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Developing a Smart Child Presence Detection in a Vehicle Using Thermal Camera

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Abstract

Children left unattended in parked cars face severe risks due to rapidly rising cabin temperatures, often leading to heatstroke or fatalities. Even on moderately warm days, interiors can reach life-threatening levels within minutes, and despite awareness campaigns, these incidents continue, highlighting the urgent need for proactive detection systems.This project presents a smart child presence detection system for vehicles using thermal imaging and deep learning, designed on preventing fatalities caused by vehicular heatstroke. The system integrates the MLX90640 thermal camera with a Raspberry Pi 5 and leverages the YOLOv8s object detection model to identify human heat signatures in real time. Unlike conventional camera-based or multi-sensor solutions, this work introduces a lightweight, cost-effective approach that ensures reliable detection regardless of lighting conditions. A key novelty of this system lies in its fully embedded implementation, performing all processing locally on the Raspberry Pi to enable fast, autonomous operation without external infrastructure. The system is designed to trigger an alert when a human is detected in the vehicle cabin, activating a buzzer and sending a thermal image notification to the caregiver via a Telegram bot. A five-minute delay mechanism is included to prevent repeated alerts unless manually reset. The YOLOv8s model was trained on a custom thermal dataset and tested under varying distances, angles, and body positions to simulate realistic in-vehicle conditions. Comparative evaluation with a commercial infrared thermometer confirmed the MLX90640's capability in detecting human heat signatures. The results demonstrate the feasibility and potential of combining thermal sensing with on-device AI for real-time child presence detection in vehicles.

1. Introduction

Children left unattended in vehicles face severe risks due to rapidly rising temperatures, often leading to dangerous heat-related illnesses or fatalities. Despite increased awareness and public campaigns, these tragic incidents continue to happen globally and locally, highlighting the critical need for reliable, proactive solutions. A recent tragic incident in Malaysia brought this issue to public attention when a hospital staff member unintentionally left a 5-year-old child in a parked car, leading to the child's heartbreaking death [1]. Such incidents serve as grim reminders of the gaps in existing safety measures. Additionally, data analysis has shown that hundreds of children lose their lives every year due to being left in overheated cars, which points out the urgency for innovative detection technologies aimed at preventing these tragedies [2].

The rapid rise in cabin temperatures caused by the greenhouse effect makes leaving children in parked cars extremely dangerous. On a 32°C day, the temperature inside a parked car can rise by 20°C within 10 minutes, reaching 70°C within 90 minutes [3][4]. Children, with smaller body size and lower heat tolerance, are more vulnerable to hyperthermia. Research identifies heat stroke at 40°C, critical thermal maximum at 42°C, and uncompensable heating above 37°C. At 35.2°C ambient temperature, a child may experience compensable heating in 20 minutes, heat stroke in 105 minutes, and critical thermal maximum in 125 minutes [5]. These findings highlight the importance of real-time monitoring systems.

Thermal heat cameras are used in human detection due to their ability to capture infrared radiation, allowing detection based on body heat rather than visible light. They are effective in low-light or high-glare conditions. Using an ultra-low-resolution thermal camera showed 91.76% accuracy at 90° and 83.52% at 45° angles [6]. Precision-Recall (PR) curves confirm the robustness of detection [6]. The integration with Raspberry Pi demonstrated the detection of human infrared radiation through temperature variations [7]. These findings support the use of thermal cameras to detect children in vehicles. Despite lower resolution and higher cost [8][6], their consistent performance in different environments and ability to detect heat signatures make them suitable. Previous work [6] used low-resolution thermal cameras but was limited by resolution and range. A system using Raspberry Pi and AMG8833 detected heat signatures but faced performance issues in complex environments [8]. Another used ESP32 with MLX90640 but lacked detailed detection algorithms [9].You Only Look Once (YOLO) is popular in object detection, especially for human detection tasks like identifying children in vehicles. YOLO is ideal due to its real-time processing, detecting objects in a single network pass [10]. A study applied YOLO to human recognition using real-time cameras and achieved high-speed detection with good accuracy in various environments [11]. YOLO was shown to effectively process thermal images, making it suitable for quick detection in safety applications. It also runs efficiently on affordable hardware like Raspberry Pi [10][11]. However, YOLO may lose accuracy in low-resolution images or when detecting small objects in crowded scenes due to its grid-based prediction [12]. Additionally, training YOLO requires significant computational resources, which may not suit all embedded systems [10]. The Telegram bot approach is a simple, inexpensive method to notify users via smartphones using the Telegram Bot API for real-time alerts. It integrates seamlessly with Raspberry Pi and works on both Android and iOS [13]. This makes it ideal for urgent cases like child detection. The setup requires minimal infrastructure, offering a quick and reliable alert system [13]. However, its main limitation is the reliance on internet connectivity; without a stable connection, notifications may not be sent, posing challenges in certain conditions [14]. Despite this, it remains effective for real-time alerts where reliable network access is available, improving notification delivery for child detection systems [15].

In this project, the MLX90640 thermal camera is used to detect human presence based on body heat. It functions effectively in different lighting conditions by capturing infrared radiation. The system is improved by using YOLOv8s for real-time human detection. YOLOv8s is selected because it supports fast and accurate object detection in one network pass, allowing continuous monitoring of thermal images. The detection process is run on a Raspberry Pi 5, which processes the thermal frames and uses the trained YOLO model to identify humans. Once a person is detected, the system sends an alert through Telegram Bot. The Telegram Bot is chosen for its ability to send real-time notifications directly to the user's smartphone. This alert system is enhanced by integrating it with Python scripts to automate the detection-to-notification process without delay.

The YOLOv8s model is applied for human detection using thermal images. The dataset was prepared by capturing multiple thermal images of the human body and using Label Studio to create bounding boxes, with a single labelled as "human". The model was trained in Google Colab for 1000 epochs. The YOLOv8 architecture itself consists of three main components: a backbone that extracts important features from the thermal images, a neck that combines multi-scale features to improve detection across different sizes, and a decoupled head that performs both bounding box regression and classification. This structure allows YOLOv8s to achieve fast and accurate real-time detection, making it suitable for implementation on resource-constrained devices such as the Raspberry Pi 5. Through this project, it aims to improve child safety in vehicles by providing an innovative solution that helps prevent incidents of children being unintentionally left behind. Leaving children unattended in parked vehicles poses a serious, life-threatening risk, as temperatures can escalate rapidly, leading to severe heat-related conditions or even fatal outcomes. Despite widespread awareness, such incidents continue to occur, highlighting the need for a reliable, and proactive solution. This initiative addresses this safety concern by creating a detection system that utilizes a thermal imaging camera to check the back seat for children. The system is intended to be activated when the vehicle's engine is turned off and sends a notification to the parent's smartphone if a child is detected. This technology prioritizes child safety by attempting to prevent tragic incidents caused by unintentional abandonment. By integrating this system into vehicles, the project provides caregivers with a dependable safety measure, significantly lowering the risk of heat-related injuries and enhancing child protection in parked cars.Children left alone in parked cars are at high risk of severe, sometimes fatal heat-related injuries, as vehicle temperatures can rise dangerously fast. Despite increasing awareness, these heartbreaking incidents persist, underscoring the need for a solution that actively safeguards children. This project proposes a system using thermal imaging technology to detect children left in vehicles, a method that not only provides a cost-effective solution but also outperforms other in-cabin sensing technologies.

This system will provide immediate alerts to caregivers when a child is detected in a stationary vehicle, offering an added layer of protection that could save lives. By addressing a critical safety gap, this project has the potential to become a valuable standard in vehicle design, helping to prevent tragedies and ensuring the well-being of children.

2. Methodology

This project focuses on developing a low-power, embedded child detection system using thermal imaging and real-time object detection. The core system architecture is built around Raspberry Pi 5, chosen for its balance between computational capability and power efficiency. The YOLOv8s deep learning model is deployed directly on the Raspberry Pi, eliminating the need for external processing units or internet-based inference services. This fully embedded approach ensures real-time detection with minimal latency and allows the system to function autonomously in resource-constrained environments such as vehicle interiors.

The system integrates the Telegram Bot API as a communication channel to provide immediate alerts. This approach avoids the complexity of building custom mobile apps or integrating third-party platforms, offering users a practical, lightweight solution for direct notification. The combination of on-device AI inference and seamless Telegram-based messaging forms the basis of a portable, scalable, and cost-effective safety mechanism

Fig.1 shows the flowchart of how the innovative detection system works step by step. It starts when the system is turned on and begins by initializing all the components. After that, the system continuously monitors the car's backseat using the thermal camera. If no human is detected, it simply ends the process. But if a human is detected, the system quickly sends a Telegram alert and activates the car alarm to notify people nearby. Then, it checks if the reset button is pressed. If yes, the system will stop running. But if not, it will wait for five minutes and repeat the process. This way, the system keeps running until someone manually resets it, ensuring no child or person is left unnoticed in a parked car.

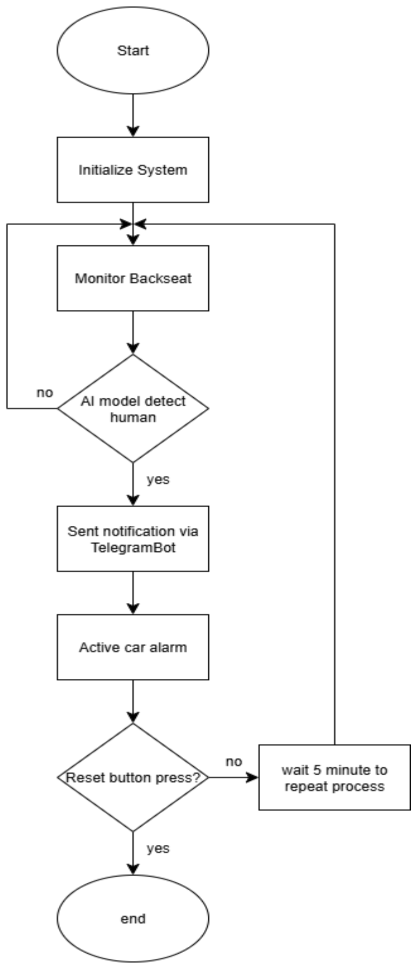


Fig. 1 *Flowchart of the system*

Based on Fig. 2, the Raspberry Pi serves as the central processing unit for the system. It receives input from the MLX90640 thermal camera, a button for reset, a power supply, and Wi-Fi for internet connectivity. The outputs from the Raspberry Pi are connected to a buzzer, which provides sound alerts, and a Telegram bot that sends notifications to a smartphone. This setup enables real-time monitoring and alerting for child safety in a vehicle, allowing the system to notify parents if a child is detected.

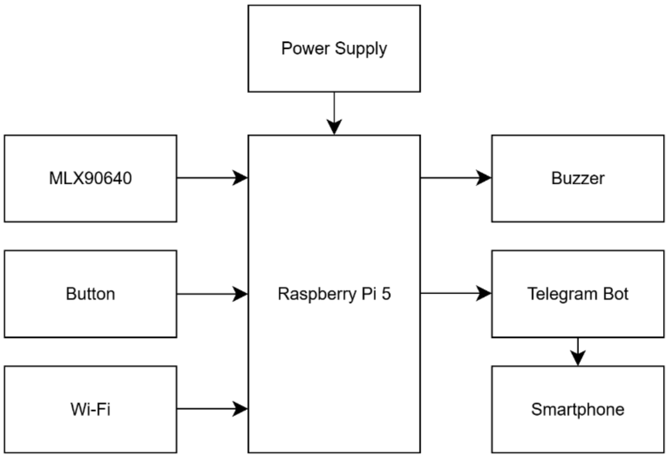
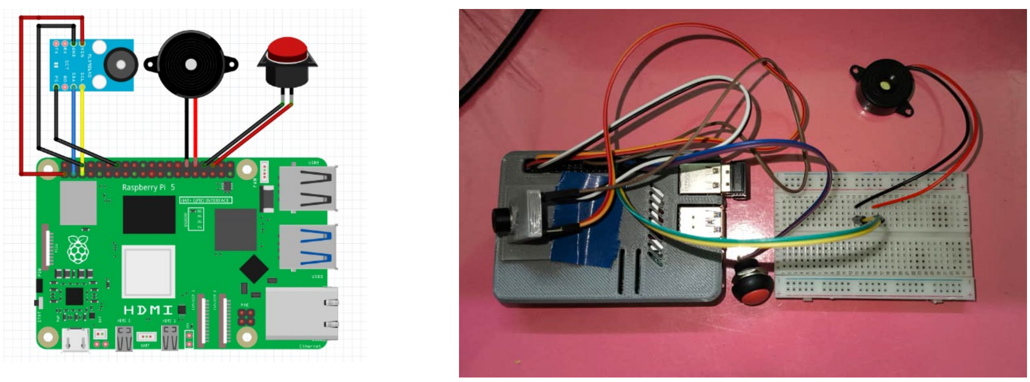


Fig. 2 *Block diagram*

2.1 Assembling the Project Components

The project's circuit was carefully designed using Fritzing software at the beginning of the assembly process, as shown in Fig.3(a). This design phase allowed for precise planning and visualization of how the MLX90640 thermal camera, buzzer, pushbutton, and Raspberry Pi would be interconnected to achieve the desired functionality. The MLX90640 thermal camera is powered by connecting its Voltage Common Collector (VCC) pin to the Raspberry Pi's 3.3V output and its Ground (GND) pin to the common ground, ensuring a stable power supply. For data transmission, the Serial Data Line (SDA) and Serial Clock Line (SCL) pins of the sensor are connected to General-Purpose Input/Output (GPIO) pins 3 and 5 of the Raspberry Pi, respectively, with the personal system/2 port (PS) pin grounded to enable proper Inter-Integrated Circuit (I2C) communication. The buzzer, responsible for alert notifications, relates to its positive terminal to GPIO pin 32 and the negative terminal to ground, allowing it to be controlled by the Raspberry Pi. Similarly, the pushbutton, which acts as a system reset or manual input, has its positive terminal wired to GPIO pin 36 and its negative terminal grounded.

Once the circuit design was finalized in Fritzing, the connections were carefully replicated in real life, as shown in Fig.3(b), where all the components are physically assembled and wired according to the schematic. This practical application of the design ensures that the thermal detection system can function as intended, with the buzzer providing audible alerts and the pushbutton enabling user interaction or system reset. The transition from the virtual schematic to a tangible hardware setup was crucial in validating the circuit's reliability and readiness for further development



(a) (b)

Fig. 3 *Figure description (a) Circuit diagram; (b) Assemble project*

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2.2 Implementation Step

This project started with the model training process in Fig. 4 using the Ultralytics YOLOv8s object detection framework on Google Colab. A custom thermal dataset was prepared and organized using the data.yaml format, then trained over 1000 epochs with an image size of 640×640 pixels. The YOLOv8s model was trained specifically to detect human heat signatures captured by the MLX90640 thermal camera. Once training was completed, the model was saved as a .pt file and made ready for use in the system.

The next step was to set up a notification system using Telegram Bot like in Fig. 5. The bot was created through BotFather in the Telegram app, and the user ID was obtained using a Python script in Thonny. The function send_telegram_image() was written to send the thermal image to the caregiver automatically whenever a person is detected in the vehicle. This communication method works smoothly with only an internet connection on the Raspberry Pi, without needing any extra server setup.

Finally, the entire system was integrated and run on a Raspberry Pi 5 using Python through the Thonny IDE shown in Fig. 6. The MLX90640 thermal camera continuously captures temperature data, which is processed by the trained YOLOv8s model in real time. If exactly one human is detected, the system activates a buzzer for five seconds and sends a thermal image alert through Telegram. A five-minute delay is added before the next detection unless manually reset. The system was tested under different distances, angles, and body positions to match real in-car conditions and ensure consistent operation.

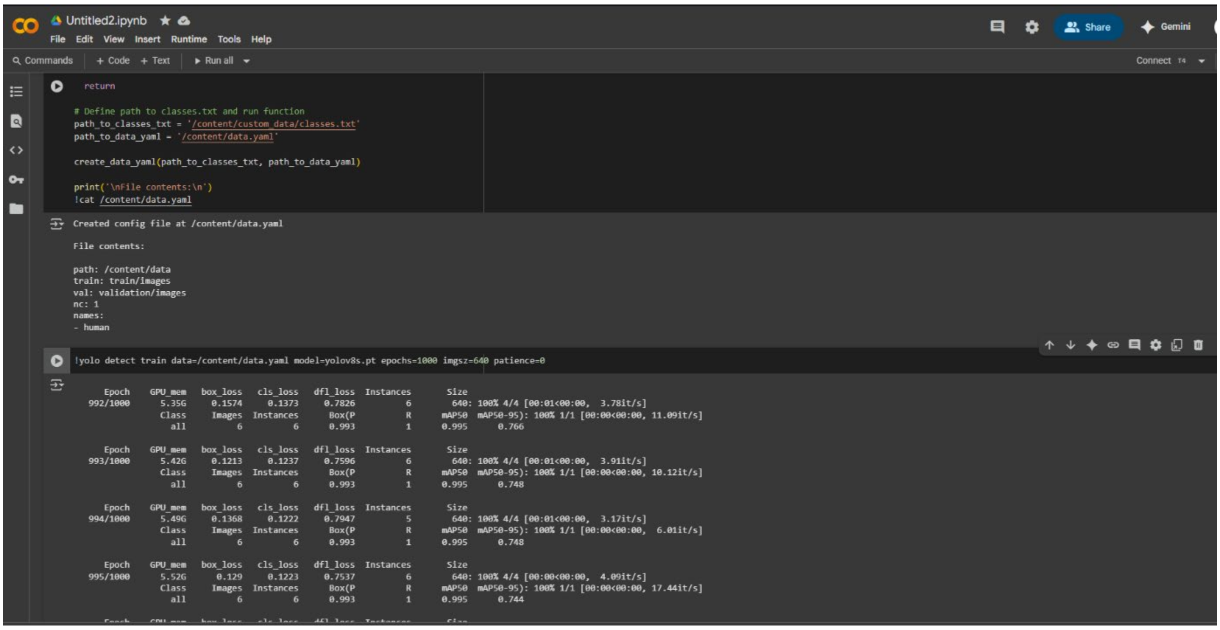


Fig. 4 *Google Colab interface*

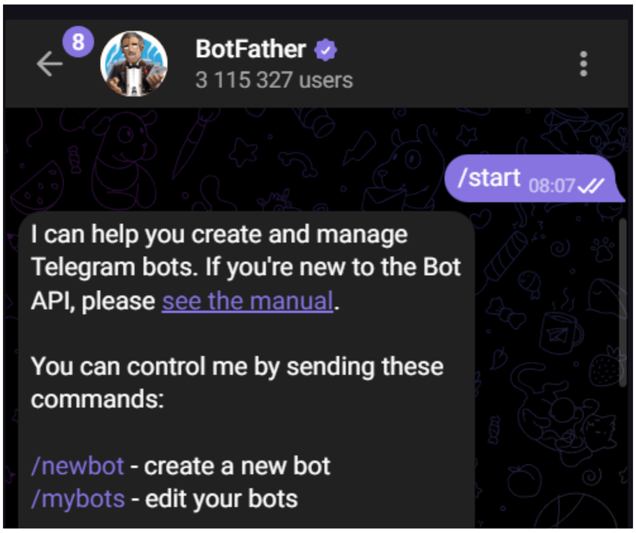


Fig. 5 *BotFather interface*

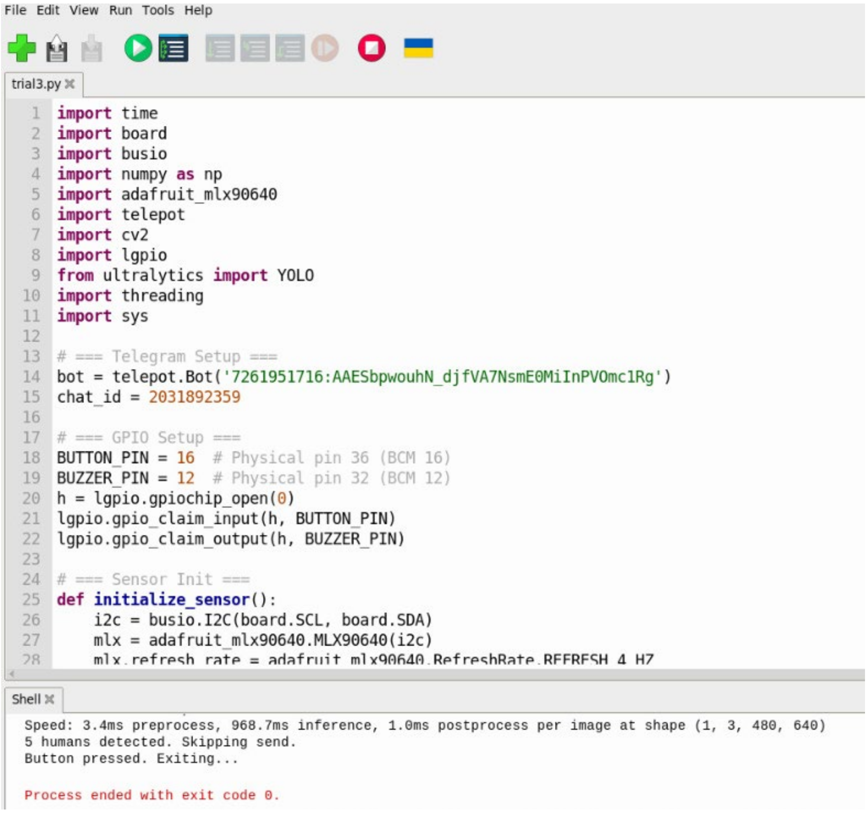


Fig. 6 *Thonny IDE interface*

3. Result and Analysis

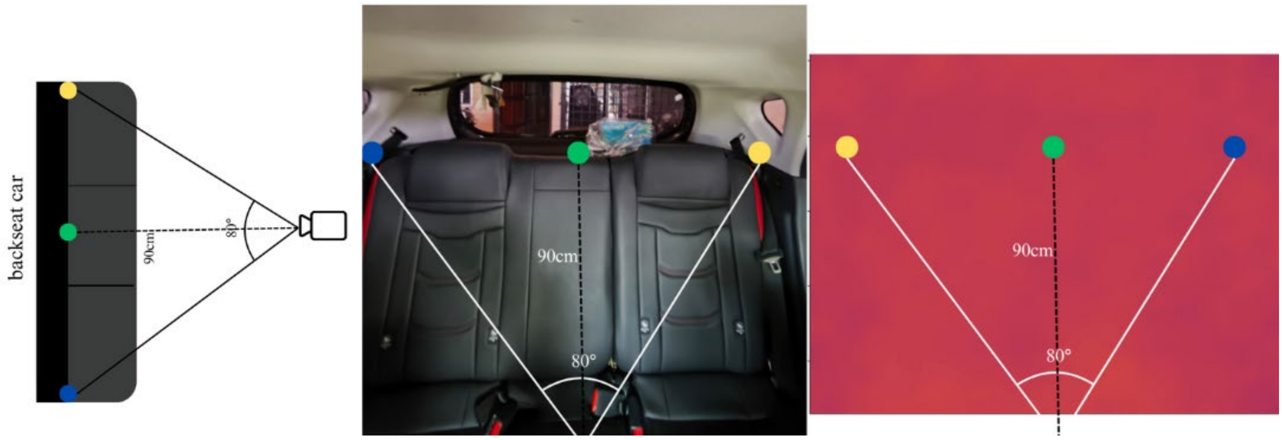
This chapter presents the detection results of the smart child presence detection system using the MLX90640 thermal camera and YOLOv8s model. The thermal camera was fixed at the top middle of the car to monitor the back seat area effectively. The system successfully detected human presence through various test conditions, including different body positions and movement. Alerts were triggered when a person was detected, and thermal images were sent to the caregiver via Telegram. These results confirm the system's ability to identify a child left in the car using real-time thermal imaging and AI.

3.1 Camera Positioning in car

Fig.7 shows the camera setup and coverage illustration for the system. Fig. 7 displays the actual prototype device mounted at the top-middle of the car's roof, with the camera tilted downward at approximately 45°. This angle was chosen to effectively cover the entire backseat area. Meanwhile, Fig. 8 top view, showing how the camera's 80° field of view and 90 cm distance can capture all seating positions from left to right (blue to yellow dot). This setup ensures that the thermal sensor can reliably monitor for human presence across the full backseat width.

Fig. 7 *Device mounted on the roof*

Fig. 8(a), Fig. 8(b) and Fig. 8(c) shows the roof top-middle view based on illustration, normal image and thermal image, respectively. The green dot represents the direct distance from the camera to the backseat, measured at around 90 cm, while the yellow and blue dots show the 80° field of view, covering each corner of the backseat. This visual illustrates that from this central placement, the camera can effectively monitor the entire width of the rear seat. Even in the thermal image, all key seating areas fall within the detectable range, confirming that this mounting position provides optimal coverage for detecting the presence of a child or passenger.



(a) **(b)** **(c)**

Fig. 8 *distance and angle of backseat camera view*

In the testing phase, an adult subject was used to simulate the presence of a child in the backseat. This substitution was made for ethical and safety reasons, as testing with children in enclosed or heated vehicle environments could pose health risks. The MLX90640 thermal camera operates based on infrared heat signatures rather than body size or visual features, meaning that the detection principle remains valid regardless of whether the occupant is an adult or a child. Both adults and children emit comparable thermal radiation within the human body temperature range (approximately 36–37 °C), allowing the system to accurately detect human presence using the same model. Fig. 9 shows an image captured from a top-down perspective, with the camera mounted at the top-middle of the car roof at an approximate distance of 90 cm from the backseat and positioned at a 45° angle. The left side of the figure displays the normal image, while the right side presents the corresponding thermal image. This configuration replicates a practical in-vehicle setup, such as a roof-mounted camera aimed toward the rear seat. Despite the angled viewpoint, the thermal image effectively captures the occupant's heat signature, demonstrating clear thermal contrast between the subject and the surroundings. The size and shape of the detected heat area suggest the presence of a smaller body, such as a child, validating that the system is suitable for child presence detection. This result confirms the camera's practical utility and robustness in real-world automotive environments, ensuring reliable occupant monitoring even when the subject is not directly facing the camera.

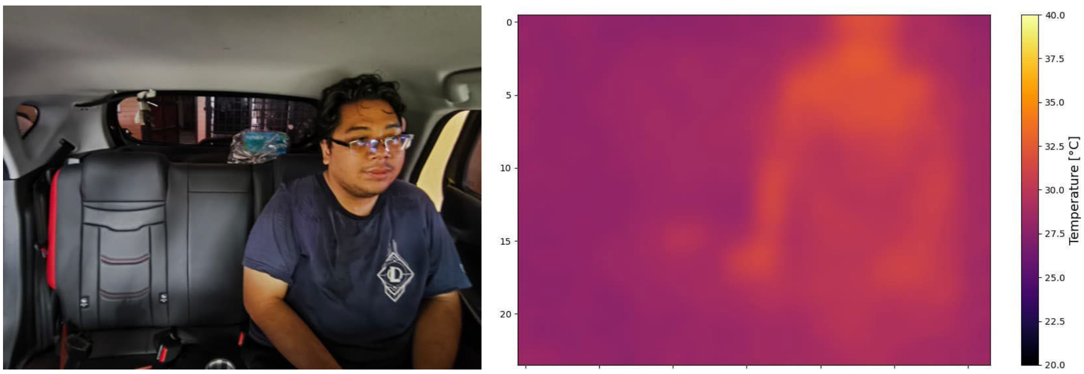


Fig. 9 *Backseat thermal view from middle of car*

Fig. 10 shows a thermal and normal image pair taken from the top-right side of the car's roof. This angled setup reflects a common alternative camera placement in vehicles. While the thermal image still successfully detects human presence, placing the camera at this side angle makes it harder to capture the full view of the backseat, especially the lower portion. Although detection still works as expected, it's a bit more difficult to get a complete thermal image of the seat area. Therefore, even though the device can be mounted on either side, it is generally preferable to install it in the middle of the roof, where it has a clearer and more balanced view of the entire backseat

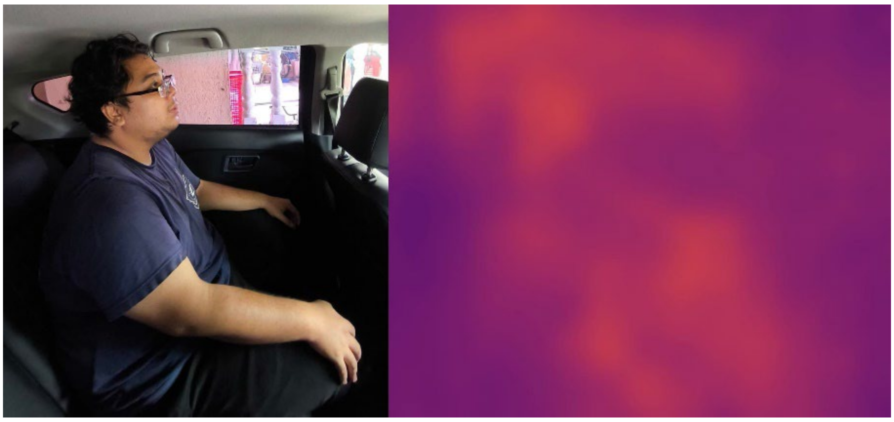


Fig. 10 *Side-angled overhead view for backseat detection*

3.2 Analysis on the Training Model Result

YOLOv8s was specifically chosen for this project because it is the most suitable model for deployment on the Raspberry Pi 5, providing a good balance between accuracy and efficiency without demanding high computational resources. Fig.11 illustrates the training performance of the YOLOv8s model used in the smart detection system. The training was carried out for 1,000 epochs, and the graphs clearly demonstrate a consistent improvement across all major performance metrics. The training progress of the YOLOv8s model is visualized through four graphs in Fig. 11(a) to Fig. 11(d). These graphs track both training behaviour and model accuracy over time. The loss graphs monitor how well the model is learning to detect and classify objects. Box loss shows how close the predicted bounding boxes are to the actual positions [16], while classification loss measures the accuracy of object category predictions [4]. The model also uses Distributed Focal Loss (DFL), which gives more focus to harder examples, helping the model improve accuracy by learning from challenging detections [17]. On the metric side, precision (P) and recall (R) give insight into the model's detection performance on how accurate and complete its predictions are. The mean average precision (mAP), especially mAP@0.5 [18], provides a summary score of how well the model performs across different object classes and detection difficulty levels.

Fig. 11(a) shows how the model's training losses decrease steadily as learning progresses. This includes box loss, classification loss, and DFL. The sharp drop at the beginning means the model is quickly learning to recognize and locate humans in thermal images. As the curve flattens out, it indicates that the model is refining its predictions and making fewer mistakes. This consistent pattern shows stable and effective training for real-time human detection in a car environment.

Fig. 11(b) shows the validation losses, which come from testing the model on new thermal images it hasn't seen before. The overall downward trend, despite minor fluctuations, means the model is successfully learning to generalize. This is important for handling different thermal conditions inside a car, such as varying lighting, background heat, or the person's position on the seat.

Fig. 11(c) shows the model's improvement in recall and precision. Precision increases early, showing it's getting better at avoiding false detections. It learns to identify every human figure in the pictures as recall increases more gradually. By the end of training, both values are high and stable, which is ideal for ensuring the system is capable of recognising someone in the backseat without missing or wrongly identifying anything.

Fig. 11(d) shows mAP@0.5 and mAP@0.5:0.95, which measure overall accuracy. The mAP@0.5 line rises quickly and stays high, showing the model manages easier detection tasks properly. The model is learning to function well even under stronger detection conditions, as evidenced by the more gradual but steady increase in the mAP@0.5:0.95 score. These results confirm that the system is suitable for use in real scenarios like detecting a child or person left in the car.

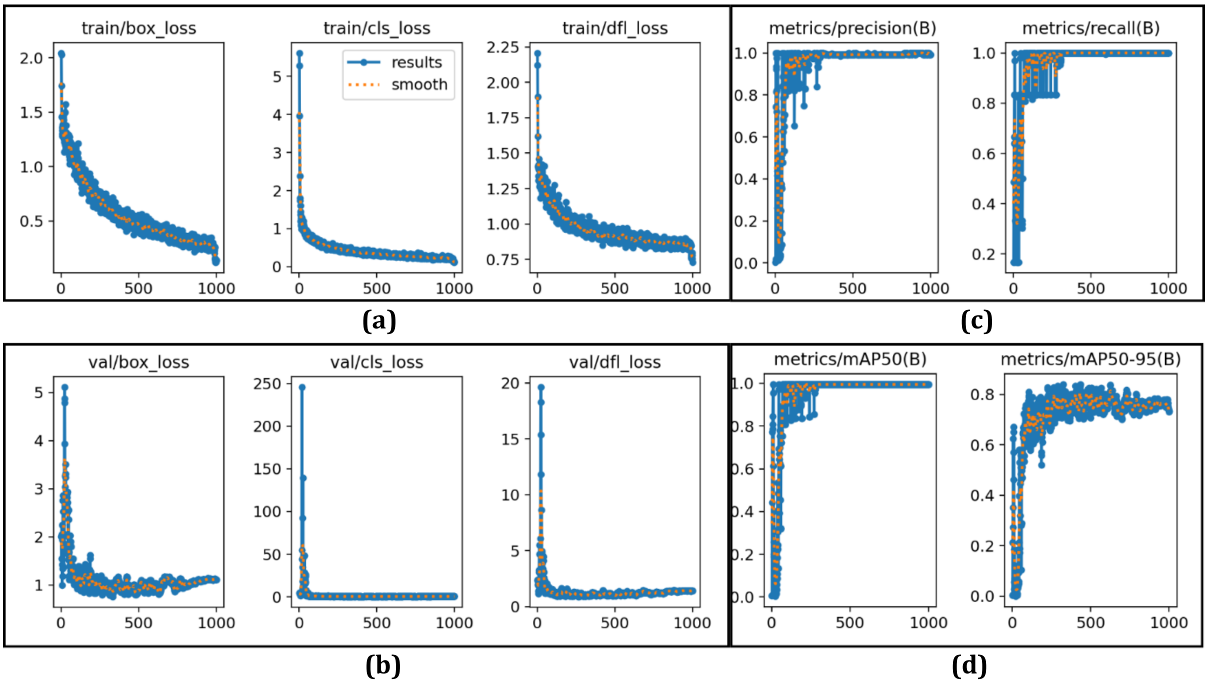


Fig. 11 *YOLOv8s training graph showing loss, precision, recall, and mAP over time*

Fig. 12 shows the F1 Score, which is the harmonic mean of precision and recall, providing a balanced assessment of a model's performance while considering both false positives and false negatives [18]. The graph includes two lines, one for the "human" class and one for all classes. Since the model is only trained to detect humans, the "human" line is the most important. The second line, which represents all classes, is included by default for comparison, but may include background or unused classes, which slightly lowers its average. The "human" line rises steadily at first as the model learns, then flattens when performance stabilizes, and slightly drops at the end likely due to small overfitting or fluctuation during later training stages. The "human" F1 Score peaks at 1.00, while the overall mean score is 0.756, showing the model performs reliably in detecting human presence in thermal images, making it suitable for backseat monitoring.

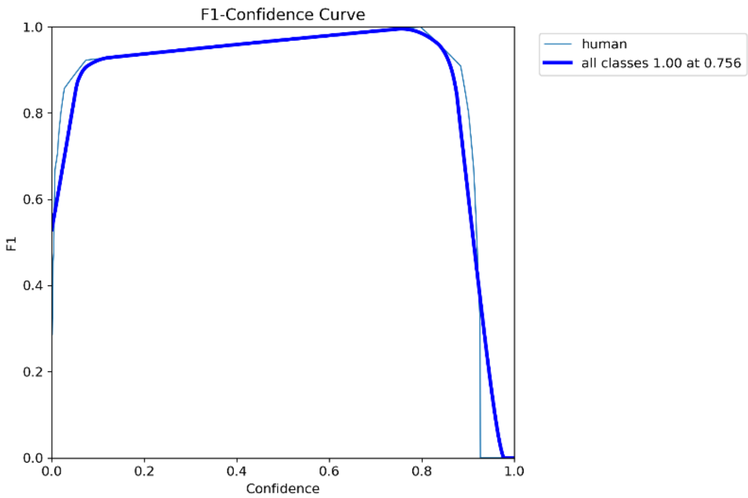


Fig. 12 *F1-score curve*

Fig. 13 shows the Precision – Confidence curve. Form the graph it show that the graph includes two lines, one for the "human" class and one for all classes. Since the model is trained only to detect humans, the "human" line is the most relevant. With a peak of 1.00 and an average of roughly 0.85, it remains consistently high across thresholds, indicating that the model is very accurate at identifying people and has very few false positives. The average precision for all classes is shown in the second line, which is primarily for comparison and may seem somewhat lower because of background or unused classes. This indicates how well and consistently the model detects the presence of people in thermal images.

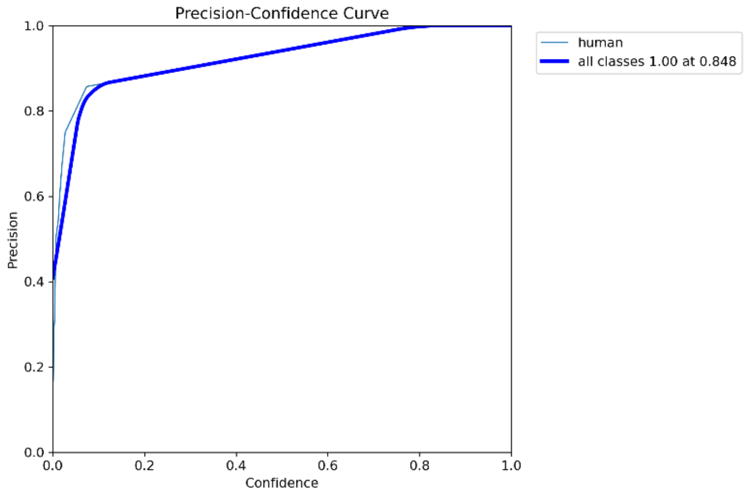


Fig. 13 *Precision-confidence curve of the YOLOv8s model*

Fig. 14 shows the Precision-Recall curve, an integral visualization for any classification problem that showcases the trade-offs between precision and recall at varied thresholds [18]. This is especially useful in this project, where detecting a human is more important than detecting other classes. The "human" line shows strong performance, staying close to the top-right corner, which indicates high precision and recall working together. The curve rises quickly, then levels off before slightly dipping, reflecting the model's stable accuracy followed by small variations in later training. This consistent shape shows the model is effective at identifying humans in thermal images while minimizing false detections

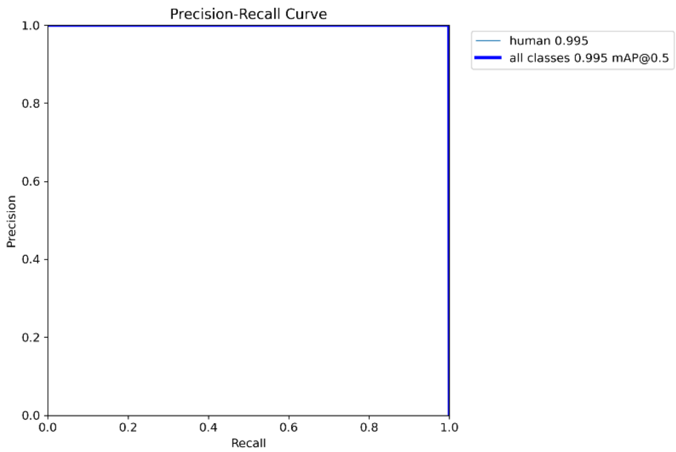


Fig. 14 *Precision-recall curve*

Fig. 15 shows the Recall curve, which demonstrates how well the model detects all relevant instances of the human class across different confidence thresholds. It reflects the model's ability to correctly identify actual human presence in thermal images. In this figure, the recall for the "human" class remains high throughout, peaking at 1.00 and maintaining a strong average. The curve rises quickly, levels out, and slightly dips near the end, indicating the model initially improves, then stabilizes, and experiences minor fluctuation at stricter thresholds. This consistent performance suggests the model is highly reliable in recognizing humans and crucial for ensuring safety in backseat detection scenarios.

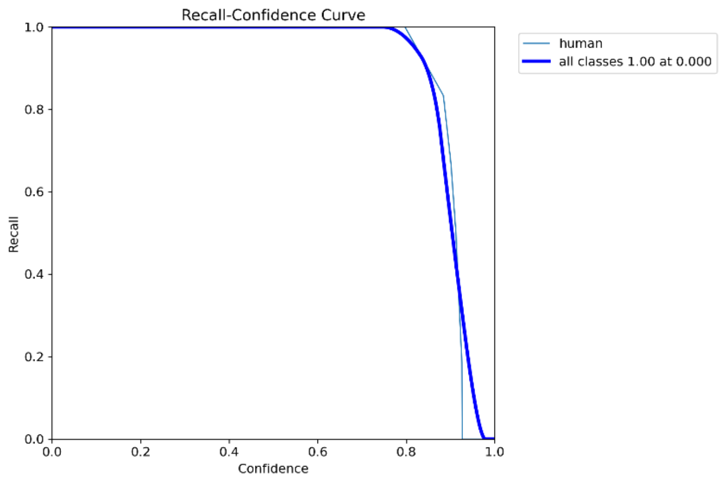


Fig. 15 *Recall-Confidence curve*

3.3 Detection Result

Fig. 16 shows the actual output of the smart detection system when it's running on the Raspberry Pi. The process starts when the MLX90640 thermal camera captures live thermal data from the backseat area. This data is continuously monitored and converted into a thermal image using OpenCV. Every frame is then saved as a temporary image and passed into the YOLOv8 AI model for analysis. The model, which was trained to recognise human presence, scans the image and identifies whether any humans are in the frame as shown in highlighted yellow box. If it detects one human, it draws a green bounding box and a white crosshair on the detected area, helping users visually confirm the exact location of the person in the thermal feed. not initialisation and hardware control

At the same time, the system outputs highlighted in blue box show a detail to the Thonny IDE shell, including the number of humans detected, the processing speed of each frame, and the size of the image being analysed. This kind of feedback is useful for debugging and performance monitoring, especially during real-time operation. The average temperature reading of the frame is also shown at the bottom-left of the image, which gives extra insight into the environment's heat level. Once exactly one human is detected, the system immediately triggers two actions, it activates the buzzer to alert anyone near the car and sends the saved image to the user's Telegram through the bot, providing a quick and direct alert even if the user is away from the car. The system will stop once the reset button is pressed, allowing it to deactivate the alert process. The reset button, as shown in Fig.3, is a physical component attached to the device and can be pressed by anyone who has access to the car, ensuring the alert can be stopped manually when the situation is verified to be safe.

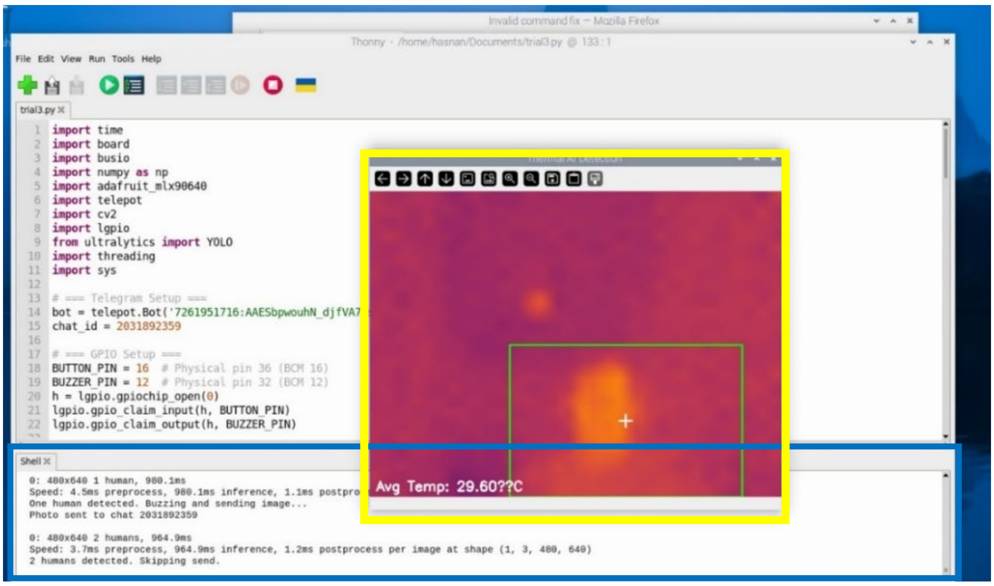


Fig. 16 *screenshot of human detection results with bounding box and runtime output*

The system is capable of automatically sending thermal images to a Telegram chat once a human presence is detected. This is made possible by using the correct bot token and chat ID, which ensure the alert reaches the intended recipient. Once the AI model confirms the presence of exactly one human in the thermal image, the system captures the frame, processes it, and sends it directly via Telegram. As seen in Fig. 17, the Telegram chat shows multiple images sent by the system at different detection intervals. The testing was conducted using an adult subject (the developer) to represent the heat signature of a child in order to demonstrate the system's functionality. This result confirms that the communication between the Raspberry Pi and the Telegram API functions reliably. Furthermore, it emphasises the system's capability to provide real-time alerts, making it particularly useful in situations such as notifying parents if a child is unintentionally left in a car.

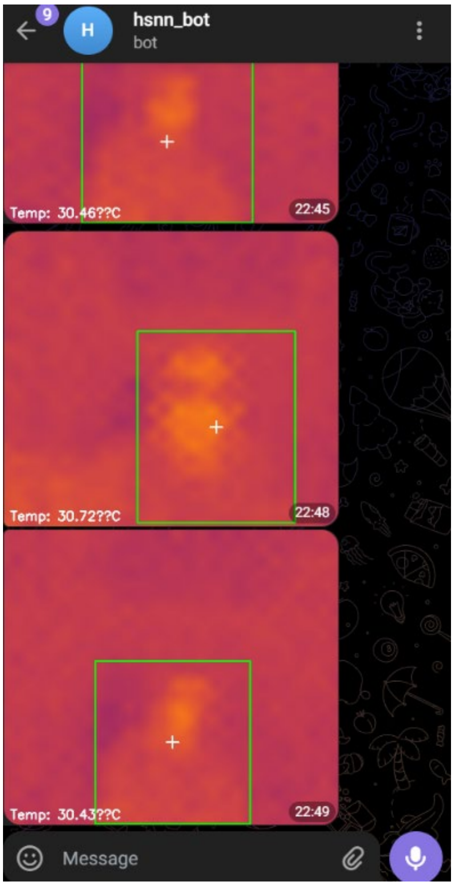


Fig. 17 *Screenshot of telegram alert messages with thermal images*

4. Conclusion

This project successfully developed a smart child presence detection system intended to reduce the risk of children being left unattended in vehicles, where rising temperatures can become life-threatening. The system not only combines a MLX90640 thermal camera with a Raspberry Pi 5 and runs an embedded AI model YOLOv8s to monitor the backseat area but also manages to be compact enough to form a small device that can be mounted on the car's roof interior. By recognizing the heat signature of a human body, it continuously observes the environment and reacts when a person is detected.

Through comprehensive testing, when the system detects the presence of a child, it activates a buzzer inside the car and sends an alert including a thermal image directly to the parent's mobile device via a Telegram bot. This enables real-time awareness and immediate response, even if the caregiver is no longer near the vehicle.

Through a series of functional tests in various positions and multiple pictures taken, the system consistently demonstrated its ability to detect human presence in different seating positions and distances. It responded as expected by triggering alarms and sending notifications without requiring any manual intervention.

This project demonstrates that an affordable and standalone thermal imaging system can be practically implemented to address a serious safety concern. By integrating basic hardware with a responsive AI and mobile communication features, the system offers a simple, yet impactful solution to help prevent avoidable tragedies involving children in cars.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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