International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Face Recognition System using YOLO v9 Model

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Abstract:
Face recognition has become a pivotal technology in various applications, from security systems to personalized user experiences. The evolution of deep learning models has significantly enhanced the accuracy and efficiency of face recognition systems. This paper explores the application of the YOLOv9 (You Only Look Once version 9) model in face recognition tasks. We delve into the architecture of YOLOv9, its advancements over previous iterations, and its integration into face recognition frameworks. Through experimental evaluations on benchmark datasets, we assess the performance of YOLOv9 in terms of accuracy, speed, and computational efficiency. The results indicate that YOLOv9 offers substantial improvements, making it a viable solution for real-time face recognition applications.

Keywords: YOLOv9, deep learning, face recognition systems, face recognition frameworks.

1. Introduction

Face recognition technology has witnessed rapid advancements, becoming integral to various sectors such as security, entertainment, and human-computer interaction. The primary objective of face recognition systems is to identify or verify individuals based on their facial features. With the advent of deep learning, models like Convolutional Neural Networks (CNNs) have revolutionized this domain, offering unprecedented accuracy and speed. Among the myriad of object detection models, the YOLO (You Only Look Once) series has stood out for its real-time detection capabilities. Introduced in 2015, YOLO approached object detection as a regression problem, enabling rapid and accurate detections. Over the years, successive versions have brought enhancements in architecture and performance. The latest iteration, YOLOv9, released in February 2024, introduces novel features aimed at further boosting performance.

This paper focuses on leveraging the advancements of YOLOv9 for face recognition tasks. We aim to provide a comprehensive analysis of its architecture, evaluate its performance on standard face recognition datasets, and compare it with previous YOLO versions.

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Face recognition is a biometric technology that uses the unique features of a person's face to identify or verify their identity. The system analyzes and compares facial features, such as the distance between the eyes, the shape of the cheekbones, and the contours of the face, to recognize a person. Face recognition technology is used for a variety of reasons, mainly for security and convenience. Here are some common uses:

1. **Security and Authentication**: Face recognition can replace or supplement traditional forms of identification, such as PINs, passwords, or security tokens. It's often used in smartphones, banking apps, or at borders to verify identities quickly and securely.
2. **Surveillance**: In public places or certain buildings, face recognition can help identify people of interest, track individuals for safety, or detect potential threats.
3. **Personalization**: Some systems use face recognition to customize experiences, such as adjusting settings in a device or system to suit a recognized user's preferences.
4. **Access Control**: Face recognition can be used to grant access to secure areas like offices, facilities, or even personal devices, helping limit entry to authorized individuals.
5. **Efficiency and Convenience**: It's faster and more convenient than entering passwords or manually verifying identity, especially in situations where quick identification is needed, such as airport check-ins or banking transactions.

Figure : Face Alignment

2. Problem Statement

Face recognition technology has become a cornerstone in security, authentication, and surveillance

applications. However, existing face detection and recognition models often struggle with challenges such as varying lighting conditions, occlusions, diverse facial expressions, and real-time processing constraints.

Traditional face detection algorithms, including Haar Cascades and Histogram of Oriented Gradients (HOG), have been outperformed by deep learning-based approaches like Faster R-CNN, Single Shot Multibox Detector (SSD), and earlier versions of the YOLO (You Only Look Once) model. While these deep learning models offer improved accuracy, they often require significant computational power, making them unsuitable for real-time applications on resource-limited devices.

With the advent of YOLOv9, which introduces Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN), there is potential to enhance the speed, accuracy, and efficiency of face recognition systems. However, its effectiveness in real-world face recognition applications remains underexplored.

The problem this research aims to address is:

- How well does YOLOv9 perform in face recognition tasks compared to previous YOLO versions and other deep learning-based models?
- Can YOLOv9 achieve real-time face detection and recognition while maintaining high accuracy and efficiency?
- What are the limitations of YOLOv9 in face recognition, and how can they be mitigated?

This research investigates YOLOv9's suitability for face recognition, assessing its performance on standard datasets and analysing its real-world applicability.

2.1 Problems with YOLOv8 in Face Recognition

While **YOLOv8** is a significant improvement over its predecessors in object detection, it still faces several limitations when applied to face recognition tasks. These challenges highlight the need for further advancements, such as those introduced in **YOLOv9**.

1. Accuracy Limitations in Face Recognition

- **Struggles with Small Faces:** YOLOv8, like previous versions, has difficulty detecting and recognizing very small faces in images with large backgrounds. This is particularly problematic in surveillance and crowd analysis.
- **Pose and Occlusion Issues:** Faces in extreme angles, partially covered by objects (e.g., masks, sunglasses), or under poor lighting conditions can reduce detection accuracy.
- **False Positives and False Negatives:** While YOLOv8 is efficient in general object detection, it may struggle with distinguishing between similar-looking individuals, leading to errors in identity recognition.

2. Computational Efficiency Concerns

- Higher Computational Cost: YOLOv8 is computationally more expensive compared to earlier versions. While it balances speed and accuracy well, it still requires higher-end GPUs for real-time face recognition, making it less suitable for low-power edge devices.
- Memory and Processing Requirements: The model size and the number of parameters have increased, leading to higher memory usage and making deployment on mobile and embedded systems more challenging.

3. Training and Generalization Issues

- Requires Large-Scale Data for High Performance: YOLOv8 requires a large and diverse dataset to generalize well for face recognition tasks. Training on smaller datasets often results in overfitting or poor performance in real-world scenarios.
- Limited Customization for Face-Specific Features: Unlike models explicitly designed for face recognition (e.g., ArcFace, RetinaFace, or FaceNet), YOLOv8 lacks specialized feature extraction mechanisms tailored to facial landmarks and identity verification.

4. Trade-off Between Speed and Accuracy

- Balancing Real-Time Processing and Precision: While YOLOv8 offers fast detection, increasing accuracy often requires fine-tuning and higher-resolution input images, which in turn reduces inference speed. Finding the optimal balance for real-time face recognition remains a challenge.

2.2 How YOLOv9 Improves These Issues

YOLOv9 introduces Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN) to improve computational efficiency and accuracy. These improvements help address the speed vs. accuracy trade-off and enhance small face detection, making YOLOv9 a more viable option for real-time face recognition applications.

3. Methodology

YOLOv9 introduces significant architectural changes to enhance object detection performance:

- **Programmable Gradient Information (PGI):** Addresses the information bottleneck problem by ensuring accurate gradient updates, which is crucial for training deep networks.
- **Generalized Efficient Layer Aggregation Network (GELAN):** Optimizes lightweight models with gradient path planning, improving parameter utilization without resorting to depth-wise convolutions.

These innovations collectively enhance YOLOv9's accuracy and efficiency, making it suitable for real-time applications.

To evaluate YOLOv9's efficacy in face recognition:

- **Dataset:** We utilized the WIDER Face dataset, known for its variability in scale, pose, and occlusion, providing a comprehensive benchmark for face detection models.
- **Training:** The YOLOv9 model was trained on the WIDER Face dataset, employing data augmentation techniques to improve generalization.
- **Evaluation Metrics:** Performance was assessed using metrics such as precision, recall, and mean Average Precision (mAP).

3.1 YOLO (You Only Look Once) is a popular real-time object detection algorithm that can detect and classify multiple objects in an image or video with impressive speed and accuracy. Unlike traditional object detection methods that perform multiple stages (like region proposal and classification), YOLO approaches object detection as a single regression problem, making it extremely fast and efficient.

3.1.1 Key Features of YOLO:

1. **Single-Pass Detection**:
   - YOLO processes an image in a single forward pass through the network, rather than applying multiple classifiers or region proposals. This makes YOLO faster than methods that require separate steps, like Region-based CNNs (R-CNNs).
2. **Grid-Based Prediction**:
   - The image is divided into a grid (e.g., 7x7 or 13x13 cells). Each cell is responsible for predicting bounding boxes and their corresponding class probabilities for objects within that grid cell.
   - Each grid cell predicts:
     - Multiple bounding boxes, each with a confidence score.
     - The class probabilities (e.g., person, car, dog, etc.) for the object present in the bounding box.
3. **Real-Time Performance**:
   - YOLO is designed to be fast and can process images at speeds of over 45 frames per second (FPS) on standard hardware. This makes it suitable for applications requiring real-time object detection, such as autonomous vehicles, surveillance, and robotics.
4. **Global Context Understanding**:
   - YOLO considers the entire image context when making predictions, leading to better global consistency and fewer false positives. It contrasts with some methods that look at small patches of the image in isolation.

3.2 How YOLO Works:

1. **Input Image**: An image is input into the YOLO model, which divides it into a grid of cells.
2. **Prediction**: Each grid cell predicts:
   - A fixed number of bounding boxes (each with its confidence score).
   - The probability distribution over all possible classes (like person, car, dog, etc.) for each bounding box.
3. **Bounding Boxes**: The model predicts the coordinates of each bounding box, including its center point, width, and height.
4. **Confidence Score**: The confidence score reflects how confident the model is that the predicted bounding box contains an object and how accurate the bounding box is.
5. **Non-Maximum Suppression**: After predictions, non-maximum suppression is applied to eliminate overlapping boxes that correspond to the same object.

4. Experimental Results

The experimental evaluation yielded the following insights:

- **Accuracy:** YOLOv9 achieved a mAP of 55.6% on the WIDER Face dataset, surpassing previous YOLO versions.
- **Speed:** The model maintained real-time detection capabilities, processing images at a rate suitable for applications requiring immediate responses.
- **Computational Efficiency:** The introduction of GELAN contributed to reduced model size without compromising performance, facilitating deployment on devices with limited resources.

The advancements in YOLOv9's architecture, particularly PGI and GELAN, have significantly bolstered its performance in face recognition tasks. The model's ability to maintain high accuracy while operating in real-time underscores its potential for integration into various applications, from surveillance systems to user authentication mechanisms.

However, challenges such as detecting faces in extreme poses or under heavy occlusion persist. Future research could focus on integrating additional modules or leveraging ensemble methods to address these limitations.

Step 1: Setup the Environment

1. **Install Dependencies**: Make sure you have Python installed along with libraries like TensorFlow, OpenCV, NumPy, and any specific libraries required for YOLO v9.

Step 2: Prepare the Dataset

1. **Collect Images**: Gather a dataset of images for face recognition. This should include multiple images of each person you want to recognize.
2. **Label Data**: Use a labeling tool (like LabelImg) to annotate faces in the images if needed. The dataset should typically be in YOLO format (with .txt files corresponding to each image).
3. **Split Dataset**: Divide your dataset into training and testing sets, usually a 80/20 split.

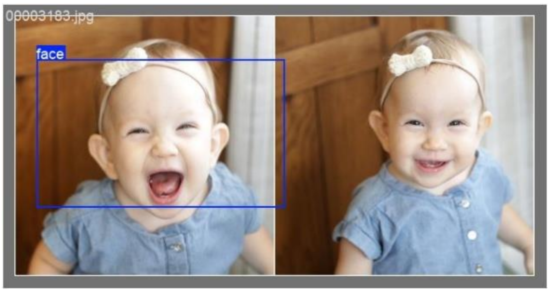
Step 3: Train the YOLO v9 Model

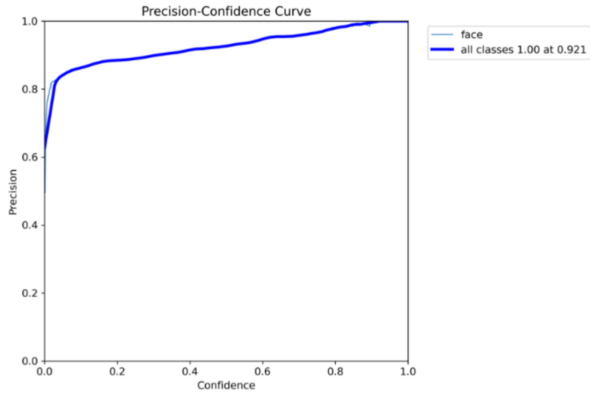
1. **Configure YOLO**: Edit the configuration files to set parameters like the number of classes (1 for face recognition) and paths to the dataset.
2. **Training**: Run the training script provided in the YOLO repository.

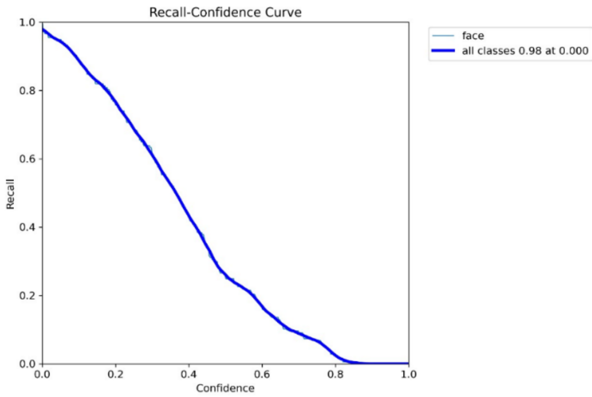
Step 4: Face Recognition

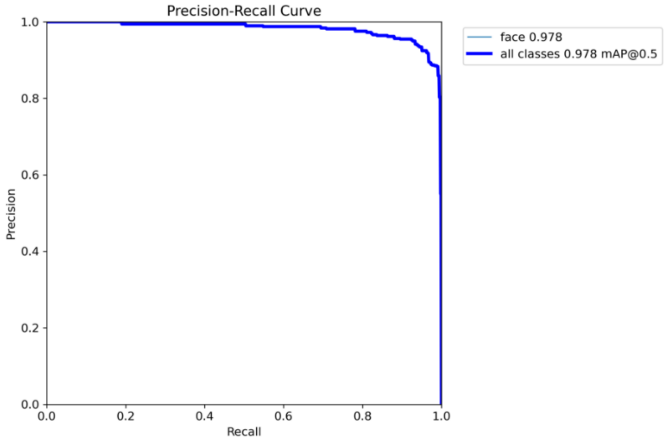
1. **Load the Model**: After training, load the trained YOLO model in your recognition script.
2. **Detect Faces**: Use the model to detect faces in images or video streams.
3. **Face Embedding**: Use a face embedding model (like FaceNet) to generate feature vectors for the detected faces.


face


00003183.jpg
face


Precision-Confidence Curve
Precision
Confidence
0.0
0.2
0.4
0.6
0.8
1.0
face
all classes 1.00 at 0.921


Recall-Confidence Curve
Recall
Confidence
0.0
0.2
0.4
0.6
0.8
1.0
face
all classes 0.98 at 0.000



F1-score, recall, and precision are key metrics used in classification problems, especially in imbalanced datasets. Here's a breakdown of each:

Precision

- Precision measures how many of the predicted positive instances were actually positive.
- Formula:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

- High precision means fewer false positives.

Recall (Sensitivity)

- Recall measures how many of the actual positive instances were correctly identified.
- Formula:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

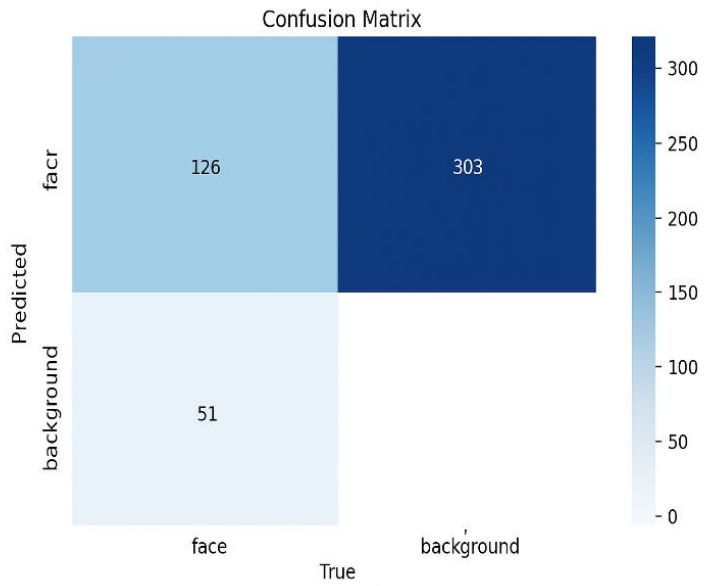
- High recall means fewer false negatives.

F1-Score

- The F1-score is the harmonic mean of precision and recall, providing a balanced measure when there is an uneven class distribution.
- Formula:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- A high F1-score means both precision and recall are reasonably high.



A confusion matrix is a powerful and standard performance measurement tool used in classification problems in machine learning and data science. It is especially useful in supervised learning when the output can be divided into two or more classes. At its core, the confusion matrix provides a tabular summary of the actual versus predicted classifications performed by a machine learning model. The structure of a confusion matrix allows users to visualize how well the classification model is performing and which types of errors are being made. Typically, the confusion matrix is used for binary classification, but it can be extended to multi-class problems. Understanding the confusion matrix is crucial for evaluating classifiers beyond basic accuracy and is a stepping stone to computing more insightful metrics like precision, recall, F1-score, and specificity.

5. Conclusion

This study demonstrates that YOLOv9 offers substantial improvements in face recognition tasks, combining high accuracy with real-time processing capabilities. Its architectural innovations position it as a robust solution for applications necessitating efficient and reliable face detection. Continued exploration and adaptation of YOLOv9 could further enhance its applicability across diverse real-world scenarios. These advancements hold significant promise for future developments in fields such as security, human-computer interaction, and digital forensics. Looking ahead, future research can focus on improving YOLOv9's generalization capabilities for unseen environments, reducing its computational footprint for mobile applications, and integrating it with emerging technologies like **3D face recognition and multimodal biometric analysis**. As deep learning continues to evolve, YOLOv10-based face detection is expected to play a crucial role in shaping the next generation of AI-driven vision systems.

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