# Real-Time Detection of Autistic Children's Activities Using YOLOv8 on Social Monitoring Robots

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**ABSTRACT**

Children with autism spectrum disorder require special attention in both therapy and daily activity monitoring. One approach that can assist is the utilization of a Social Monitoring Robot (SMR) with the capability of automatic activity monitoring. This study aims to develop a real-time activity detection system for children with autism using the You Only Look Once version 8 (YOLOv8) algorithm on the SAR platform. The system is designed to recognize key activities such as eating, studying, and walking, through video input from a webcam processed by a Raspberry Pi. The recognition process involves detecting bounding boxes and assigning confidence scores to the child and their activities. The detection results are then visualized through a Human Machine Interface (HMI). Based on the testing, the system is capable of detecting and classifying children's activities with a fairly high level of reliability under real-world environmental conditions. These results suggest that implementing YOLOv8 in an SMR-based monitoring system has the potential to enhance supervision and intervention for children with autism in a more responsive and personalized manner.



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## 1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that significantly impacts a child's communication, behavior, and social interaction. One approach that shows great potential in supporting therapy for children with ASD is the use of Social Monitoring Robots (SMR), which are social robots designed to interact empathetically and non-physically. According to Cano et al., SMRs can establish effective communication that helps children build better social connections [1]. This is supported by Costa et al., who in their systematic review, noted that SMRs have been shown to improve social engagement and cognitive abilities in children with ASD [2].

As technology advances, computer vision is increasingly being applied to recognize the activities and behaviors of children with ASD. Wei et al. developed an image-based activity recognition system capable of detecting characteristic movements of autistic children in real-time [3]. Facial expression detection is also an important approach in recognizing children's emotional states, and deep learning models like YOLOv8 have proven effective in this task. Hosney et al. demonstrated that the AutYOLO-ATT algorithm, based on YOLOv8, successfully recognized autistic expressions with high accuracy [4], while Gu et al. introduced YOLOv8-SMART to identify micro-expressions that are difficult to observe directly [5].

However, the effectiveness of SAR does not solely depend on visual detection capabilities but also on the ability to understand children's engagement and emotions. Syriopoulou-Delli and Gkiolnta explain that technology that can adapt to a child's needs is crucial in social training for children with ASD [6]. This approach is also supported by Raptopoulou et al., who highlight the role of personalized long-term interactions in enhancing trust and the effectiveness of robotic therapy [7].

Engagement measurement serves as a key indicator in evaluating the effectiveness of SMR interactions. Gautam et al. demonstrate that image signal processing techniques can be used to assess children's attention during therapy through facial and body posture analysis [8]. In addition to technology, parental involvement has also been shown to have a significant impact. Amirova et al. found that parental support during robotic therapy sessions strengthens children's engagement and accelerates social development [9].

Research conducted by Ye (2024) demonstrated that the YOLOv8 algorithm is capable of monitoring elderly conditions, particularly in detecting fall events in real time with an accuracy of approximately 92%, making it highly effective for home-based safety monitoring systems [10]. Furthermore, Khawam, Al-Hashimi, and Abdulateef (2025) developed a daily activity monitoring system using YOLOv8-Pose and found that the model could distinguish normal activities from fall incidents with a low false-positive rate, indicating its suitability for autonomous monitoring in domestic environments [11]. Meanwhile, Hendrawan and Kolandaisamy (2023) conducted a comparative study on the use of YOLOv8 for human monitoring under various lighting and environmental conditions, and their results showed that YOLOv8 provides more stable and accurate human detection performance compared to earlier models, making it highly relevant for computer-vision-based monitoring systems [12].

Based on the findings of the three studies above, which demonstrate the effectiveness of YOLOv8 in various human-monitoring scenarios, this research introduces a distinctly different application focus. Unlike those prior works that primarily address fall detection or general human activity monitoring, the present study applies YOLOv8 specifically to recognize children’s activities within the context of interaction with a social companion robot. The proposed system performs real-time behavioral monitoring using a single YOLOv8 model without incorporating additional methods such as face recognition or GPT-based classification, resulting in a simpler, more practical implementation that directly targets child activity detection as an indicator of engagement during human–robot interaction.

## 2. RESEARCH METHOD

This research method is used to design and build a real-time monitoring system for autistic children's activities using YOLOv8 on the Social Monitoring Robot (SMR) platform. This research consists of several stages: literature study, hardware observation, system design, simulation, implementation, and thorough testing.

### 2.1. Research Framework

This research adopts a systems engineering-based methodology stage, which includes six main phases:

1. Literature Study
   This stage involves in-depth research and analysis of relevant literature, such as scientific journals, books, and online sources. Equipment Observation – Observing hardware specifications such as Raspberry Pi, cameras, and HMI.

2. Equipment Observation
   At this stage, carry out inspection and analysis of all equipment that will be used in the research, including hardware such as cameras, computers, and robots, as well as relevant software.

3. Mechanical Design
   This stage focuses on designing the physical structure of the robot or system, including the frame, component placement, and integration of sensors or actuators.

4. System Simulation
   At this stage, the architecture of the face detection system is designed, an appropriate algorithm is selected or developed, and simulations are conducted to predict the system's performance in detecting faces and activities of autistic children.

5. Hardware and Software Implementation
   This phase involves prototyping the system, including component selection, hardware assembly, software development, and integration of the two. You will implement the YOLO model, integrate it with the robot, and develop software for control and interaction.

6. Testing
   At this final stage, comprehensive system testing is carried out to evaluate the performance and robustness of the face and activity detection system.

### 2.2. Block Diagram System

Block diagrams are the basis of one of the most important parts in designing a tool. Each block part has its own function. From the block diagram, the author can more easily understand the working principle of the circuit as a whole, and the designed system can be built well.

A complete explanation of the block diagram in Figure 1 is as follows:

1. Input, Camera (Low/ High Light): The camera captures facial images in low or high light conditions.
2. Process, The Raspberry Pi acts as the brain to carry out input commands, then it is controlled according to the working system that has been created.
3. Output, Face and Activity Information Detected (Bounding Box, Confidence Score): The System produces information about faces and activities detected on the HMI (LCD).

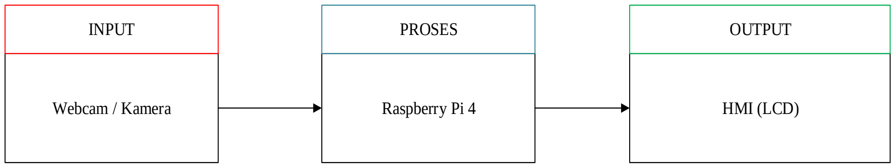



**Figure 1.** Block Diagram System

### 2.3. System Flowchart

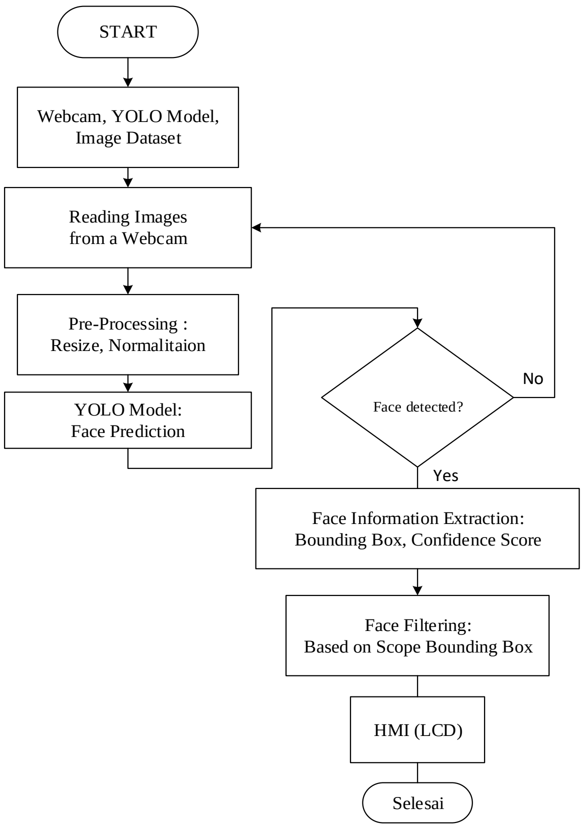



**Figure 2.** Flowchart System

Figure 2 illustrates the overall workflow of the face detection system, beginning with the "Start" symbol, which signifies the initiation of the process. The subsequent stage is System Initialization, during which the primary system components are activated, including:

1. Webcam: Activated and verified to ensure readiness for real-time image acquisition.
2. YOLO Model: A pre-trained face detection model is loaded into system memory.

3. Image Dataset: Prepared for use in system testing and validation.

Following initialization, the system proceeds to the Image Capture stage, where image frames are continuously acquired from the webcam for the purpose of detecting facial features and activities associated with individuals with autism. The acquired images are then forwarded to the Pre-processing stage, which enhances the visual quality to meet the input specifications required by the YOLO model. This stage typically involves:

1. Resizing: Adjusting the image dimensions to conform to the input size expected by the model.
2. Normalization: Scaling pixel intensity values to a defined range, typically between 0 and 1.

Subsequently, the pre-processed images are input into the Face Prediction stage, wherein the YOLO model performs facial detection and generates output data, including bounding boxes and confidence scores. The process then advances to the Face Detection Check stage, where the system evaluates whether a face or activity has been successfully detected. If the detection is successful, the process proceeds to Face and Activity Information Extraction, which involves retrieving bounding box coordinates and corresponding confidence scores. In cases where no valid detection occurs, the system reverts to the Image Capture stage for further processing.

Once the facial data is successfully extracted, a Face Filtering stage is conducted to refine the detection results based on specific criteria, such as minimum face size and confidence threshold, to enhance the system's accuracy. Finally, all valid detection results, including both facial and activity-related information, are presented on the Human-Machine Interface (HMI), typically in the form of an LCD display. The process concludes with the "Finish" stage, indicating the termination of the detection operation.

### 2.4. Electronic Circuits

Electronic design is a systematic process that includes establishing system specifications, selecting appropriate components, designing circuits, and conducting simulations—either online or through specialized software. This process aims to ensure that the simulated design can be easily realized in physical form during the implementation stage of the design process.

1. Raspberry Pi 4: Main computer running YOLOv8.
2. Arduino Mega: Control additional motors and actuators.
3. Logitech C270 Webcam: Capture images of children's activities.
4. 7 Inch LCD: Displays detection results to the user.
5. 2200mAh LiPo Battery & UBEC Stepdown: Provides Power to the entire system.

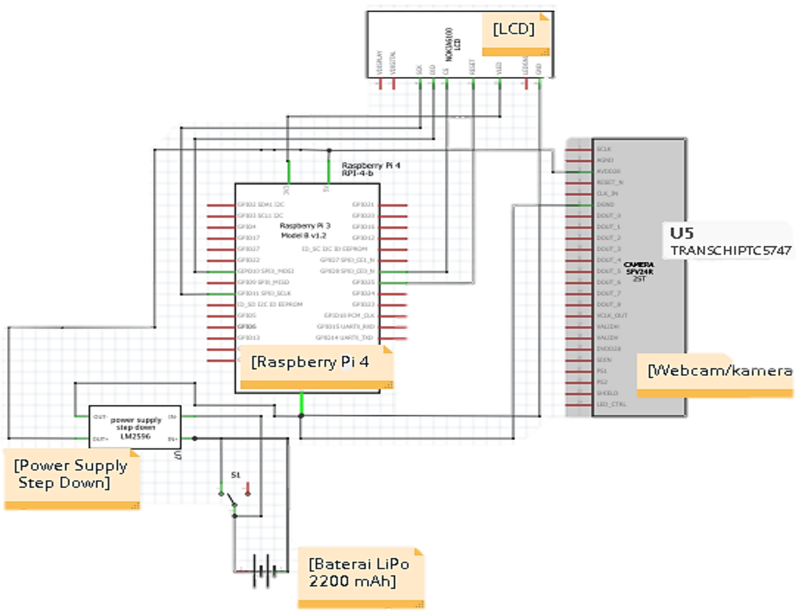



**Figure 3.** Electronics Circuit

Figure 3 The circuits electronics shows how all hardware components in the activity detection system are connected. The Raspberry Pi 4 acts as the main controller, receiving video input from the USB camera and sending detection results to the LCD display. Power is supplied by a 2200 mAh LiPo battery, which is regulated by an LM2596 step-down module to provide safe voltage for the Raspberry Pi. Overall, the diagram illustrates the wiring, power flow, and communication between components needed for the system to operate independently.

### 2.5. Artificial Intelligence (AI)

Artificial Intelligence (AI) is branch knowledge computer focused on development capable system copy intelligence humans , such as learning , reasoning , and decision making decisions . In the Industry 5.0 era, AI plays a vital role in human-machine collaboration, increasing productivity, and enabling better service personalization [13]. The integration of AI in business has revolutionized various sectors by automating processes, improving operational efficiency, and driving product and service innovation [14]. However, the application of AI also raises ethical challenges, including issues of algorithmic bias, transparency, and accountability, which require a robust ethical framework to ensure the responsible development and use of AI [15].

### 2.6. Deep Learning

Deep learning is a branch of AI that uses deep neural networks to extract features and make automatic predictions from raw data, especially visual data. CNNs have proven to be effective in human activity classification and detection due to their ability to recognize spatial features of images [16]. The development of YOLOv8 by Jocher et al. enhances the ability to detect objects in real time with high precision and speed [17]. In addition, the integration of deep learning- based face recognition systems with cloud services such as Google Cloud Vision and Microsoft Azure Face1 API improves the accuracy of face identification in various conditions [18]. The combination of these technologies provides a strong foundation for real-time activity monitoring and face identification systems.

### 2.7. You Only Look Once (YOLO)

You Only Look Once (YOLO) is an object detection algorithm based on deep learning that enables classification and prediction of object positions in a single stage, making it ideal for real-time applications. Its latest version, YOLOv8, carries a faster and more accurate anchor-free architecture. Bakirci's study (2024) showed that YOLOv8n is able to detect vehicles efficiently in intelligent transportation systems [19]. The development of a lightweight version of YOLOv8 that achieves high precision in vehicle detection, while maintaining YOLOv8's stable performance when detecting traffic signs during both day and night.

YOLOv8 is an object detection algorithm based on deep learning that adopts an anchor-free architecture, improving efficiency and making it superior in real-time applications. This model has been enhanced using FasterNet and CBAM attention module, which is able to improve the vehicle detection accuracy up to 98.3% in real-world testing [20]. The integration of Coordinate Attention and BiFPN has also been shown to improve the performance of YOLOv8 in recognizing traffic signs in various complex conditions [21]. In addition, YOLOv8 is effective in detecting small objects such as drones, even in fast-moving and changing lighting conditions [22].

## 3. RESULT AND DISCUSSION

### 3.1. Yolo V8 Training Result

The yolov8 model was trained using a dataset of autistic children's activities consisting of three main classes: learning , eating , and walking . The training process was done for 50 epochs with as following results:

1. Train/ box_loss, train/ cls_loss, and train/ dfl_loss values show a trend decline, good convergence until reaching minimum values below 0.8, 0.5, and 1.1, respectively.
2. val/box_loss, val/cls_loss, and val/dfl_loss values also decreased consistently, indicating that the model did not experience overfitting.
3. precision(b) and recall(b) metrics approached 0.97 and 0.95, respectively, indicating the model's ability to detect and recognize objects very well.
4. map50 value reached 0.98, and map50-95 reached 0.82, indicating that the model's generalization performance was quite high.

Figure 4 shows the training data results.

### 3.2. Evaluation of Detection of Accuracy

Classification performance evaluation was conducted using a confusion matrix on validation data. The results as Table 1.

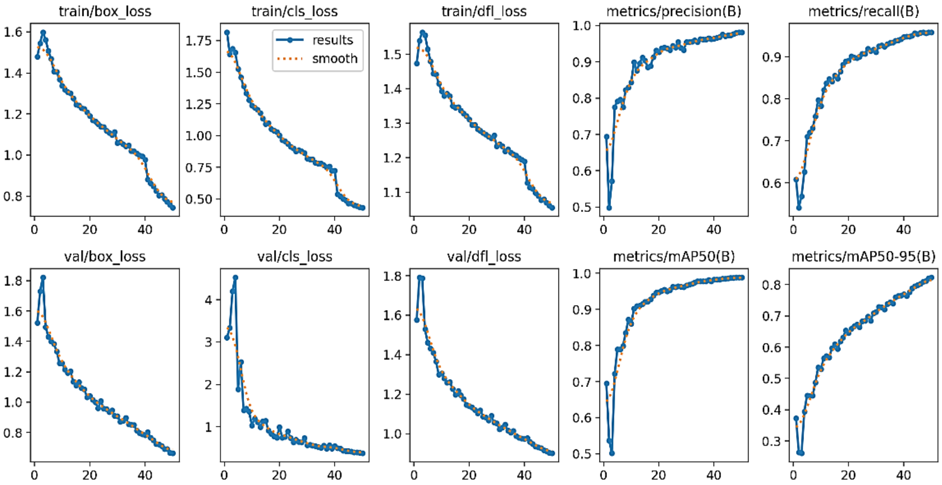



**Figure 4.** Results Training Data

**Table 1.** Training Dataset.

| Class activity | Prediction Correct | Wrong prediction | Total sample |
|---|---|---|---|
| Eat | 961 | 44 | 1005 |
| Study | 1023 | 29 | 1052 |
| Walk | 2905 | 252 | 3157 |
| Background | ( No displayed ) | - | - |

The largest error rate occurred in walking activities were misclassified as background. amounting to 252 data, but this did not affect the detection time. Result daya detection can be seen in Figure 5.

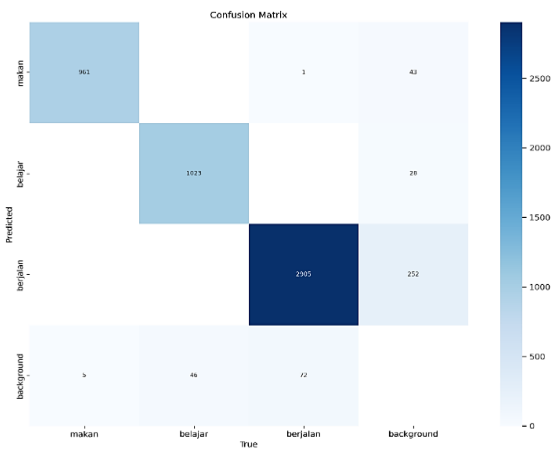



**Figure 5.** Results Data Detection

Analysis of 3 classes:

1. Class “eat”
   a. True positives (TP): 961
   b. False positives (FP): 1 (learning) + 43 (running) = 44
   c. False negatives (FN): 5 ( entered to the background)
   d. Precision = 961 / (961 + 44) ≈ 95.62%
   e. Recall = 961 / (961 + 5) ≈ 99.48%

2. Class “study”
   a. TP: 1023
   b. FP: 0 ( eat ) + 28 ( walk ) = 28
   c. FN: 1 (predicted as food) + 46 (predicted as background) = 47
   d. Precision = 1023 / (1023 + 28) ≈ 97.33%

e. Recall = 1023 / (1023 + 47) ≈ 95.61%

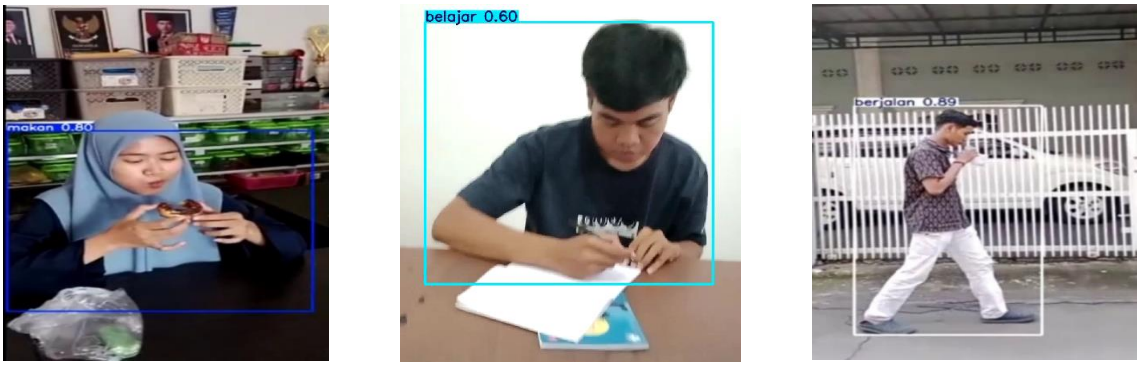
3. Class “Walking”
   a. TP: 2905
   b. FP: 5 (eat) + 46 (study) + 72 (background) = 123
   c. FN: 28 (predicted learning) + 252 (predicted background) = 280
   d. Precision = 2905 / (2905 + 123) ≈ 95.95%
   e. Recall = 2905 / (2905 + 280) ≈ 91.21%

## 3.3. Real-Time Detection Proof

The system was tested in a real environment using three activity test videos:

1. **Learning video**: the system is able to recognize the child's activity of sitting and looking at the table with high accuracy. The bounding box appears stable with the label “ learning ” above 90% confidence.
2. **Eating video**: detection is performed on eating activity characterized by the hand approaching the mouth. The model successfully marks this activity correctly, although sometimes double classification occurs with “learning”.
3. **Walking video**: walking activity is identified from body position, movements, and posture changes. Detection is performed with high accuracy, although the frame rate drops if the lighting is poor.

This detection is done in real-time using Raspberry Pi 4 and Logitech C270 camera, and displayed on 7-inch HMI LCD. The system's average inference time is in the range of 40–50 ms per frame, with a stable frame rate of 20–25 frames per second (fps), depending on the lighting conditions. (a) Eat Detection, (b) Study Detection, (c) Walking Detection can be seen in Figure 6.




(a) (b) (c)

**Figure 6.** (a) Eat Detection, (b) Study Detection, (c) Walking Detection

## 3.4. Analysis

Based on the training, validation, and real-time testing results, the system demonstrates strong performance in recognizing the activities of autistic children with high precision, particularly for learning and walking activities. This indicates that the implemented model has effectively captured distinctive visual patterns associated with these behaviors, allowing it to make accurate predictions in controlled and real-world conditions. The high level of precision suggests that the feature extraction and classification processes are well-optimized, reducing the likelihood of misclassification, which is crucial in sensitive applications such as activity monitoring for children with autism.

In addition to its accuracy, the system also shows strong robustness against noise in images, including irregular and complex backgrounds. This robustness ensures that performance remains stable even when environmental conditions are less than ideal, such as variations in lighting or background clutter. Furthermore, the system is proven to operate reliably on lightweight devices such as the Raspberry Pi, highlighting its efficiency in terms of computational resources. This capability demonstrates significant potential for real-world implementation, particularly in foundations, therapy rooms, or home-based monitoring systems where compact, low-power, and cost-effective solutions are highly desirable.

Moreover, these findings collectively emphasize that the proposed system is not only technically reliable but also practically applicable in real-life settings. The combination of high precision, robustness to visual noise, and stable performance on resource-limited hardware indicates that the system can be deployed continuously without requiring complex infrastructure. This makes it especially suitable for supporting therapists, educators, and caregivers in monitoring autistic children’s daily activities in a non-intrusive manner. By providing consistent and accurate activity recognition in real time, the system has the potential to enhance therapeutic evaluations, improve supervision effectiveness, and contribute to more personalized and responsive intervention strategies.

## 4. CONCLUSION

In conclusion, the YOLOv8 algorithm has been successfully implemented for real-time detection of autistic children's activities using webcam input, focusing on three main activity classes: eating, learning, and walking. The confusion matrix evaluation shows excellent model performance, particularly for eating and learning activities, which achieved precision and recall rates above 95%. Although the walking activity exhibits lower accuracy due to being frequently misclassified as background, this limitation does not significantly affect the main system objective, as the background class is not a priority in the evaluation. Moreover, the ability of YOLOv8 to perform fast and accurate one-shot detection makes it highly suitable for real-time applications, especially for socially assistive robots (SMRs) that require rapid and reliable activity recognition.

For future research, improvements should focus on enhancing the detection performance of walking activities, which currently pose the main challenge. This can be addressed by increasing the quality and diversity of the dataset, particularly by collecting more representative walking samples and applying data augmentation techniques to improve model generalization. Furthermore, future studies may investigate the integration of temporal information from video sequences to enhance the capture of motion patterns, potentially leading to a significant improvement in walking detection accuracy. Further optimization for deployment on embedded systems and real-time robotic platforms is also recommended to strengthen the system's applicability in practical therapy and assistive environments.

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