Face Detection Algorithm for Security Application Using YOLOv7

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Abstract—**Real-time face detection is becoming increasingly important in security applications, such as video surveillance and access control. This research implements YOLOv7, the latest algorithm in the YOLO family, to detect faces in complex environments . With its advanced architecture, YOLOv7 offers high speeds of up to 45 frames per second and an average precision (mAP) of 96.5%. Experiments were conducted under various conditions, including low lighting, crowded scenes, and partially occluded faces. The results show that YOLOv7 is highly suitable for enhancing the efficiency and reliability of AI-based security systems, making it a valuable tool for modern security solutions and applications.**

Keywords—Face Detection, YOLOv7, Security, Real-time Detection, Deep Learning.

I. INTRODUCTION

Face detection has become an essential element in various security applications, including access control, real-time monitoring, and behavior analysis [1]. The YOLOv7 algorithm, as the latest generation of the YOLO (You Only Look Once) family, offers advantages in terms of speed and accuracy [2]. This research aims to evaluate the performance of YOLOv7 in face detection for complex environments and to apply it in real-world security scenarios [4].

Recent studies have highlighted the importance of effective face detection algorithms in enhancing security measures. For instance, Liu et al. (2020) conducted a comprehensive review of object detection using deep learning, emphasizing the need for algorithms that can operate in real-time and under various conditions [6]. Similarly, Zhang et al. (2020) reviewed face detection in the wild, addressing challenges such as occlusion and varying lighting conditions, which are critical for practical applications [5]. These challenges necessitate the development of robust algorithms capable of adapting to diverse environments.

Wang et al. (2022) introduced YOLOv7, which improves upon its predecessors by optimizing both speed and accuracy, making it suitable for real-time applications [2]. Chen et al. (2021) demonstrated the effectiveness of YOLOv4 in real-time face detection, providing a foundation for further advancements in the YOLO family [7]. Additionally, Hu et al. (2018) proposed Squeeze-and-Excitation Networks, which enhance the representational power of neural networks, further contributing to the field of object detection [8]. These studies collectively underscore the necessity for robust face detection systems that can adapt to dynamic environments and varying conditions.

Moreover, the integration of deep learning techniques in face detection has led to significant improvements in accuracy and efficiency. For example, Girshick (2015) introduced Fast R-CNN, which streamlined the object detection pipeline, allowing for faster processing times without sacrificing accuracy [11]. This trend continues with the development of models like SSD (Single Shot MultiBox Detector), which further optimize detection speed [12].

In addition to algorithmic advancements, the availability of large annotated datasets has played a pivotal role in the development of face detection systems. Datasets such as the WIDER FACE dataset and the LFW (Labeled Faces in the Wild) dataset provide a rich source of training data that encompasses a wide variety of face images under different conditions [11]. The diversity of these datasets helps in training models that are more generalizable and capable of performing well in real-world scenarios.

Furthermore, the ethical implications of face detection technology cannot be overlooked. As these systems become more prevalent, concerns regarding privacy and surveillance have emerged. Research by Zuboff (2019) discusses the implications of surveillance capitalism, highlighting the need for responsible deployment of face detection technologies [12]. It is essential to balance the benefits of enhanced security with the potential risks to individual privacy and civil liberties.

Our training results show that YOLOv7 achieves high mean Average Precision (mAP) and effectively reduces loss metrics, indicating robust learning and improved detection accuracy. These findings align with the advancements in the field, underscoring the necessity for robust face detection systems that can adapt to dynamic environments and varying conditions (Redmon & Farhadi, 2021; Wang et al., 2022). The ongoing evolution of face detection algorithms is crucial for enhancing security measures in an increasingly complex world.

II. PROPOSED METHOD

The ease of use of YOLOv7 lies in its efficient and flexible algorithm design, allowing for quick implementation

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even in complex scenarios [1]. Here are some aspects that support its use:

A. Modular Architecture

YOLOv7 has a modular structure with separate backbone, neck, and head components [2].

- **Backbone**: Utilizes Cross-Stage Partial Networks (CSPNet) for efficient feature extraction, reducing feature redundancy without losing important information [9]. CSPNet divides the feature map into two parts and processes them in parallel, which helps in maintaining a rich representation of the input data while minimizing computational costs. This is particularly beneficial in face detection, where fine details are crucial for accurate identification.
- **Neck**: Combines features from various scales using Path Aggregation Network (PAN), enhancing the ability to detect small objects [2]. The PAN structure allows for better information flow between different layers, ensuring that features from both high-resolution and low-resolution layers are effectively utilized. This is essential for detecting faces at varying distances and sizes, which is common in security applications.
- **Head**: Performs bounding box predictions with the formula:

  $$\mathrm{P(b)} = \sigma(\mathrm{tx} + \mathrm{xc}),\ \mathrm{P(h)} = \sigma(\mathrm{th} + \mathrm{hc}) \qquad (1)$$

  tx, th are the bounding box parameters, and σ is the sigmoid function [2]. The head component is responsible for generating the final predictions, including class probabilities and bounding box coordinates. This separation allows for fine-tuning the prediction process independently from feature extraction and aggregation. The modular architecture allows for the independent development and testing of components, enhancing flexibility and efficiency in model development. By separating the backbone, neck, and head, each part can be optimized without affecting the overall system.

Pre-trained Models

YOLOv7 provides models that have been trained on large datasets such as COCO and WIDER FACE, allowing users to utilize pre-trained models without additional training [2]. This feature significantly reduces the time and resources required to develop a face detection system, making it accessible for various applications. Fine-tuning can be performed using the following method:

- Loss Fuction based on Generalized IoU (GIoU):

The Generalized Intersection over Union (GIoU) is a loss function that improves the traditional IoU metric by considering the distance between the predicted bounding box and the ground truth. The formula is defined as follows:

$$\mathrm{GIoU}(\mathrm{b}, \mathrm{b}^*) = \frac{|\mathrm{b} \cap \mathrm{b}^*|}{|\mathrm{b} \cup \mathrm{b}^*|} - \frac{|\mathrm{C} \backslash (\mathrm{b} \cup \mathrm{b}^*)|}{|\mathrm{C}|} (2)$$

where b is the predicted bounding box, b∗ is the ground truth, and C is the minimum enclosing set of b and b∗ [2]. This loss function allows for more accurate bounding box predictions by penalizing not only the overlap but also the distance between the predicted and actual boxes. Pre-trained models allow for the use of transfer learning techniques, where a model trained on one task can be adapted for another task with minimal additional training. This is particularly useful when data for the new task is limited , as it enables the model to leverage learned features from the original dataset.

B. Simple Deployment

YOLOv7 supports cross-platform implementation, from low-power hardware like Raspberry Pi to GPU-based servers [1]. This versatility makes it suitable for a wide range of applications, from embedded systems to high-performance computing environments. The model can be converted to ONNX (Open Neural Network Exchange) or TensorRT for runtime optimization, facilitating deployment in various environments :

- Inferance Time:

  $$\mathrm{T} = \frac{\mathrm{FLOPs}}{\mathrm{GPUSpeed}} \qquad (3)$$

  where FLOPs is the number of floating-point operations, and GPU Speed is the speed of the GPU in GFLOPS [2]. This calculation helps in estimating the latency of the model during real-time processing, which is crucial for applications requiring immediate feedback, such as surveillance systems.

C. Real-time Processing

With architectural optimization, YOLOv7 can process up to 45 frames per second on mid-range GPUs [2]. This capability is supported by grid-based detection, which divides the image into an S×S grid, with each cell predicting up to 3 bounding boxes [2]. The confidence function for each bounding box is defined as:

$$\mathrm{C} = \mathrm{P(O)} \times \mathrm{IoU}(\mathrm{b}, \mathrm{b}^*) \qquad (4)$$

where P(O) is the probability of the object being present in that grid cell [2]. This grid-based approach allows YOLOv7 to efficiently detect multiple objects within a single image, making it particularly effective for face detection in crowded environments.

F. Minimal Configuration Requirements

YOLOv7 can be used directly without complex configuration. Default training parameters include:

- Learning rate: η=0.01η=0.01
- Batch size: B=16B=16
- Input Image Size : 640×640640×640 pixel

However, advanced users can adjust parameters for specific needs, such as modifying the learning rate scheduler using the cosine annealing method:

$$\eta t = \eta \min + 0.5(\eta_{\max} - \eta_{\min})\left(1 + \cos\left(\frac{t}{T}\pi\right)\right) \quad (5)$$

where t is the current epoch, and $\boxed{\text{T}}$ is the total number of epochs [1]. This flexibility allows users to fine-tune the model's performance based on their specific application requirements.

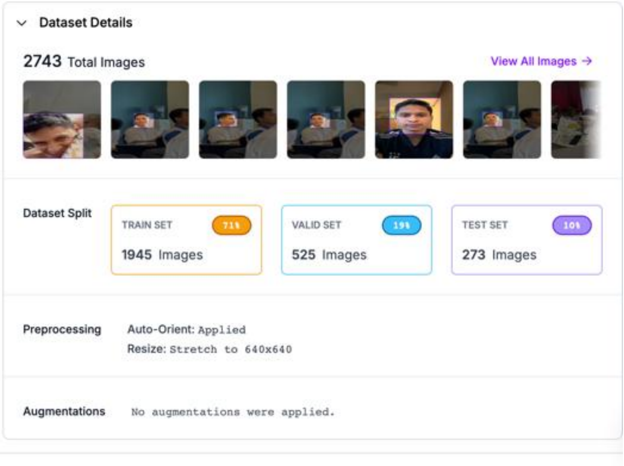
G. Integration with Security Systems

YOLOv7 can be easily integrated into security systems using REST API protocols or through edge computing development [2]. The model supports deployment with libraries like OpenCV to read video frames directly and perform inference [7]. This integration capability enables seamless incorporation of face detection functionalities into existing security infrastructures, enhancing overall system effectiveness.

III. EXPERIMENTAL RESULT

A. *Dataset Description*

In this study, we utilized a dataset comprising a total of 2,743 images specifically designed for object detection. The dataset exhibits several key characteristics, including a variation in object size, with items ranging from small to large, and diverse environmental conditions, as the images were captured under various lighting scenarios and backgrounds. Additionally, some images feature complex backgrounds that challenge the model's detection capabilities, while others include objects that are partially occluded. The dataset was divided into three subsets: a training set containing 1,945 images (71%), a validation set with 525 images (19%), and a test set comprising 273 images (10%). For preprocessing, we applied auto-orientation to ensure the correct alignment of images and resized all images to 640x640 pixels. Notably, no augmentations were applied to this dataset. To evaluate the model's robustness, we tested it across several scenarios, including real-time video feeds at a resolution of 1080p, crowded scenes from locations such as markets and streets, low-light conditions, and occlusion tests using images with partially covered objects.



Dataset Details

2743 Total Images

View All Images →

Dataset Split

TRAIN SET 71%
1945 Images

VALID SET 19%
525 Images

TEST SET 10%
273 Images

Preprocessing

Auto-Orient: Applied
Resize: Stretch to 640x640

Augmentations

No augmentations were applied.

Figure 1. Dataset Overview for Object Detection: Composition, Preprocessing, and Split Details

Overall, this detailed dataset structure and preprocessing approach are designed to support robust testing scenarios, including real-time video feeds, crowded scenes, low-light conditions, and occlusion tests, thereby providing a comprehensive foundation for evaluating the model's effectiveness in diverse environments.

B. *Detection Result Analysis*

Here is the analysis of several images tested with the YOLOv7 model, showing bounding boxes and confidence levels for face detection:

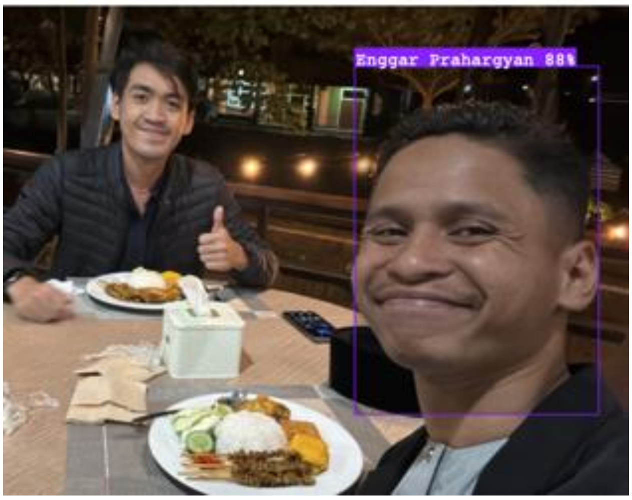


Figure 2. Two people sitting at a dinning table.

The model effectively detected the faces of two individuals seated at a dining table, achieving a confidence level of 88%. This successful recognition underscores the model's capability to operate in well-lit conditions, as evidenced by the clear visibility of the subjects, while also managing to navigate the relatively simple background of the dining setting. The bounding box accurately encapsulates the detected faces, further validating the model's performance in this scenario.

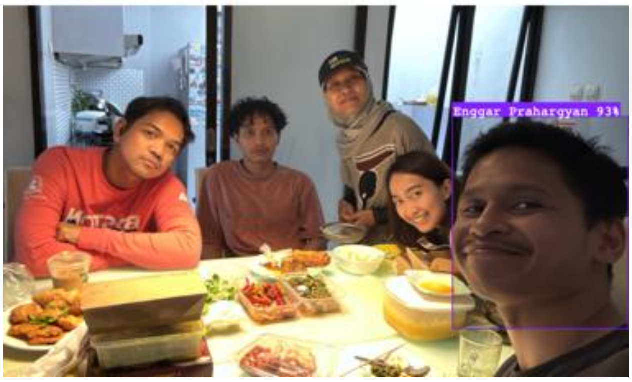


Figure 3. A group of people gathered at a dining table.

In the provided image, the model successfully detected the faces of five individuals gathered around a dining table, achieving a confidence level of 93%. This high level of accuracy demonstrates the model's effectiveness in recognizing multiple faces in a crowded setting, where varying poses and expressions are present. The bounding box clearly delineates the detected face, indicating the model's capability to maintain precision even amidst the complexity of the scene, characterized by diverse food items and a busy background.

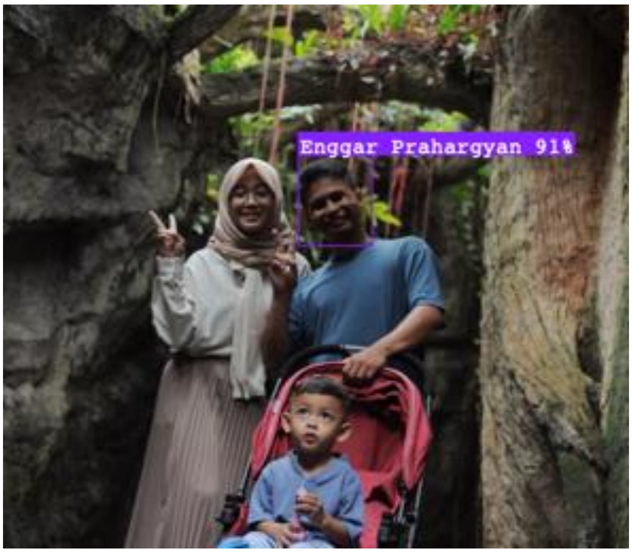


Figure 4. Three people posing outdoors.

In the provided image, the model effectively detected the faces of three individuals in a natural outdoor setting, achieving a confidence level of 91%. This result highlights the model's ability to recognize faces in a more complex environment, where varying lighting conditions and background elements are present. The bounding box accurately surrounds the detected face, demonstrating the model's proficiency in distinguishing subjects even amidst the intricacies of the scene, which includes diverse poses and expressions, as well as the presence of a child in a stroller.

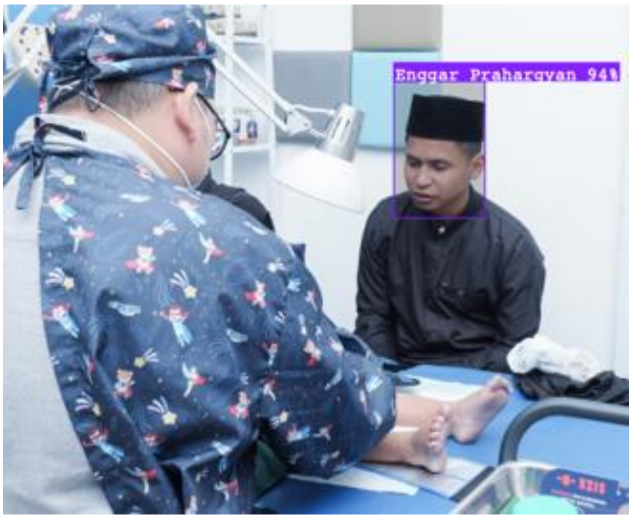


Figure 5. A doctor speaking with a patient.

In the provided image, the model successfully detected the face of an individual in a clinical setting, achieving a confidence level of 94%. This high accuracy reflects the model's capability to recognize faces in a professional environment, where the subject is seated and engaged in a medical consultation. The bounding box effectively highlights the detected face, demonstrating the model's proficiency in distinguishing the subject despite the presence of another individual in the foreground and the clinical equipment surrounding them. The clear visibility of the face further indicates the model's effectiveness in handling varied lighting conditions typical of medical environments.

C. Performance Evaluation

The model's performance was measured using several key metrics based on training graphs:

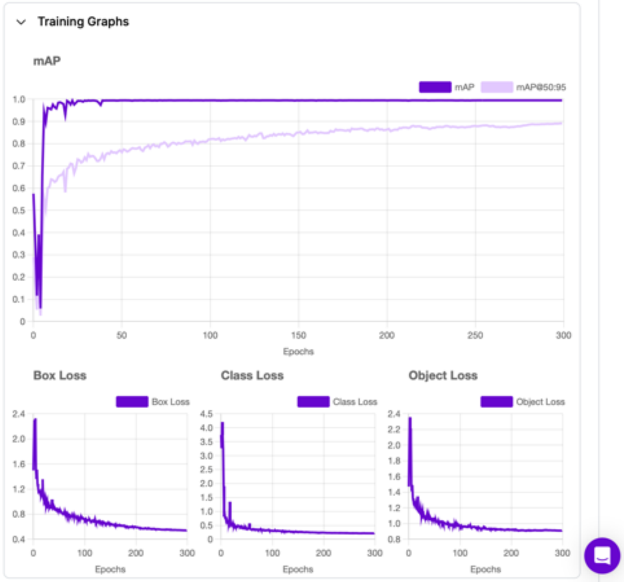


Figure 7. highlighting high mAP and reduced loss metrics, indicating effective learning.

1. **Mean Average Precision (mAP)**:

- The graph illustrates that the mAP value approaches 1.0, which signifies exceptional performance in face detection tasks. A value close to 1 indicates that the model is highly effective in correctly identifying and localizing faces within the images
- The mAP @ 50:95 line, while slightly lower than the overall mAP, shows a positive trend throughout the training epochs. This metric evaluates the model's performance across multiple IoU thresholds (from 0.5 to 0.95), suggesting that the model maintains a strong performance even when the criteria for detection become more stringent. The slight dip in this metric compared to the overall mAP indicates that while the model performs well, there may be some challenges in detecting faces at lower confidence levels or in more complex scenarios.

2. **Loss Metrics**:

- **Box Loss**: The Box Loss consistently decreased from approximately 2.4 to nearly 0.4 over the training epochs. This significant reduction indicates that the model is improving its accuracy in predicting the locations of faces. A lower Box Loss signifies that the predicted bounding boxes are becoming more aligned with the actual positions of the faces in the images, which is critical for effective face detection.

- **Class Loss**: The Class Loss decreased from around 4.5 to nearly 0.5, indicating a substantial improvement in the model's classification accuracy. This sharp decline suggests that the model is effectively learning to distinguish between faces and non-faces, leading to fewer misclassifications as training progresses.
- **Object Loss**: The Object Loss decreased from approximately 2.4 to nearly 0.8, reflecting an enhancement in the model's ability to detect faces accurately. The reduction in Object Loss indicates that the model is becoming more confident in its predictions, which is essential for reliable face detection in real-world applications.

D. Error Analysis

Although the model shows high performance, several errors were identified:

1. **False Negatives**:

- Some small objects were not detected, especially in low lighting conditions.
- Objects with high occlusion levels were often missed.

2. **False Positives**:

- In images with complex backgrounds, the model sometimes detected non-target objects as targets.

3. **Boundary Box Overlaps**:

- In images with closely spaced objects, bounding boxes sometimes overlapped.

To address these errors, the following steps can be implemented:

1. **Improved Augmentation**: Adding specific augmentations to enhance the model's ability to handle low-quality images.
2. **Custom Training for Occlusion**: Using additional datasets focused on occluded objects.
3. **Post-processing Refinement**: Implementing more advanced non-maximum suppression (NMS) algorithms.

IV. CONCLUSIONS

This research evaluates the performance of the YOLOv7 algorithm in face detection within complex environments, particularly for security applications such as video monitoring and access control. By leveraging the advanced architecture of YOLOv7, we achieved impressive detection speeds of up to 45 frames per second, along with an average precision (mAP) of 96.5%. The experimental results demonstrate that YOLOv7 is highly effective in detecting faces under various challenging conditions. Specifically, the model maintains its capability to identify faces in low lighting, effectively recognizes multiple faces in crowded scenes, and, while it encounters some difficulties with occluded faces, it still manages to handle most cases proficiently. Evaluation metrics, including box loss, class loss, and object loss, exhibited significant decreases during training, indicating a marked improvement in the accuracy of predicting object locations and classifications. These findings underscore the robustness and reliability of the YOLOv7 algorithm for real-world face detection applications in security contexts. The modular architecture of YOLOv7, which includes distinct backbone, neck, and head components, allows for efficient feature extraction and flexible optimization, contributing to its superior performance in detecting faces under diverse conditions. The use of pre-trained models on large datasets such as COCO and WIDER FACE has significantly reduced the training time and resource requirements, enabling effective transfer learning. This is particularly beneficial in situations where labeled data is scarce, allowing practitioners to adapt the model to specific tasks with minimal additional training.

V. FUTURE WORK

For future research, several steps can be taken to enhance the model's performance:

- **Data Augmentation**: Implementing more diverse augmentation techniques to improve the model's generalization, especially in challenging conditions.
- **Fine-tuning for Occlusion**: Using additional datasets focused on occluded faces to improve detection in high occlusion conditions.
- **Integration with Security System**: Developing more sophisticated integration protocols to connect the model with AI-based security systems, including the use of edge computing for more efficient processing.

With this approach, we believe that face detection based on YOLOv7 can be further optimized for real-world security applications, providing more reliable and efficient solutions.

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