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KidShield - Hazard Detection

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Abstract: This project presents a real-time home hazard detection and alert system using computer vision and deep learning. YOLOv3 is employed to identify dangerous objects like knives and guns in a live video feed. When a hazard is detected near a person, the system triggers visual overlays and audio alerts using text-to-speech. It processes frames continuously, drawing labeled bounding boxes to distinguish threats from safe objects. Pre-trained YOLOv3 weights and COCO dataset classes are utilized for accurate detection. This approach improves home safety by enabling continuous, automated monitoring and minimizing human error.

I. INTRODUCTION

In an era where smart technologies are becoming integral to daily life, ensuring safety within our homes is more crucial than ever. This project introduces a real-time object detection and proximity alert system aimed at minimizing accidents caused by hazardous objects. By leveraging computer vision, the system continuously scans the environment and detects objects that pose potential risks. When someone gets too close to a dangerous item, the system promptly issues visual and audible alerts, providing timely warnings to prevent harm. The solution combines automation, real-time monitoring, and multi-sensory feedback to ensure immediate user awareness, even in the absence of active supervision. Its core focus is on enhancing safety through preventive alerts and clear communication of danger. Whether for children, the elderly, or anyone in the household, this system acts as a virtual safety assistant, making modern homes not just smarter, but significantly safer.

II. LITERATURE SURVEY

Several studies and projects have explored the use of computer vision for enhancing safety in various environments. Research on object detection using models like YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), and OpenCV-based detection systems has shown promising results in real-time identification of objects. These methods enable efficient monitoring with minimal latency, making them suitable for real-time safety systems. Prior work has also explored integrating sensors and alarms to provide alerts, especially in industrial and healthcare settings, to prevent accidents due to proximity to hazardous zones or objects.

In recent advancements, multi-sensory alert systems—combining visual and audio cues—have been recognized as effective in grabbing attention and prompting immediate user response. Several home automation solutions now include AI-powered detection, but many lack a focused approach toward danger-specific proximity detection. This project builds on previous findings by implementing a simple, responsive system that combines real-time video processing, object classification, and warning mechanisms, particularly tailored for home safety applications.

III. EXISTING SYSTEM

Traditional home safety solutions typically rely on a combination of physical safeguards and manual vigilance. Common tools include smoke detectors, fire alarms, door and window sensors, motion detectors, and security cameras. While these devices are effective for general security and emergency detection, they do not offer context-aware hazard detection or real-time proximity alerts related to dangerous objects. Their alerts are mostly triggered by environmental changes (such as smoke or motion) rather than specific recognition of hazardous items or behaviors. In recent years, some smart home systems have integrated basic AI capabilities, such as person detection or activity recognition, primarily for security purposes. However, these systems often lack fine-grained object classification, particularly for identifying potentially dangerous household items like knives, scissors, or firearms. Moreover, existing smart systems generally provide alerts only when motion is detected or predefined zones are breached, without considering the actual risk posed by the object or its proximity to residents. Surveillance cameras, though widely used, mainly serve a passive role, recording video without automatically analyzing or alerting for imminent dangers. This results in dependence on human monitoring or post-incident review, which is not practical for preventing accidents in real time. Some industrial or healthcare environments utilize more advanced proximity sensors and computer vision to detect hazards, but these solutions tend to be complex, costly, and not tailored for everyday home use.

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Thus, there is a significant gap in home safety technology for an intelligent system that can continuously detect hazardous objects, evaluate their proximity to individuals, and trigger timely multi-sensory alerts to prevent accidents. Existing systems lack this proactive, automated hazard recognition, making the development of a real-time hazard detection and alert system based on deep learning both necessary and highly valuable.

IV. PROBLEM STATEMENT

Sometimes, dangerous things like knives or scissors are left around at home, and people might not see them before getting hurt. There isn't a smart system that can watch and warn us quickly to stay safe.

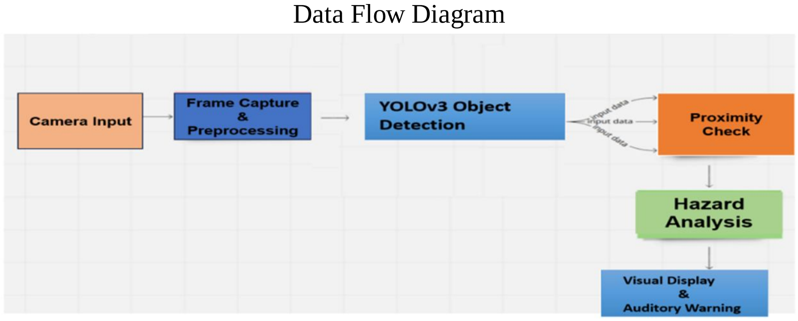
1) Most home safety tools don't notice when someone is too close to something that can hurt them. We need a way for the house to tell us right away if something dangerous is near.
2) Even with cameras and alarms, homes can't always warn people about risky objects before accidents happen. Kids and adults need a system that can spot dangers and alert them right away to keep everyone safe.

V. PROPOSED SYSTEM

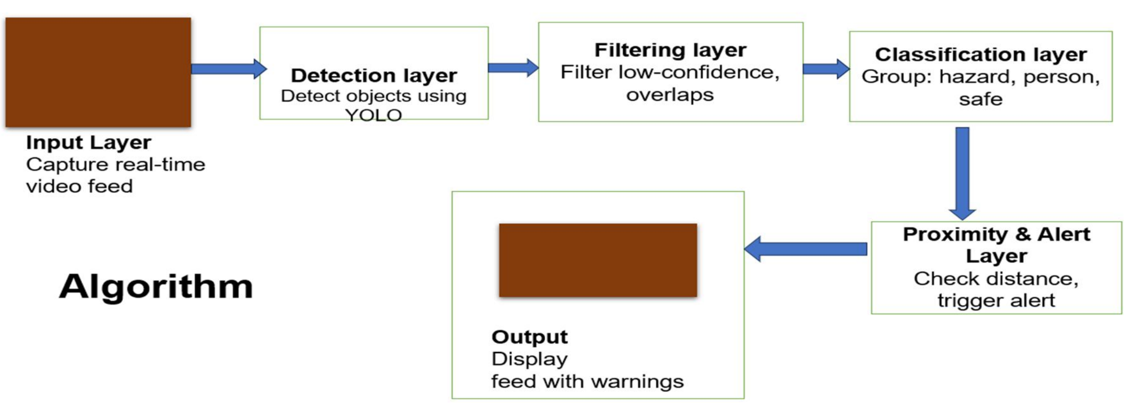
The proposed system by authors on aims to record all student participation based on the generated unique QR code of each course for each class day. The instructors, in turn, copy this QR code and paste it on the first slide to be displayed in the lecture. If the instructor policy is to allow late students in his class and would like to mark them as present or late, then the QR code should also be copied on one of the four corners of as many slides as the instructor wishes. When the students are in class, the first thing that should be done is to pull out their smart phones, open the Mobile Module, and scan the QR code, then the Server Module runs an identity check on the registered students. This is done by comparing the facial image sent per transaction with the stored image on file for the student in question, the system will then control the location of student. Finally, a location check will be performed.

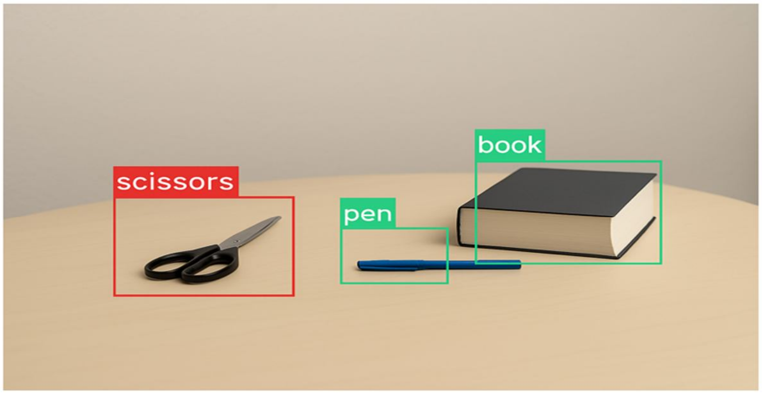
Our proposed model differs in a manner that should be easy to apply and quick in recording attendance during a class session; by focusing on creating a simple student attendance tracking system that can be used to take attendance which is both fast and affordable in comparison to the other methods.

Data Flow Diagram



VI. IMPLEMENTATION





x , y = top-left of box

w , h = width & height

Center = (x + w/2, y + h/2)

$$\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

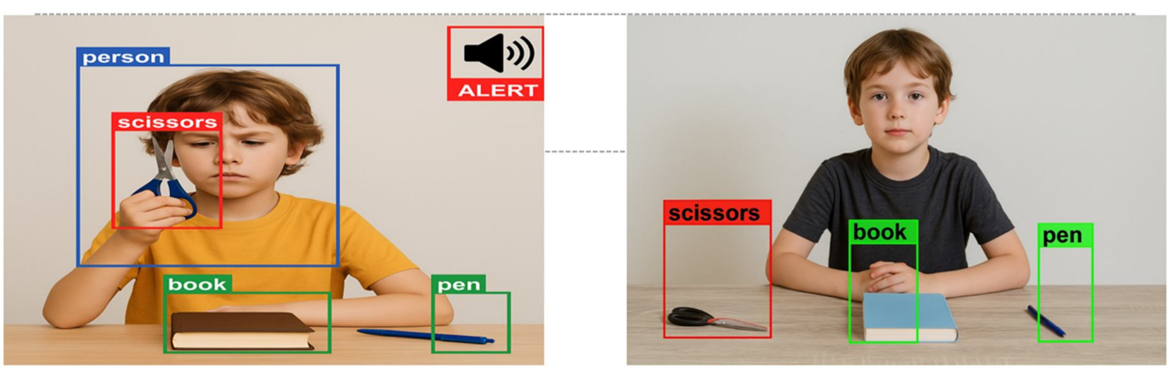
Used to measure how close the child is to the knife/stove.

Object	x	y	w	h	Center (x, y)
Child 1	120	200	60	150	(150, 275)
Child 2	300	220	65	155	(332.5, 297.5)
Scissors	180	210	40	20	(200, 220)

✅ Output Meaning:

If distance < 100px → 🔴 Danger

If distance > 100px → ✅ Safe



✂ Scissors

➤ Scissors Center = (200, 220)

1. Child 1 Center = (150, 275)

$$= \sqrt{(200-150)^2 + (220-275)^2}$$
$$= \sqrt{50^2 + (-55)^2} = \sqrt{2500 + 3025} = \sqrt{5525} \approx \boxed{74.3}$$

2. Child 2 Center = (332.5, 297.5)

$$= \sqrt{(332.5-200)^2 + (297.5-220)^2}$$
$$= \sqrt{132.5^2 + 77.5^2} = \sqrt{17556.25 + 6006.25} = \sqrt{23562.5} \approx \boxed{153.5}$$

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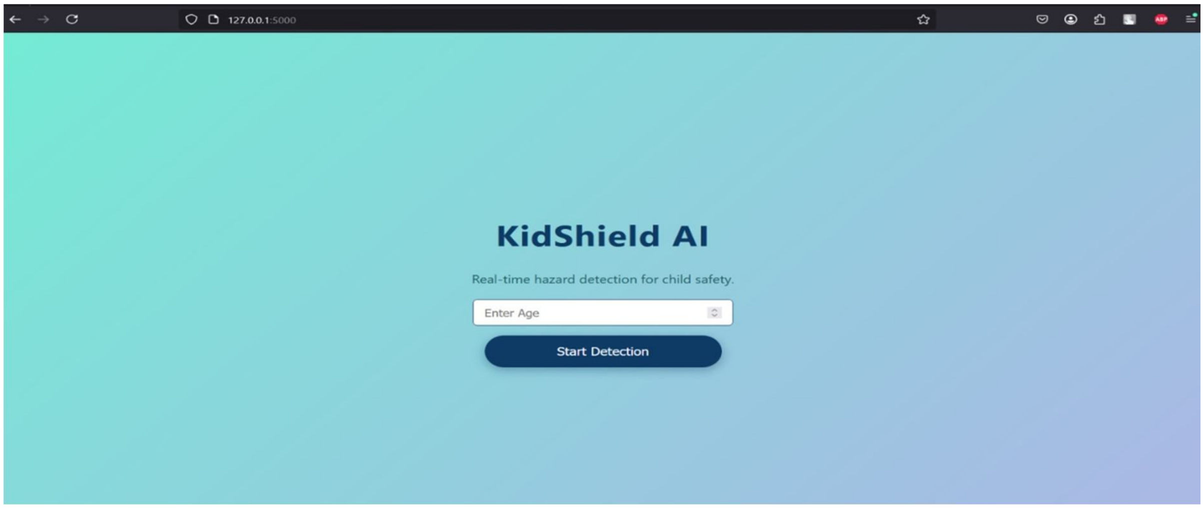
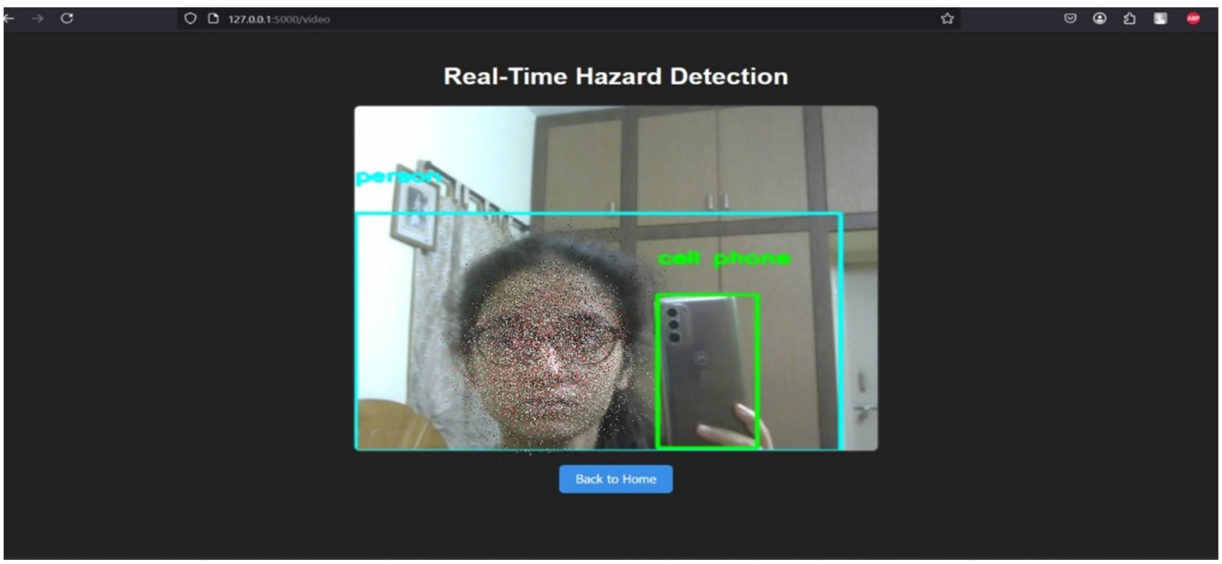
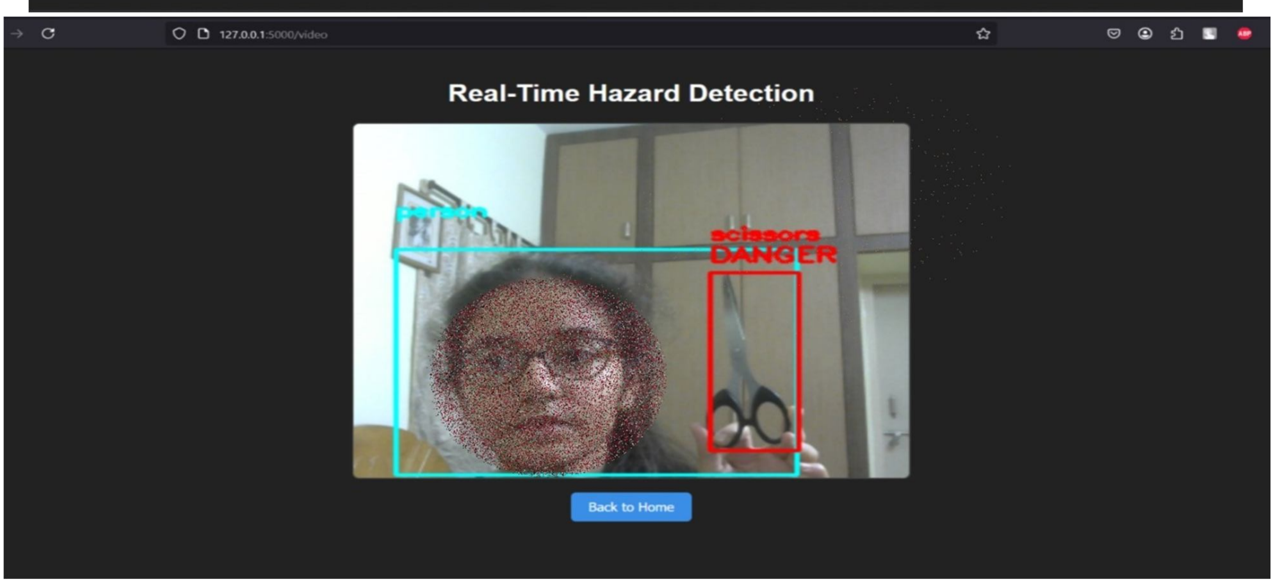
VII. RESULTS







VIII. CONCLUSION

This project has successfully developed an intelligent, real-time home hazard detection and alert system using state-of-the-art deep learning and computer vision technologies. By employing the YOLOv3 object detection model, the system is capable of accurately identifying a range of hazardous objects, such as knives, scissors, and firearms, within a live camera feed. The incorporation of proximity-based detection ensures that alerts are only triggered when dangerous objects come close to a person, minimizing unnecessary warnings and focusing on critical situations. The dual-mode alert system, combining visual overlays with audible text-to-speech warnings, ensures that users are immediately informed of potential threats, even if they are not actively observing the video feed.

This approach overcomes the significant limitations of traditional home safety methods that rely on manual monitoring or simple sensor triggers, which often lack context or timely response capabilities. The automated and continuous nature of this system reduces human error and improves the overall safety of the home environment, making it particularly beneficial for vulnerable populations such as children, elderly individuals, and persons with disabilities.

Furthermore, the system's use of pre-trained YOLOv3 weights and the COCO dataset enables efficient deployment without the need for extensive custom training, making it scalable and adaptable to various household settings. The project illustrates the practical application of AI in creating smarter and safer living spaces. Looking ahead, this system can be enhanced by expanding its detection capabilities to include a wider variety of household hazards, such as electrical appliances, chemicals, or slippery surfaces. Integrating additional sensors like infrared or ultrasonic distance detectors could improve proximity accuracy. Moreover, coupling the system with home automation platforms could enable automatic actions—such as locking cabinets or shutting off appliances—when hazards are detected. Personalized alert settings and remote monitoring features could further increase usability and convenience.

Overall, this project highlights the transformative potential of AI-driven hazard detection in promoting safer homes, reducing accident risks, and providing peace of mind to residents. It lays a strong foundation for future innovations that blend technology with everyday safety needs.

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