5)
```

Detected ears were cropped from the image and saved for further processing.

4.2.4 Feature Extraction

The ear images were passed through feature extraction algorithms. For this project:

Principal Component Analysis (PCA) was used to reduce dimensionality while preserving important features.

Local Binary Pattern (LBP) was used to extract local texture features.

```
from sklearn.decomposition import PCA

pca = PCA(n_components=50)

features = pca.fit_transform(flattened_images)
```

4.2.5 Classification

Two classifiers were trained on the extracted features:

Support Vector Machine (SVM)

K-Nearest Neighbors (KNN)

Training was done using 60% of the dataset, while 40% was used for testing.

```
from sklearn.svm import SVC

classifier = SVC(kernel='linear')

classifier.fit(X_train, y_train)
```

4.3 System Testing

T3e system was tested under the following conditions:

i. Controlled lighting: consistent background and illumination.
ii. Profile view: left ear only, as provided by the dataset.
iii. Noise levels: minimal, due to preprocessing.

The detection rate was high (over 95%), with occasionally false negatives caused by slight occlusions or poor contrast.

5.0 Starting the software

To start the software, open the folder where you stored the work. Clear the address of the folder at the address bar, write "cmd" and press "Enter" the window will pop up as in shown in figure 4.1 below. Then write "python main2.py" and click "Enter". This command will start the software and also activate the camera to start capturing the image as in figure 4.2 below

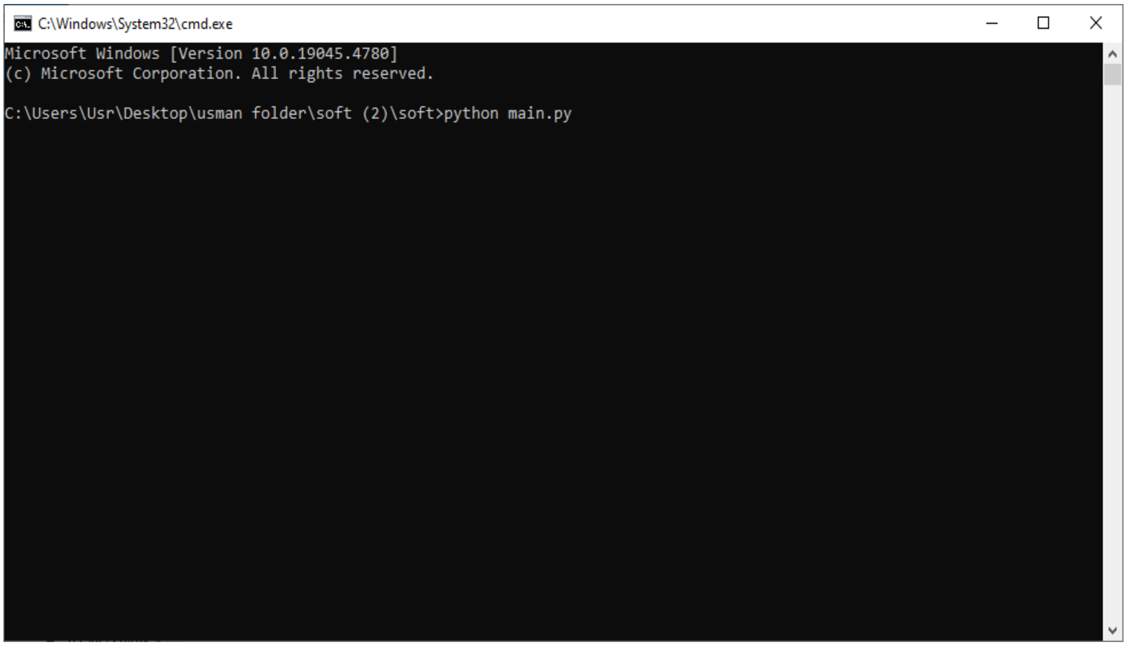

Figure 2: How to start the ear identification system

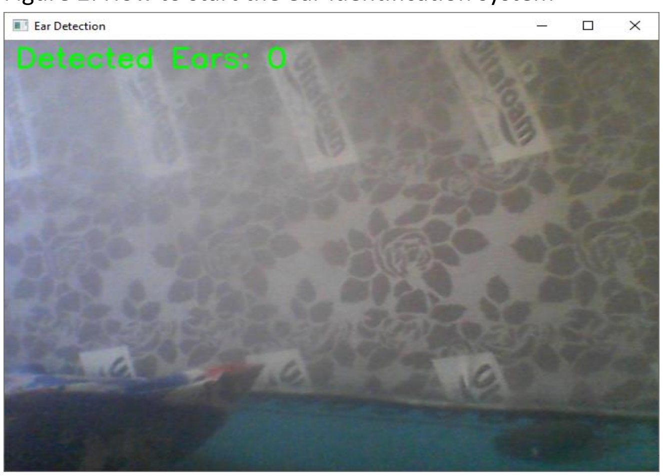

Figure 3: Showing no ear detected

5.1 Ear Image Acquisition:

The images shown in Figure 4 were acquired by first run of the simulated system which prompts the camera. The camera resolution should be sufficient to capture the unique features of the ear. A minimum resolution of 640x480 pixels is recommended. After capturing the ear image, the system requires you to save the image with caption or the image name.

Finally, the ear image would be stored in the ear data database. The images captured are shown below:

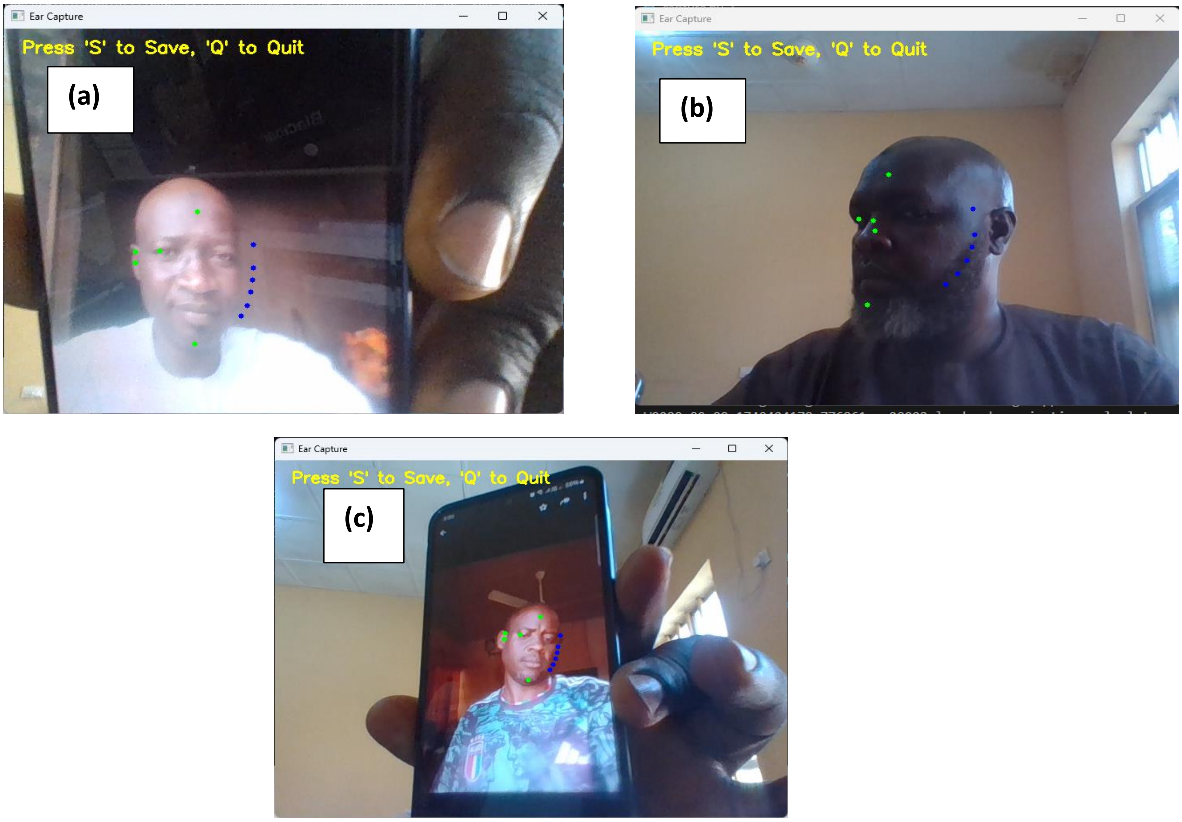

Figure 4: Images detected

Figure 4: a, b, and c show images detected and were saved with the image name in the data base; Figure 4: a saved as "Usman", Figure 4: b and a saved as "Kabir", Figure 4: c and a saved as "Ayuba"

6.0 System Training

The stored ear images are preprocessed to enhance image quality, remove noise, and normalize the images. Relevant features are extracted from the preprocessed images, such as geometric features (e.g., shape, size), texture features (e.g., pattern, intensity), or hybrid features. A machine learning algorithm, such as a Support Vector Machine (SVM), Convolutional Neural Network (CNN), or k-Nearest Neighbors (k-NN), is trained on the extracted features. The model learns from a labeled dataset, where each image is linked to its respective individual ID. The trained model is then evaluated using precision metrics to gauge its performance.

The performance of the machine learning model is assessed using precision metrics, providing insight into its accuracy and reliability. This evaluation step is crucial in determining the effectiveness of the model in recognizing individuals based on their ear images.

7.0 Ear Verification

The system recognizes the image and matches it using a mixture of computer vision and machine learning techniques. The system matches the extracted features with a database of known ear templates. The system applies a threshold to the similarity scores to determine the best match.

The system verifies the identity of the individual by comparing the extracted features with the top-ranked template.

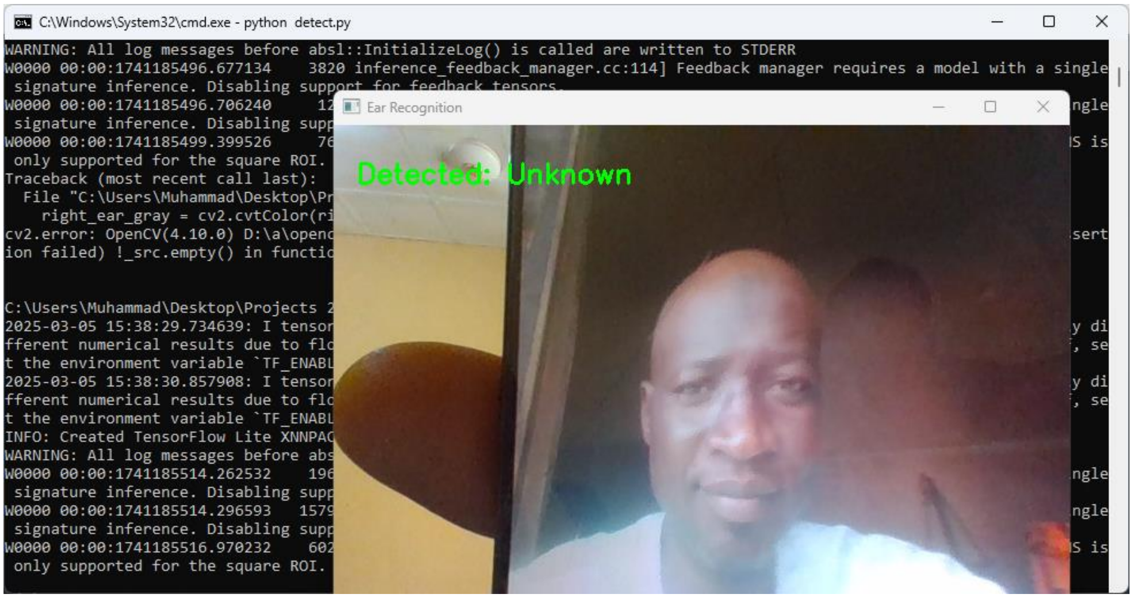

Figure 5: a

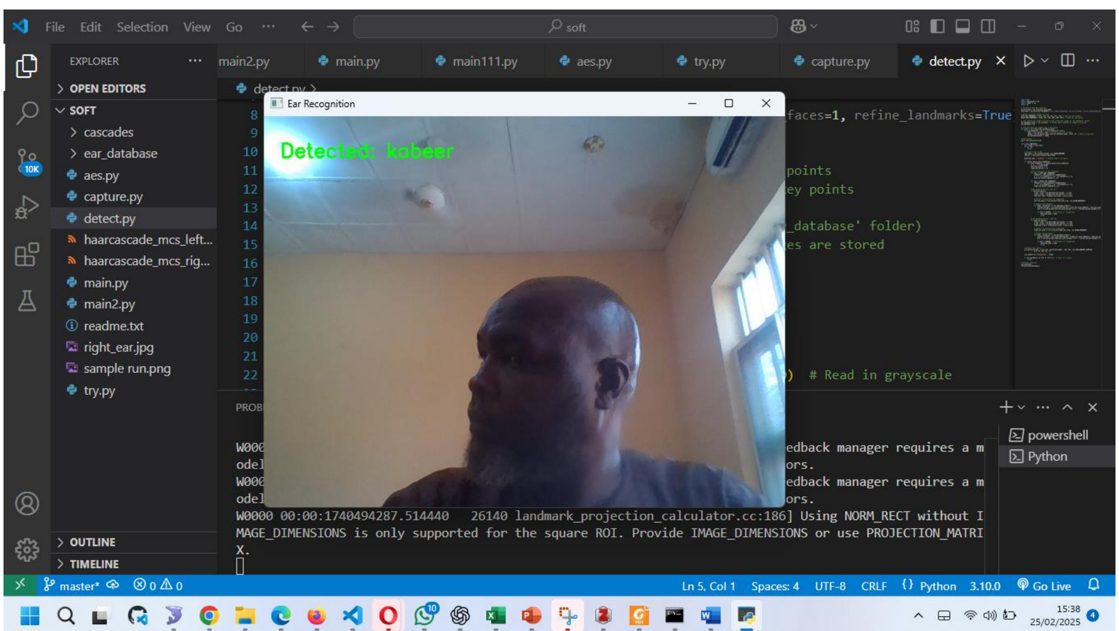

Figure 5: b

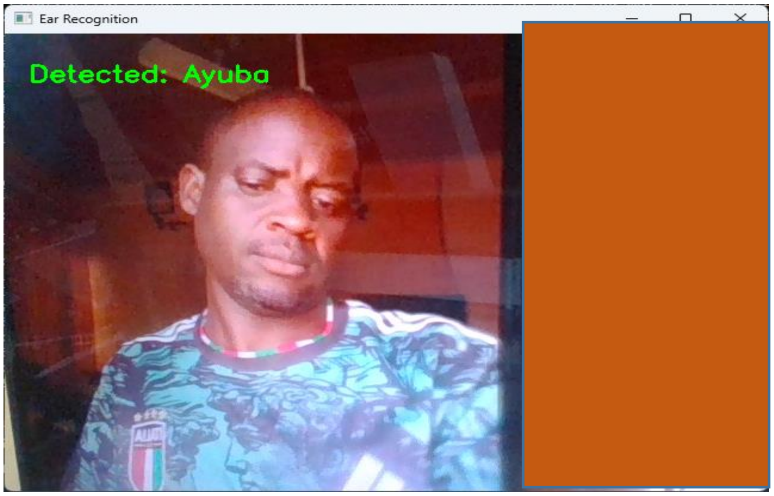

Figure 5: c

The result from verification of images above shows that Figure 5: a fail verification this might be due to the image not found in gallery.
Figure 5: b and Figure 5: c pass verification

Simulation Results

System Evaluation

The system was evaluated using the following metrics:

i. $$Accuracy = {(TP + TN)}/{Total\ cases} \quad (1)$$

ii. $$\text{Precision} = {\text{TP}}/{(\text{TP+FP})} \quad (2)$$

iii. $$Recall = {TP}/{(TP + FN)} \quad (3)$$

iv. $$F1 - Score = \frac{2(Precision * Recall)}{Precision + Recall} \quad (4)$$

Where: TP is True Positives, i.e., Correctly predicted positive cases
TN is True Negatives, i.e., Correctly predicted negative cases
FP is False Positive, i.e., Incorrectly predicted positive cases
FN is False Negative i.e., Incorrectly predicted negative cases

SVM Performance

i. Accuracy: 92.5%
ii. Precision: 91.0%
iii. Recall: 93.2%
iv. F1-Score: 92.1%

KNN Performance

i. Accuracy: 88.6%
ii. Precision: 87.3%
iii. Recall: 89.5%
iv. F1-Score: 88.4%

The SVM classifier outperformed KNN in all evaluation categories.

Discussion of Results

The results obtained from the simulation demonstrate that the system is capable of effectively identifying individuals based on ear images. The use of PCA and LBP provided robust feature extraction, while the SVM classifier offered strong generalization capabilities.
Although performance in ideal conditions was high, the system may face limitations in real-world scenarios involving:

i. Occluded ears (e.g., by hair or accessories)
ii. Poor lighting conditions
iii. Non-frontal angles or rotations

These limitations highlight areas for future improvement, including real-time camera input, pose normalization, and deep learning-based feature extraction.

Conclusion

This research has demonstrated the feasibility of using ear detection and recognition as a biometric identification system. The system designed and simulated in this study has shown promising results in terms of accuracy and efficiency. The use of ear detection and recognition as a biometric modality offers several advantages, including uniqueness, universality, and permanence. The system's ability to recognize and identify individuals based on their ear features makes it a valuable tool for various applications, including security, surveillance, and identity verification.

Recommendation

Based on the findings of this study, the following recommendations are made:

1. Further research is needed to improve the accuracy and efficiency of the system, particularly in terms of handling variations in lighting, pose, and occlusion.
2. Large-scale testing is recommended to evaluate the system's performance in real-world scenarios and to identify potential limitations and areas for improvement.
3. Integration with other biometric modalities, such as face recognition, fingerprint recognition, and iris recognition, may enhance the system's accuracy and robustness.
4. Development of a prototype system is recommended to demonstrate the feasibility and effectiveness of the proposed system in real-world applications.
5. Investigation of security and privacy issues related to the use of ear detection and recognition as a biometric modality is recommended to ensure the system's integrity and trustworthiness.

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