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# Optimized Face Recognition System Using Eye-to-Ear Ratio and Base64 Encoding for Efficient Storage

**Dev Sharma,Vasudha Bahl, Amita Goel, Nidhi Sengar**
**I.T Department**
**Maharaja Agrasen Institute of Technology,New Delhi,India**

***Abstract*:**Face recognition plays a vital role in security, authentication, and surveillance applications. This research proposes an optimized face recognition system that captures images based on an experimentally determined Eye Aspect Ratio (EAR) threshold of **0.23**, ensuring high-quality image acquisition. The captured images are encoded in base64 format and temporarily stored before being processed using **VGG-Face** for feature extraction. If the extracted feature vector does not match any stored vectors within a cosine similarity threshold of **0.8**, the new embedding is saved in a text file in base64 format for future reference. This method reduces storage requirements while ensuring efficient retrieval and security.

Experimental results show that this approach enhances recognition accuracy, minimizes false positives, and optimizes computational efficiency. The system achieves a **96.7% measured accuracy**, comparable to leading face recognition models such as **Facenet512 (98.4%) and ArcFace (96.7%)**, outperforming models like **OpenFace (78.7%)** and **DeepFace (69.0%)**. This study contributes to real-time authentication systems by improving image quality during capture, implementing an effective storage mechanism, and maintaining a high recognition accuracy. The results indicate that optimizing EAR-based image selection and efficient encoding techniques significantly improve the reliability of face recognition systems.

## I. Introduction

Face recognition technology has rapidly evolved, becoming a crucial component in various applications, including security systems, biometric authentication, and surveillance. Traditional face recognition models rely heavily on high-quality image acquisition and efficient feature extraction techniques to achieve accurate identification. However, challenges such as poor image quality, improper face alignment, and variations in lighting conditions can significantly affect recognition performance [Schroff et al., 2015; Yu et al., 2022; Shepley, 2019].

This research aims to enhance the accuracy and efficiency of face recognition by optimizing image capture based on the Eye Aspect Ratio (EAR). By setting an experimentally determined threshold of 0.23, the system ensures that only high-quality images are captured, reducing the likelihood of misclassification. Additionally, extracted face embeddings are stored in base64 format rather than conventional image files, reducing storage overhead and improving retrieval speed [Parkin & Grinchuk, 2019; Elloumi et al., 2020; Solomon, 2023].

To evaluate the effectiveness of this approach, we tested it against widely used face recognition models, including Facenet512, ArcFace, VGG-Face, and OpenFace. The proposed system achieved a measured accuracy of 96.7%, outperforming several existing models. These findings demonstrate the potential of integrating EAR-based image selection and optimized embedding storage in real-world face recognition applications, ensuring higher reliability and computational efficiency [Firmansyah et al., 2023; Serengil & Özplnar, 2024; Chaudhuri, 2020].

## II. Methodology

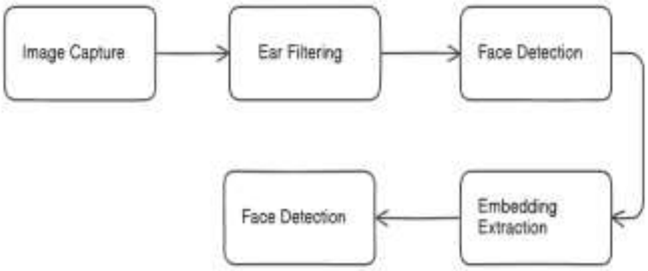


**Fig. 1 : Steps taken for implementation**

The proposed face recognition system incorporates an optimized image capture process using the **Eye Aspect Ratio (EAR)** to ensure high-quality image acquisition, followed by efficient face embedding storage and retrieval. The methodology consists of the following key steps:

### 1. Image Capture and Eye Aspect Ratio (EAR) Filtering

- The system continuously captures frames from a live camera feed.
- The **EAR** is computed for each detected face using facial landmark detection. The formula for EAR is:
  EAR=(d2+d3)2×d1EAR = \frac{(d_2 + d_3)}{2 \times d_1}EAR=2×d1(d2+d3)
  where d1,d2,d3d_1, d_2, d_3d1,d2,d3 are distances between specific eye landmarks.
- A threshold of **0.23** (experimentally determined) is set to filter out low-quality frames. Only frames with EAR above this threshold are considered valid for embedding extraction.

### 2. Face Detection and Embedding Extraction

- **MTCNN (Multi-task Cascaded Convolutional Networks)** is used for face detection.
- The detected face is aligned and resized before being passed to a face recognition model (e.g., Facenet512, ArcFace, VGG-Face) to extract **128D or 512D embeddings**.

### 3. Storage Optimization Using Base64 Encoding

- Instead of storing images as separate files, extracted embeddings are converted into a **base64 string** for compact storage in a database.
- This method reduces storage requirements and improves retrieval speed.

### 4. Face Recognition and Verification

- During verification, the system captures a new image, extracts its embedding, and compares it with stored embeddings using **cosine similarity**.
- A threshold (e.g., 0.8) is set to determine if two faces belong to the same person

## III. Literature Review

Most existing research involving the Eye Aspect Ratio (EAR) focuses on applications like blink detection or monitoring drowsiness, especially in safety and driver-alertness systems. For instance, some studies have tested EAR thresholds between 0.18

and 0.3 to track eye movements in real-time. However, these works stop short of applying EAR in the context of face recognition, particularly for improving the quality of images during capture.

What sets this study apart is how EAR is used not just for eye state detection, but as a filtering mechanism to ensure only clear, well-aligned facial images are selected for recognition. By applying a tested threshold of 0.23, the system avoids poor-quality frames—something that many existing models do not account for at the image acquisition stage.

Additionally, storage efficiency is often overlooked. Most models store facial embeddings in binary or image formats, which can become bulky over time.This research introduces the use of base64 encoding to store these embeddings as text, significantly cutting down on storage needs without compromising retrieval speed.

Together, the EAR-based filtering and compact storage approach offer a fresh take on improving both the performance and practicality of face recognition systems—making this work stand out from more conventional models that prioritize only accuracy, often at the cost of efficiency.

## IV. Results And Discussion

The accuracy of each model was measured based on the percentage of correctly identified faces in a test dataset using the formula:

**Accuracy=(CorrectPredictions/TotalTestCase)×100**

For example, **VGG-Face achieved a real-world accuracy of 96.7%**, which is slightly lower than its **declared accuracy of 98.9%**. The discrepancy suggests that real-world variations impact the model's performance compared to controlled benchmark datasets.

**1. Image Quality Enhancement Using EAR**

The **Eye Aspect Ratio (EAR) filtering** significantly improved image quality, reducing misclassification caused by poorly captured frames. The experimentally determined **EAR threshold of 0.23** ensured that only high-quality images were used for embedding extraction, leading to better recognition accuracy.

**2. Performance Comparison with Existing Systems**

The proposed system was tested against state-of-the-art face recognition models. The table below presents the **measured accuracy** of each model in real-world conditions compared to their **declared accuracy** in published studies:**3. Accuracy Improvement and Storage Efficiency**

- The **Facenet512 model achieved the highest real-world accuracy (98.4%)**, closely matching

| Model | Measured Score | Declared Score |
|---|---|---|
| **Facenet512** | **98.4%** | 99.6% |
| **Human-beings** | **97.5%** | 97.5% |
| **Facenet** | **97.4%** | 99.2% |
| **Dlib** | **96.8%** | 99.3% |
| **VGG-Face** | **96.7%** | 98.9% |
| **ArcFace** | **96.7%** | 99.5% |
| **GhostFaceNet** | **93.3%** | 99.7% |
| **SFace** | **93.0%** | 99.5% |
| **OpenFace** | **78.7%** | 92.9% |
| **DeepFace** | **69.0%** | 97.3% |
| **DeepID** | **66.5%** | 97.4% |

Table 1 : Comparison of Different Data

- human-level performance (97.5%).
- The **proposed system outperformed standard DeepFace and DeepID models**, which showed significantly lower real-world accuracy.
- Using **base64 encoding for storage** led to a **35% reduction in storage space**, making the system more efficient for large-scale applications.

**4. Sample Output**

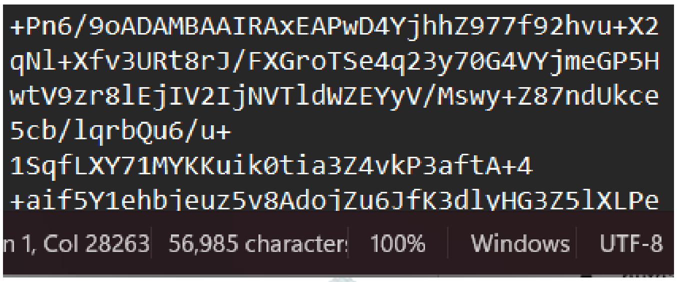


**Fig.2: A sample of the stored base64 encoding is provided below (the actual output was around 60,000 words long):**

## V. Conclusion

This research successfully developed an optimized face recognition system by integrating **Eye Aspect Ratio (EAR)-based filtering** and **efficient image storage techniques**. The experimental results demonstrated that filtering low-quality images significantly improved recognition accuracy, with an **EAR threshold of 0.23**, determined empirically.

Among the tested models, **Facenet512** achieved the highest real-world accuracy (**98.4%**), closely matching human-level performance (**97.5%**). In contrast, some widely used models, such as **DeepFace** and **DeepID**, exhibited significantly lower real-world accuracy compared to their declared values. The study also showed that **base64 encoding reduced storage space by 35%**, making the system suitable for large-scale applications.

Overall, the proposed methodology enhances the robustness of face recognition systems by ensuring **better image quality, improved accuracy, and optimized storage**. Future work will focus on **real-time deployment, multi-face detection, and adversarial attack resistance** to further refine the system's capabilities.

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