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SAFELINK: A MULTIMODAL SMART WEARABLE DEVICE FOR PERSONAL SAFETY

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Abstract
In the modern era, Safety is become serious concern for the people of all over the world and several cases are reported regarding kidnapping, harassment and mobile snatching/street robbery. In many situations victims do not have access to their mobile phones because criminals snatch them away or sometimes because phone usage is restricted in certain places such as schools. For this reason, they cannot immediately contact their guardian/family member in case of emergency, urging the need for some safety gadget that is effectively accessible in emergency. Although technological interventions are available, they are usually limited by internet availability and provide one-mode activation systems. This research proposes a multimodal smart wearable device as a real-time safety tool, that combines three independent triggering modules, i.e. weapon detection with YOLOv8, a multilingual voice command recognition system (English, Urdu, and Sindhi), and a manual panic button. Whenever the device is triggered by any of these modules, the device records visual evidence, records accurate GPS positioning and sends an SMS alert with a live location link to pre-registered contacts, without need for an internet connection. The testing in controlled and field conditions has shown the detection accuracy of gun and knife above 90% and the approximate end-to-end time to produce and deliver an alert is 5 seconds. The findings support the idea that SAFELINK is a highly responsive and practical personal safety mechanism that can effectively address the critical gaps within the current safety technologies.

1. INTRODUCTION

A basic human right is personal safety, which is always at stake because of increasing assault, harassment, abduction, and other related cases around the world. Violence and insecurity have resulted in an extreme need for innovative protective measures. Current safety gadgets (Reddy et al., 2023; Pardey et al., 2026; Shetty et al., 2026), which are commonly dependent on smartphone applications or constant presence of an internet connection, cannot work in cases where no network is present or the victim is otherwise physically impaired. The proposed research fills these systemic gaps by the conceptualization and design of SAFELINK, a wearable device, which is an independent entity and uses a multi-layered, offline-enabled method of emergency detection and response. The combination of state-of-the-art artificial intelligence to identify threats, inclusive multilingual voice recognition, and a redundant manual trigger with strong GSM-based communication makes SAFELINK independent even in distant or infrastructurally challenging areas, thus giving people a tangible feeling of security.

The main goal of this research is to develop and test fully offline wearable safety solutions. In particular, this study aims to: (1) design a manual panic button that can serve as a simple and reliable trigger to initiate the alarm, (2) design a multilingual voice command recognition module which is capable of recognizing emergency phrases in English, Urdu and Sindhi language to ensure its accessibility in the diverse linguistic environment of Pakistan, (3) develop an AI-based weapon detection system using YOLOv8 that can work efficiently on low-power edge devices, and (4) integrate all three activation methods in a single device that is internet-independent, automatically captures visual evidence and can provide precise GPS coordinates and an SMS alert with a live location link to pre-registered contacts within seconds of activation. This research integrates manual panic button, voice commands, and automated threat detection into a single wearable device, proposing a substitute for current safety devices that require internet or offer a single activation method, with a more complete and universally accessible personal safety solution.

2. Literature Review

The world of wearable safety devices has been reshaped by Internet of Things (IoT) and embedded systems. These include wearables, which gather physiological information with the help of sensors, and GPS wearables to track. Reddy et al. (2023) developed an IoT-based wearable, which could notify users on a mobile app by using many sensors and an ESP32 microcontroller, but relied on Wi-Fi connectivity. Similarly, Srikarna et al. (2023) came up with an off-line communication GSM and GPS child safety device but expressed worries regarding privacy of data and false alarms. Comparable IoT-based wearable safety systems have also been proposed by Tunggadewi et al. (2021), Mallapur et al., and Malaj (2023), each targeting child or personal safety through similar sensor-and-connectivity based approaches. Kane et al. (2024) and Gopalakrishnan et al. (2023) presented automatic IoT-based emergency response systems for women's safety, while Arya and Sharma (2024) explored an alternative threat-detection approach using EEG and eye-blink signals to trigger alerts. Ranjeeth et al. (2020), Srinivasan et al. (2020), and Chowdhury et al. further contributed smart wearable devices focused specifically on child safety monitoring. Parikh et al. (2020) and Moodbidri and Shahnasser (2017) proposed wearable safety devices for women and children respectively, while Awolusi et al. (2019) and Rahmani et al. (2022) provided broader reviews of IoT applications in wearable sensing and safety monitoring, underscoring the growing research interest in this domain.

Hyndavi et al. (2020) utilized environmental and physiological sensors to detect the threat automatically, whereas Hossain et al. (2021) utilized a FlexiForce pressure sensor, VR3 voice module, and YOLOv3-based weapon recognition with the help of Arduino and Raspberry Pi. This showed an innovative multimodal solution, but more data was required to enhance AI precision. Sakib-Ahmad et al. (2021) created a weapon detection system that uses computer vision and was highly precise but was not placed in the wearable form factor.

There is also the exploration of Smartphone based solutions. Pardey et al. (2026) created SHIELD, a mobile application that combines live location tracking, audio-video recording, and SOS alerts using Firebase but is dependent on cloud connection. Likewise, Shetty et al. (2026) suggested BEHANA, an AI-based application that applies machine learning in predictive risk analysis and sentiment analysis via NLP. Pushpa et al. (2026) built an IoT-based women safety system that incorporated a GPS tracking system and GSM communication to respond to threats in real-time. Dhamdhere and Ponnusamy (2026) proposed an AI-Enhanced Wearable Technologies system that combined physiological sensors, voice recognition, and a weapon detection method using YOLOv3, but found it necessary to use larger datasets. One of the uniform gaps throughout the literature is that no small, energy-saving, fully autonomous wearable has ever been developed that can combine high-precision AI detection, natural voice activation, and instant manual override into one internet-free gadget. SAFELINK is conceived to fill this void, offering a unified and reliable solution for critical situations.

Novelty of the Study

Current safety gadgets only have one activation method and are frequently dependent on internet connectivity. Unlike others, SAFELINK integrates three distinct features into a single wearable gadget that does not require any internet connection, allowing such cross-disciplinary features as AI weapon detection and voice commands in English, Urdu and Sindhi. None of the other devices mentioned in the literature have all three of these capabilities.

3. Material and Methods

3.1 System Workflow

SAFELINK uses a distributed processing architecture, which maximizes performance and provides real-time responsiveness. The system consists of two basic processing units which are a Raspberry Pi 4 Model B and an ESP32 microcontroller. This split allows the distribution of computational resources efficiently; the Raspberry Pi performs resource-intensive computations with the help of the YOLOv8 model to analyze the video in real-time and detect weapons and log them, whereas the ESP32 performs the sensor integration, trigger processing, GPS data acquisition, and GSM communication. The hardware modules are connected through UART serial and GPIO pins and a local Wi-Fi network is created by the ESP32 (as an access point) and ensures a smooth and uninterrupted data exchange between the two processors through TCP socket-based communication. The detailed block diagram of this system architecture is given in **Figure 1.**

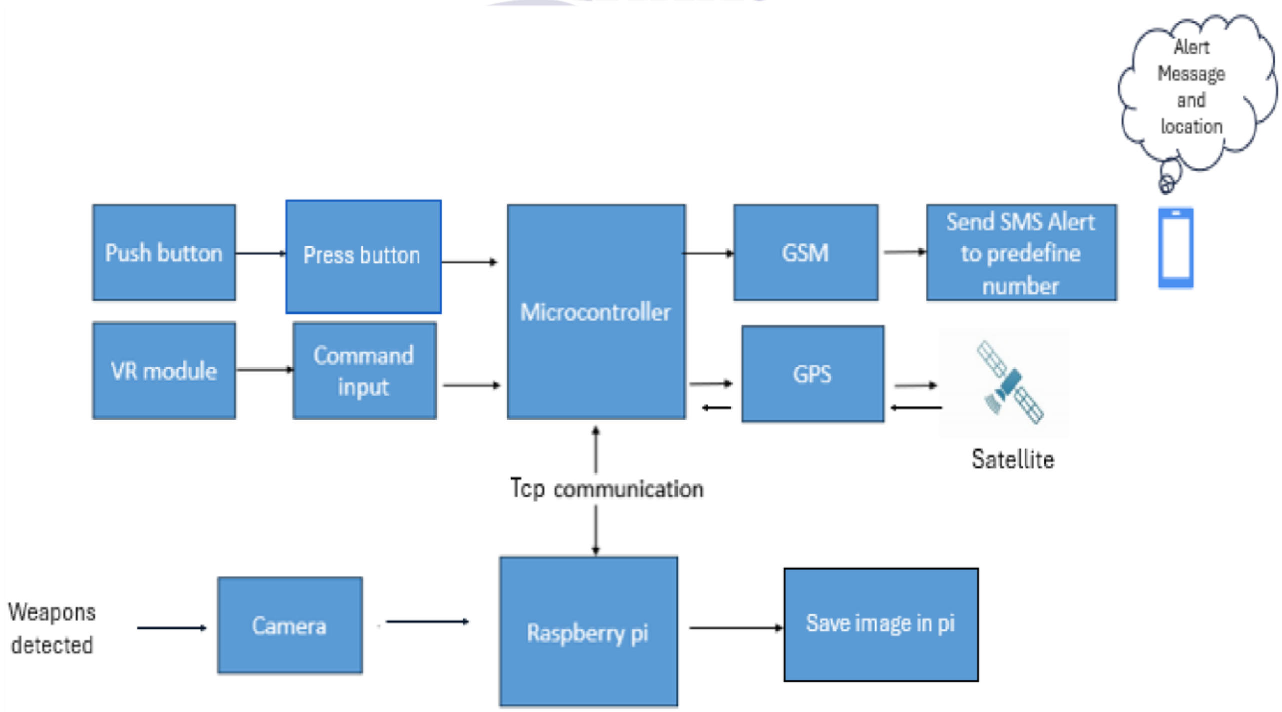

Figure 1. System Interconnection Diagram

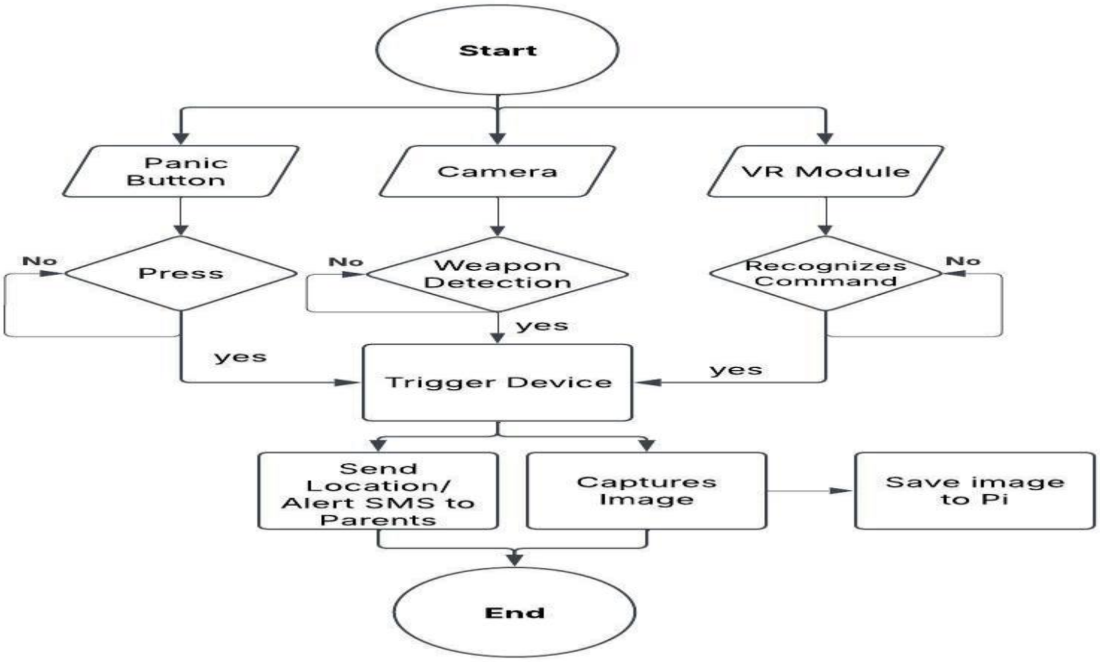

Figure 2. System workflow

3.2 Hardware Components and Integration

The device will include a combination of a set of specially designed hardware elements, all of which are chosen based on reliability, low power consumption, and wearability:

• **Raspberry Pi 4 Model B:**
It is the main processing unit of AI with 4GB RAM that provides enough computational resources to execute the YOLOv8 model in real-time processing video streams that are captured by the camera unit.

• **OV5647 Camera Module:**
This is a 5-megapixel camera, which is integrated into the CSI port of the Raspberry Pi. It is the visual feed of continuous monitoring and the one that takes the timestamped evidence images when an alarm goes off.

• **ESP32 Microcontroller:** The ESP32 is the brain of the system that helps in all input triggers, receiving information on the GPS module, and activating the GSM module to transmit SMS. Its low-power operation and dual-core architecture are perfect in handling multitasking.

• **NEO-6M GPS Module:** the GPS module provides real-time data on geolocation with an accuracy of upto 2.5 meters, which is essential to guide emergency services in the precise direction

• **GSM800L Module:** The quad-band GSM module allows the transmission of SMS alerts regardless of internet connectivity, which makes it reliable in communication under a variety of environments

• **VR3 Voice Recognition Module:** The module is capable of being used without hands. It is trained to identify certain phrases of emergency in various languages.

• **Panic Button:** A simple push-button switch offers direct and immediate manual control for the user to have the alert triggered by the user as a critical fail-safe We used a wiring plan to assemble all the portions of the device. This plan is shown in a clear circuit diagram shown in Figure 3. The diagram aids us to see that it is all interconnected. As an example, it demonstrates the way the ESP32 board communicates with the GPS and GSM modules via special communication lines (so-called UART). It also depicts the location of the emergency panic button (plugged into a pin named GPIO 32) and the location where the camera is connected to the Raspberry Pi (via the CSI port). This is the diagram that we needed to build the prototype properly. Figure 4 shown complete hardware integration based on Figure 3

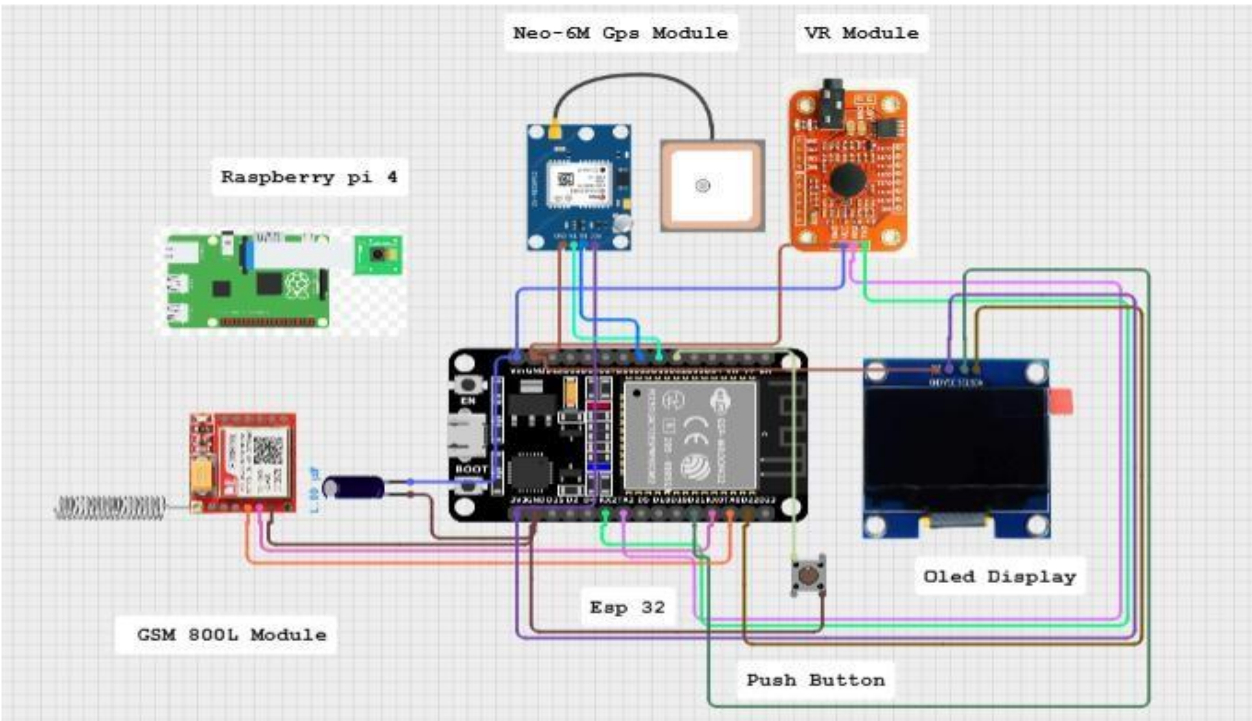

Figure 3. Circuit Diagram of the proposed system

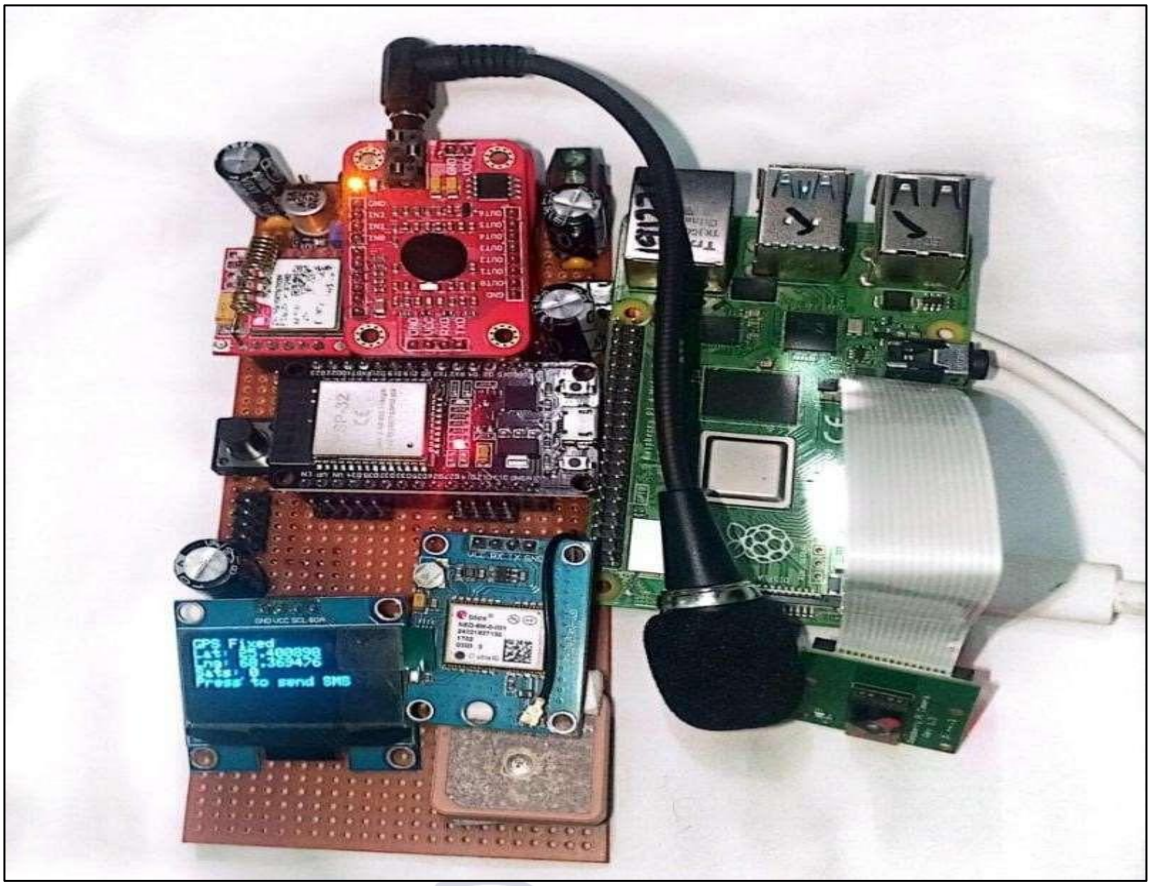

Figure 4. Hardware prototype of the proposed system

A combination of Python on the Raspberry Pi and the Arduino IDE on the ESP32 firmware was used to create the software ecosystem. Important libraries and frameworks comprised of Several key software libraries were used to build the system. Ultralytics YOLOv8 was applied to the high-speed, accurate weapon detection model to train and deploy it. OpenCV (cv2) was used to capture images, process video streams, and perform simple image manipulations. PyTorch served as the deep learning system where the models were trained. PiCamera2 gave optimum control and access to the Raspberry Pi camera hardware. NumPy handled all numbers in the system, and most importantly the camera image data, which were processed as NumPy arrays; this library makes the image pixels subject to mathematical operations that are fast and efficient, which is essential to the preprocessing processes prior to the image being processed by the AI model

3.3 Dataset Acquisition and Preprocessing

Our dataset is composed of a wide range of close to 2,300 images of guns and knives, provided by the public repositories from Castillo Lamas et al. (2021) and Roboflow Universe, and controlled captures. Weapon type, weapon orientation, weapon scale, weapon lighting (outdoor/indoor), complexity of the background and partial occlusion were given more importance to increase model strength. Each image was then manually annotated using the Roboflow platform as shown in Figure 5 with two classes: Gun and Knife. Preprocessing of the dataset was done by auto-orrection of the image (orientation), followed by resizing to 640x640 pixels and then partitioning it into training (70 percent) it includes 1611 images, validation (20 percent) includes 452 images, and test sets (10 percent) include 237 images.

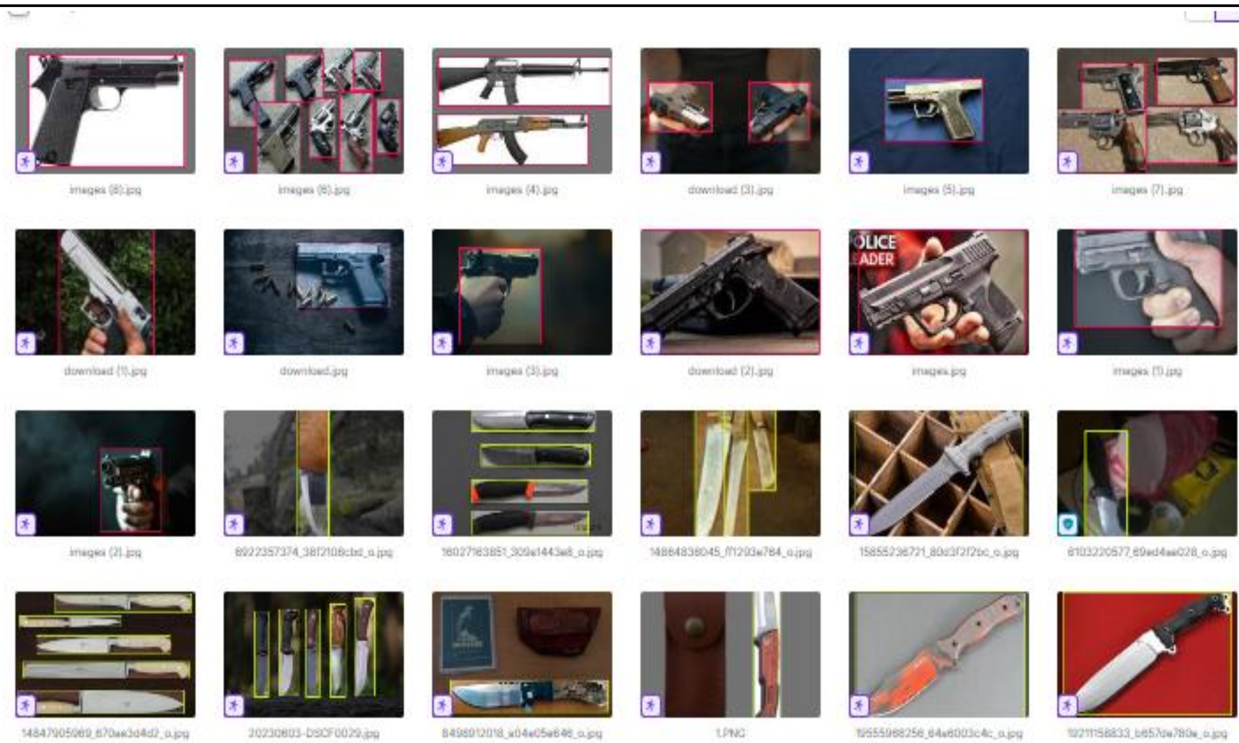

Figure 5. Dataset samples

3.4. Model Training and the Setup for Experiment

We trained two object detection models and evaluated their performance i.e. YOLOv8n and YOLOv11n. Both models were trained on Google Colab using an NVIDIA T4 GPU to speed up the training process. The training process was implemented using Python and Ultralytics YOLOv8 framework, alongside the OpenCV, PyTorch, and NumPy libraries for image capturing, pre-processing, and handling tensors. Both models were trained for 50 epochs with a batch size of 16 with the Adam optimizer and an initial learning rate of 0.001, allowing a fair comparison. We used the standard metrics Precision, Recall, F1-Score and mean Average Precision at a 0.5 IoU threshold (mAP@0.5) to evaluate the performance of each model. Moreover, we followed the training process carefully by observing the loss functions and then interpreted the training process of each model.

Choosing the appropriate artificial intelligence model to use in detecting weapons was a challenging task. We had to have a system that would be able to provide high accuracy with the tight power and computational constraints of our wearable device. We made a careful comparison of two state of the art models, YOLOv8, and YOLOv11, to make the best selection. Both were trained on our own set of more than 2,300 annotated weapon images and both performed well. In addition to the accuracy, there were practical deployment factors that were critical. YOLOv8 is more power efficient and faster on our Raspberry Pi hardware compared to YOLOv11 due to its lower computational footprint. This efficiency will be reflected in a longer battery life and a more predictable real-time performance, which is not a compromise in a wearable safety device, which needs to be reliable in terms of longevity. Thus, YOLOv8 was chosen as the ultimate model that would be used in our system. Its combination of accuracy, reliability of threat detection, and better efficiency on resource constrained hardware offers a better balance that is required to have a trustworthy and practical personal safety solution.

4. RESULTS AND DISCUSSION

The thorough prototype testing confirmed its operational preparedness and functionality as a multimodal safety device. This section will present the outcomes of individual module testing and integrated system tests to show how each component performs independently and how they integrate as a system to provide a coherent safety system.

4.1 Panic Button Performance

The manual panic button, which is connected to ESP32 microcontroller, proved to be highly reliable and fast in the tests. Whenever triggered, the system took less than one second to react, and it immediately showed the alert Panic Button on the OLED screen (Figure 6 a). The SMS is sent to registered contacts regularly within 5 seconds of activation, with a clickable Google Maps link to the exact location of the user (Figure 6 b). It also sends captured command to pi camera to capture that moment evidence

Figure 6: (a) Panic Button (b) SMS Alert with location

4.2 Multilingual Voice Command Recognition

The VR3 voice recognition module successfully recognized all three trained emergency phrases: "Help" (English) as shown in Figure 7 (a), "Bachao" (Urdu) shown in Figure 7(b), and "Maddad kayo" (Sindhi) as shown in Figure 7(c). Testing under various ambient noise conditions showed the system maintained reliable activation without generating false alarms from background conversation or environmental sounds moreover, the output is customized so that we can easily understand the mode through which over device is triggered.

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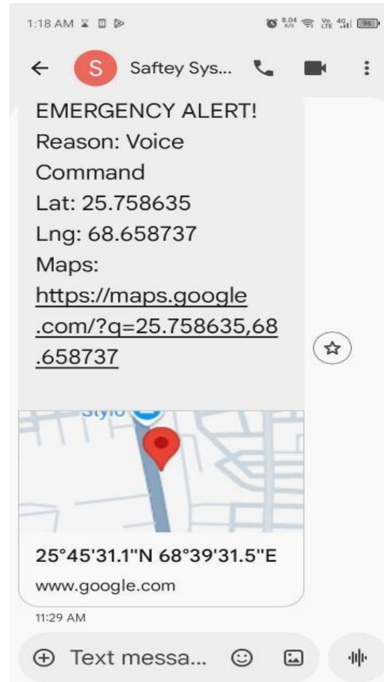
(b) Alert Detect by Urdu Cammand(Bachao)

(c) Alert Detect by Sindhi Command (Maddad Kayo)

d) Voice Alert Activation and SMS Dispatch



(e) SMS Received that is sent by voice alert

Figure 7: Detection result of Urdu, Sindhi, and English command alert

4.3 Weapon Detection Model Training results

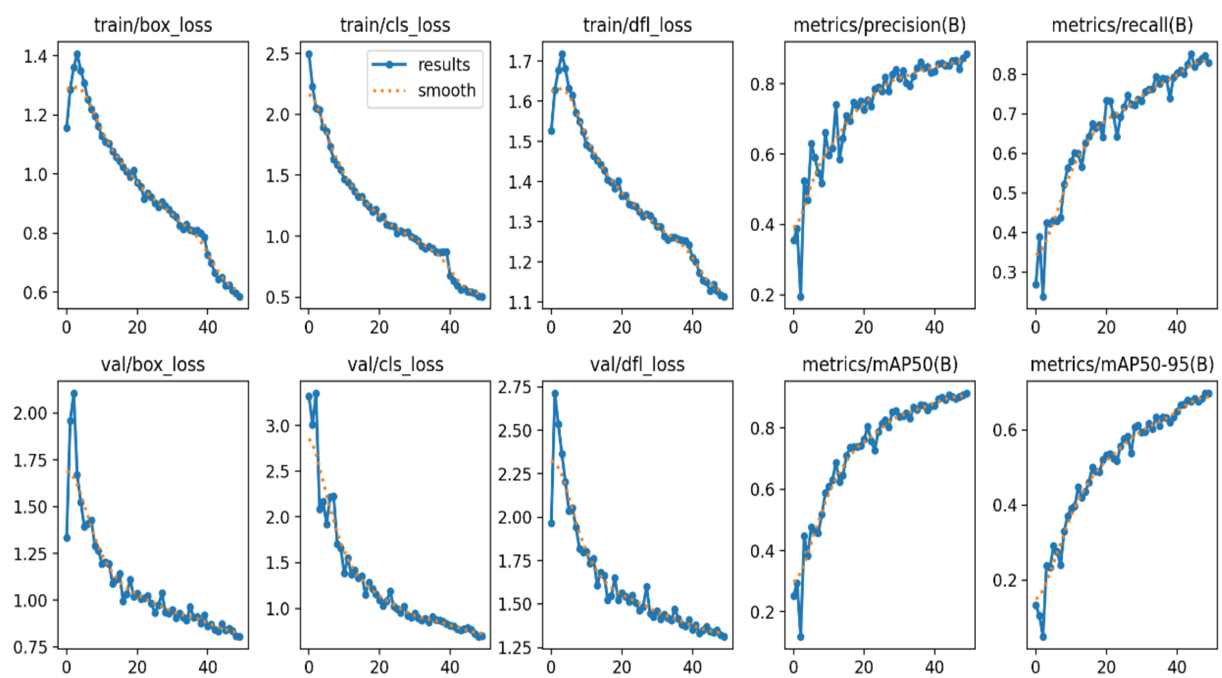


Figure 8 (a): YOLOv8 Training and Validation Curves (50 Epochs)

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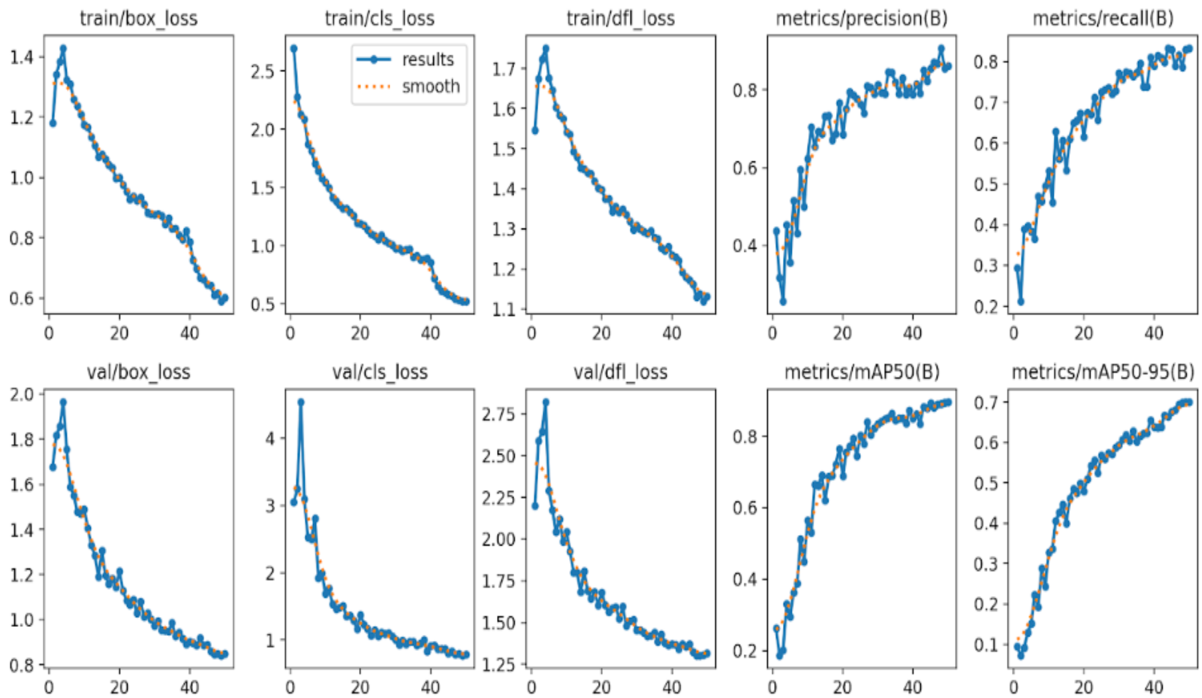

Figure 8(b): YOLOv11 Training and Validation Curves (50 Epochs)

The box loss, classification loss and DFL loss exhibit a consistent downward curve for both the training and validation sets without any overfitting in either case as shown in Figure 8(a, b), for both models. It can be seen that the precision and recall curves of YOLOv8 reach the final value around 0.90 with very small fluctuations, while the curves of YOLOv11 converge near 0.84 with a small difference.

4.4 Confusion Matrix

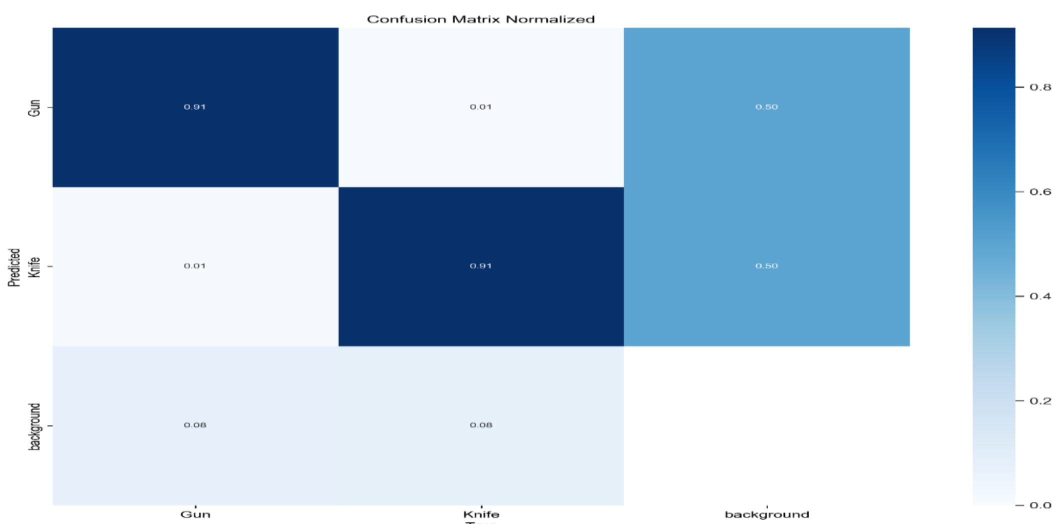

Figure 9(a): YOLOv8 Normalized Confusion Matrix

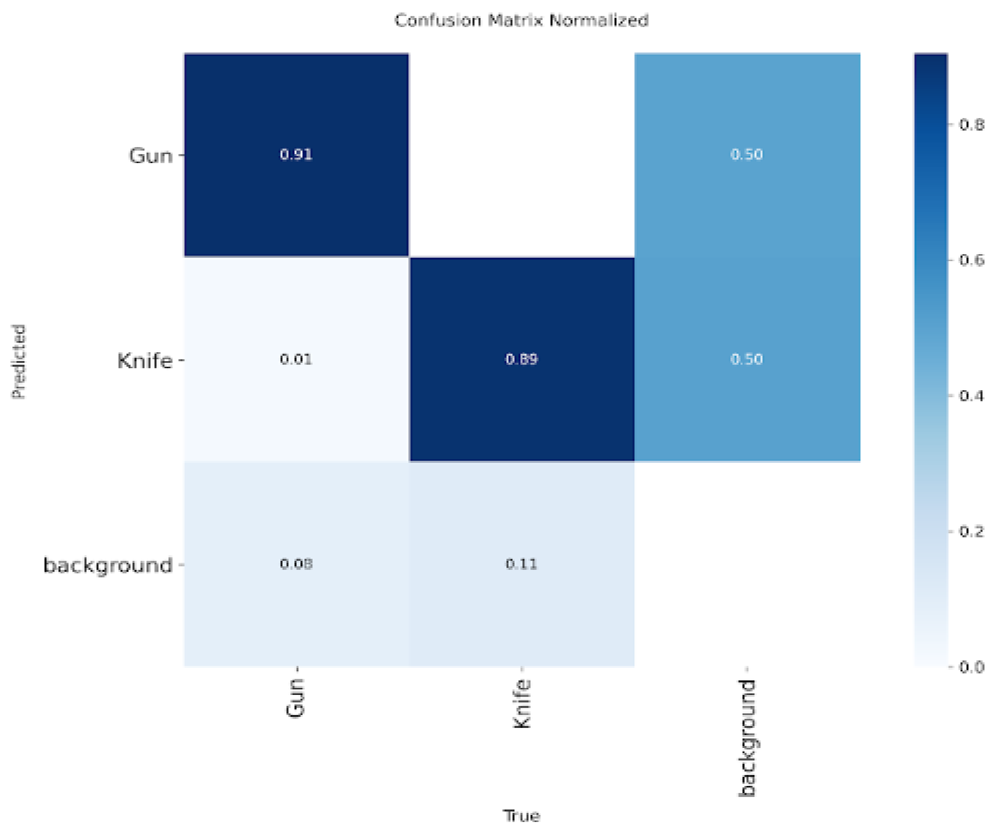

Figure 9(b): YOLOv11 Normalized Confusion Matrix

Model testing conduct on Validation set and we clearly see that YOLOv8 correctly detected 91% of the gun and 91% of the knife instances as shown in Figure 9 (a), and YOLOv11 correctly detected 91% of the gun and 89% of the knife instances as shown in Figure 9(b). We can see that there is hardly any cross-class confusion between the two classes, guns and knives, and YOLOv11's slightly lower knife detection rate is consistent with its lower overall mAP@0.5 (0.84 vs. 0.912), in line with the findings in Table 1.

Table 1: Performance Comparison of YOLOv8 and YOLOv11

Metric	**YOLOv8**	**YOLOv11**
Overall Accuracy (mAP@0.5)	0.912	0.894
Gun Average Precision (AP)	0.931	0.938
Knife Average Precision (AP)	0.894	0.851
Gun Precision (@0.5 confidence)	0.845	0.842

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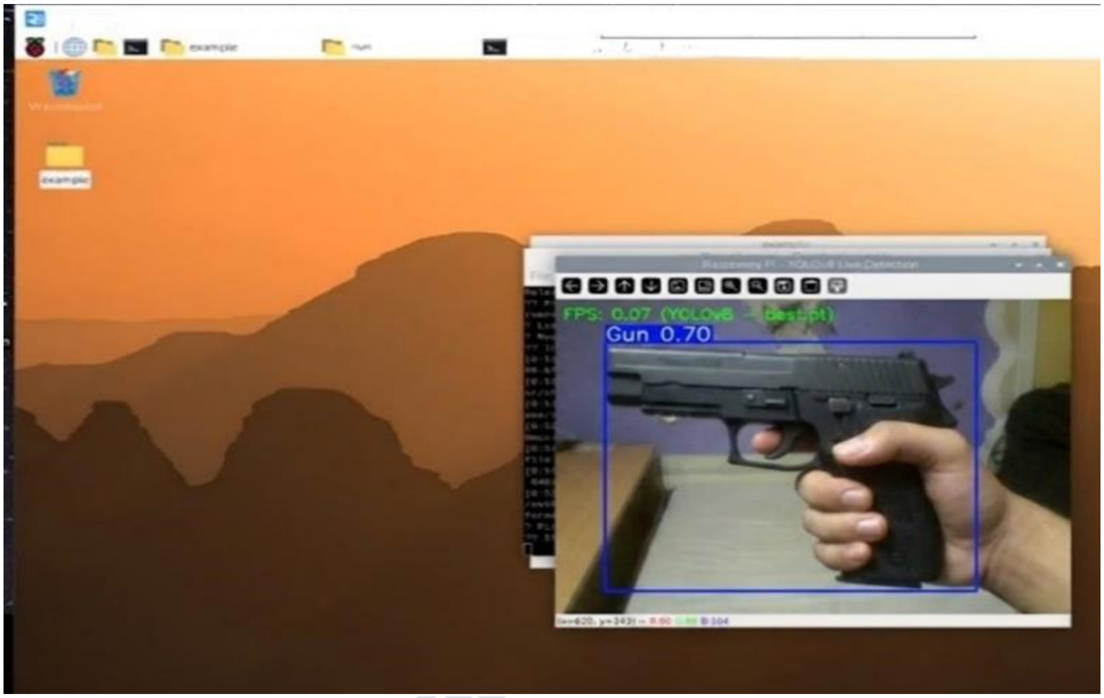
Knife Precision (@0.5 confidence)	0.683	0.668
Gun Recall (@0.5 confidence)	0.913	0.905
Knife Recall (@0.5 confidence)	0.913	0.893
Optimal F1-Score (peak)	0.86 (at conf. 0.573)	0.84 (at conf. 0.486)
Computational Efficiency	Higher	Lower

The numerical analysis showed the stable superiority of YOLOv8**.** Table 1 demonstrates that YOLOv8 has a higher overall accuracy with a mean average precision of 0.912 than 0.84 with YOLOv11. More to the point, YOLOv8 had superior recall, i.e., it was much more efficient at identifying all the weapons in a scene and was not prone to overlooking a potential threat. This is a very high recall rate that is necessary in a safety device where one missed read may be very critical. We tested our model YOLO8 before deploy on hardware as shown in Figure 10.

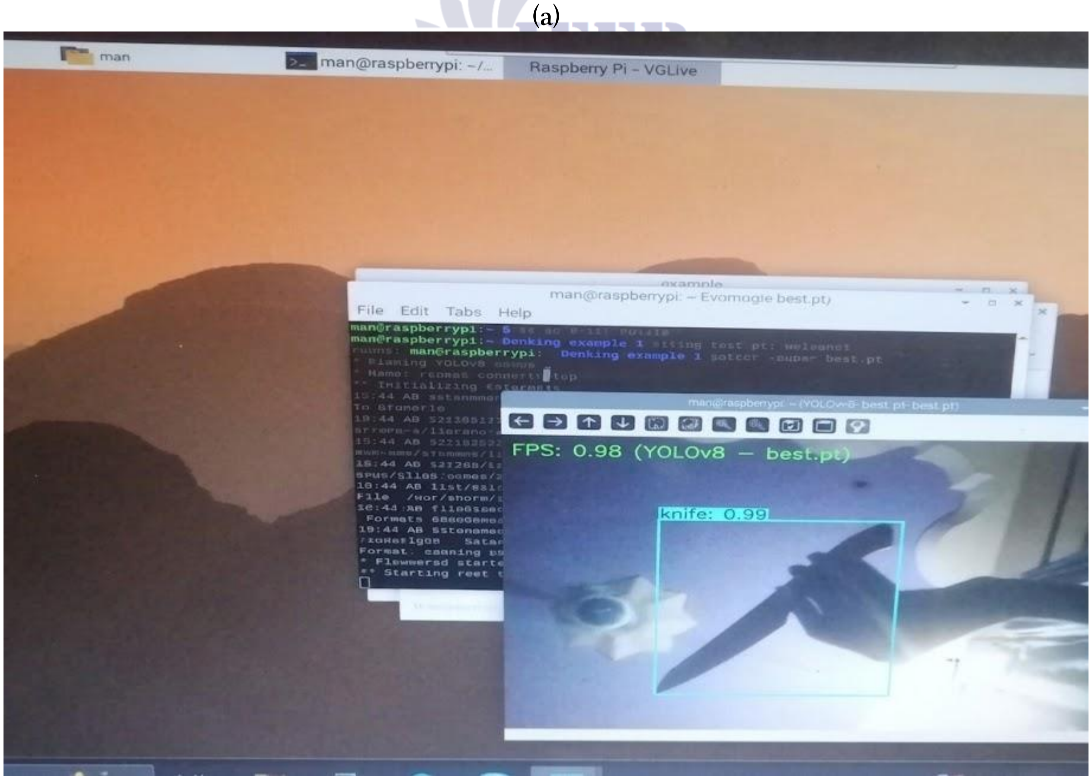
Figure 10: Yolo 8 Testing On-unseen data

4.5 Weapon Detection Performance on Hardware

The weapon detection module was developed using YOLOv8 and ran well in real-time on Raspberry Pi 4. The system successfully detected gun and knife in controlled testing conditions as Shown in Figure 11. The system proved to be strong under different lighting conditions and was consistent throughout even when the system was subjected to lengthy operation.



(a)

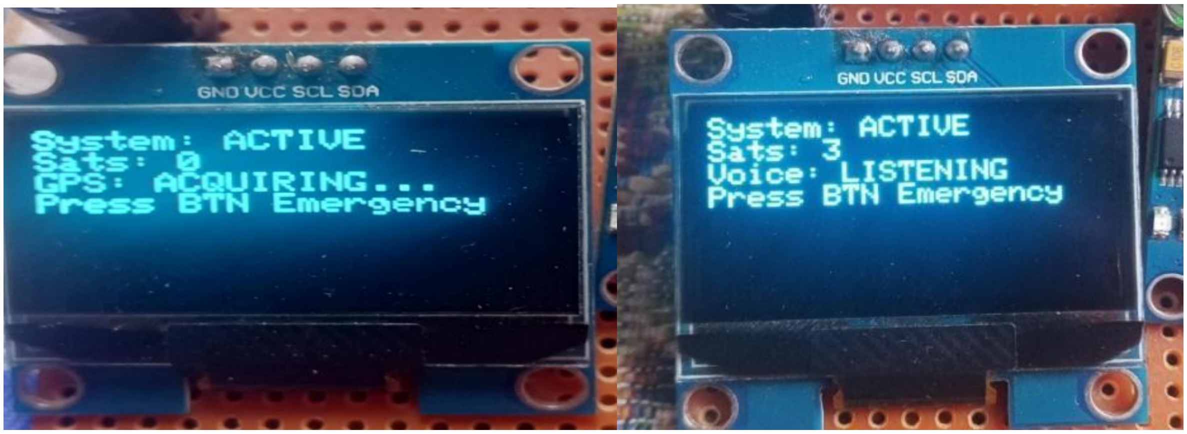


(b)

Figure 11: (a) Gun Detection (b)Knife Detection Result on pi

4.6 GPS and GSM Communication Reliability

The NEO-6M GPS module was able to maintain a consistent location data of 15-30 seconds to cold start. The GSM800L module proved to be 100% successful in SMS delivery and the average time of transmitting messages was 4-6 seconds. Location coordinates were efficiently transformed into URLs that can be clicked to Google Maps to give emergency contacts immediate and actionable location data.



Figures 12: GPS Searching and Connecting

4.7. Evidence Capture and Storage

The evidence capture system worked perfectly with all trigger modes, automatically recording timestamped 480x480 pixel images to the Raspberry Pi local storage. All the images were given names in the format of evidence_YYYY-MM-DD-HH-MM-SS.jpg and were stored in the. dedicated /home/pi/Evidence/ directory as shown Figure 13.

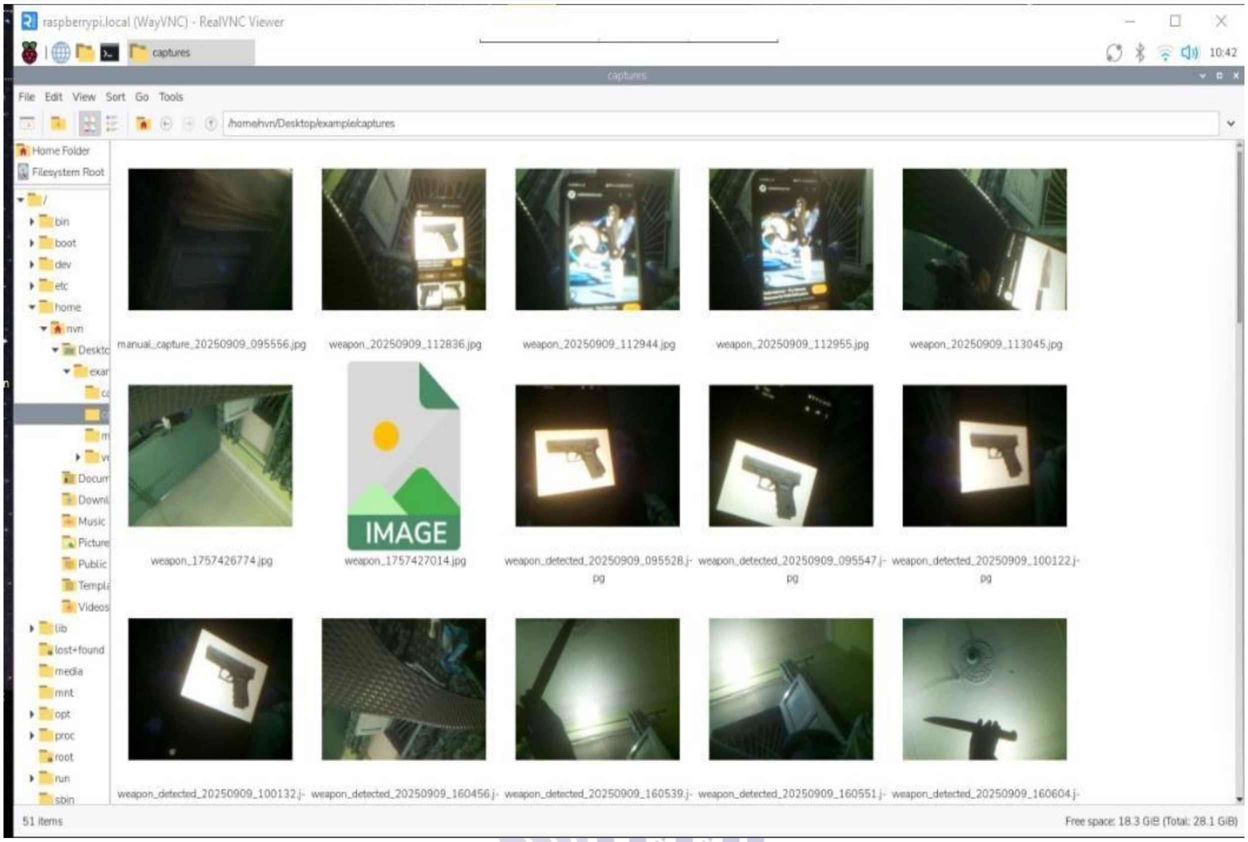


Figure:13: Evidence capturing and saving it into pi

4.8 Integrated System Performance

The Safelink device has a standard boot-up and functionality process, graphically presented on the OLED display. When it is turned on, the screen displays Starting... as illustrated in Figure 14(a) as the system loads all hardware modules and loads the YOLOv8 model. In about 2 seconds, the ESP32 creates a local Wi-Fi network and goes into a ready state, showing its local IP address (e.g., 192.168.4.1) and voice module is enabled with Voice: Listening (Figure 14 b).

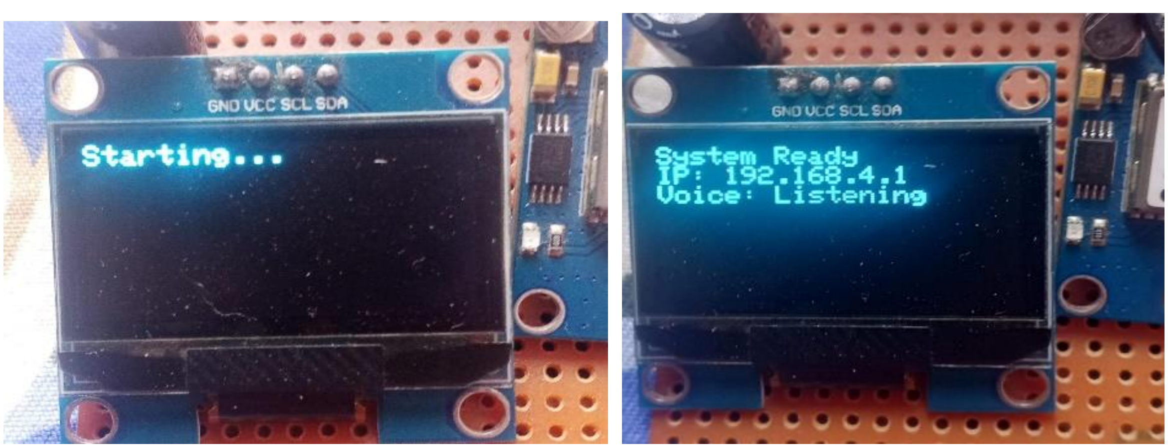


Figure 14: OLED display (a) starting system (b) initializing system.

The system goes into continuous monitoring after a short 3 seconds start up time. The display reads out in detail current real-time status: "System: ACTIVE" and the number of connected GPS satellites at any point in time, GPS acquisition status, and a reminder indication, "Press BTN Emergency" (Figure 15). During this stage, all three detection modes work simultaneously: the AI model analyses live camera feed, the voice module is ready to hear pre-set emergency instructions, and the panic button is waiting to be triggered manually.

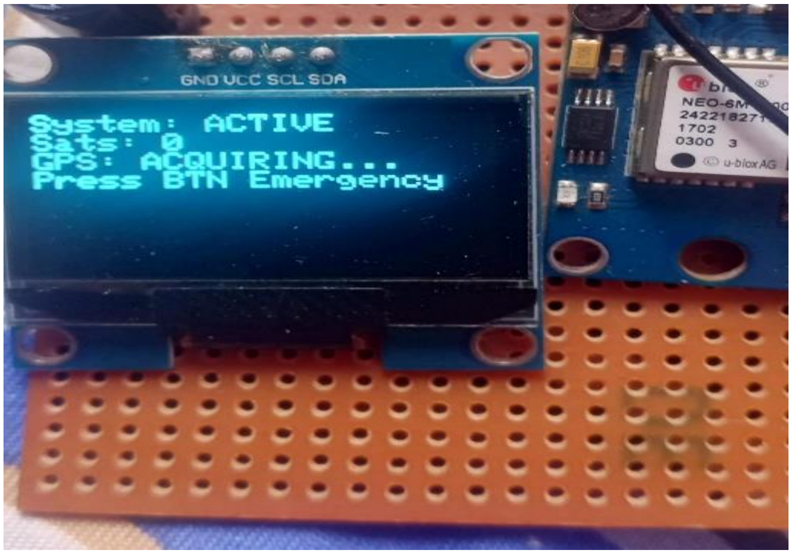


Figure 15: OLED display in monitoring mode, showing

When any of the input sources detect any threat, the OLED display will update in real-time to reflect the triggering event, such as: ALERT: Weapon Detected, VOICE Triggered, or PANIC Activated. At the same time, the cohesive emergency response procedure is implemented: (1) an evidentiary image is taken with a time stamp and stored locally, (2) the current GPS position is obtained, and (3) an emergency SMS is sent via GSM with the exact location, a link to Google Maps, and the activation mode (e.g. Weapon Detected by Camera, Voice Command Triggered, or Panic Button Pressed). An example of alert SMS created by camera-based detection includes as shown in Figure 16.

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Figure 16. Alert SMS sent when weapon was detected

The system returns to the continuous monitoring state seamlessly once the alert cycle is complete to be ready for the next threat. This multimodal, closed-loop operation shows the reliability, contextual awareness and user-centric design of the system in its safety applications in real world.

Table 2. The measured performance across the three activation modalities

Trigger Mode	**Average Activation Time**	**Evidence Capture**	**SMS Delivery Time**
Manual Panic Button	< 1.0 second	Yes	4–6 seconds
Voice Command	1.5 seconds	Yes	4–6 seconds
AI Weapon Detection	1 seconds	Yes	4–6 seconds

The manual panic button responded the quickest as shown in Table 2, whereas voice activation had a slight delay of audio processing and confirmation of the key word. The weapon detection was an AI-driven system that was fully automated, providing an additional layer of proactive security by itself. The system in all instances was able to capture timestamped evidentiary images, retrieve GPS coordinates and send SMS notifications including location links within 6 seconds of the trigger activation.

5. Conclusion

This study has effectively created and tested SAFELINK, a multimodal smartwatch gadget, to improve personal safety by providing proactive and convenient technology. By uniting three autonomous activation triggers, an AI-enabled weapon detecting system, a useful multilingual voice recognition module, and a physical panic button as a single and integrated platform, the project succeeded in fulfilling its main goals because the system does not rely on internet connectivity to work. Using an optimized YOLOv8 model showed that it was possible to use edge hardware to threat perceive real-time and with high accuracy, and that the accuracy of gun and knife detection was high with a fast response time. System testing Integrated system testing ensured that all components worked well and in harmony to the vision of a device that can react to any emergency in an autonomous and quick manner.

This provides considerable proof of concept of intelligent wearable safety systems. By going further than reactive designs and exploiting efficient SAFELINK, which offers a basis on-device artificial intelligence, is the future of personal security technology. Though issues with power efficiency and miniaturization still exist, this prototype shows clearly how integrated AI and IoT can be used to develop more responsive, reliable, and inclusive safety solutions to various people in diverse environments and circumstances.

6. Future Work

SAFELINK will be further developed in the following areas to bring the system to a product ready for market. Power efficiency can be achieved by introducing sleep/wake cycles, use of dedicated hardware accelerators like Google Coral and moving to a more efficient single-board computer which will prolong battery life. Further, the form factor will be reduced even more through custom PCB design and ergonomic casing, which will allow it to be worn without it being in anyone's way. In terms of detection, the AI algorithm will be expanded to detect and recognize gestures and moves by a human that signal aggression, before the weapon is drawn, preventing the system from being alerted to threats even before they are armed. The reliability of SMS communications will be enhanced, and integration of emergency calling will ensure that communications are carried out if the network is not performing well. Guardian interface to provide real-time control over alerts and monitoring of victim's location by registered contacts. With these improvements, SAFELINK can grow from a working prototype into a safety tool that people everywhere, especially those most at risk, can trust and rely on.

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