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CrossBot: An AI-Driven Smart Robot for Enhancing Pedestrian Safety at Crosswalks

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***Abstract*—Pedestrian safety remains a critical concern, with thousands of fatalities and injuries reported annually, particularly among children under 16 during road crossings. This research introduces CrossBot, an AI-powered smart robot designed to enhance pedestrian safety by providing real-time detection and intelligent decision-making at intersections. Unlike traditional systems that rely on traffic-light infrastructure, CrossBot employs advanced machine learning (ML) algorithms to accurately detect vehicles, pedestrians, and cyclists. Using large datasets from LiDAR sensors and video cameras, the ML models are trained to perform real-time analysis of road conditions. Deployed on a mini-computer and programmed in Python, the system integrates sensor data to make intelligent, real-time decisions, ensuring pedestrians and cyclists are guided safely through crossings. This comprehensive solution offers robust detection and decision-making capabilities, with the potential to significantly reduce pedestrian-related accidents at crossroads.**

***Index Terms*—Smart Robot; Pedestrian Road Crossings; Artificial Intelligence; Crossing Guard Robot; Pedestrian Safety, CrossBot.**

I. Introduction

Pedestrian safety is a growing concern as pedestrian fatalities and injuries continue to rise, with 6,516 pedestrians killed and approximately 55,000 injured in vehicle collisions in 2020 alone [1]. Vulnerable groups such as children under 16 are particularly at risk, especially in school zones. According to the National Highway Traffic Safety Administration (NCSA), schoolchildren face heightened danger when crossing streets, particularly in areas lacking traffic lights or stop signs [2]. In California alone, six million students attend 10,453 public schools, with over 3.1 million being elementary school-aged children. Notably, school districts in Los Angeles, Oakland, and San Francisco rank among the most dangerous for pedestrian safety [3]. For example, Jardin de la Infancia School in Los Angeles reports one of the highest incidences of traffic-related accidents, with 271 car accidents, 72 pedestrian accidents, and 54 bicycle accidents recorded within a short period.

To mitigate risks, school personnel often assist children in crossing streets during peak pedestrian traffic hours, but this support is limited to specific times, leaving children unassisted for much of the day. Younger students struggle to assess when it is safe to cross the street, leading to potentially fatal accidents [4]. Despite these risks, few studies propose innovative solutions beyond improving existing traffic-light infrastructure [5], [6].

To address these gaps, we propose a novel approach that builds on the groundwork from our earlier work on pedestrian detection and avoidance systems [7]–[9]. The current system incorporates additional sensors, including LiDAR for detecting vehicle inflow and visible light cameras for vehicle detection, offering a more elaborate framework for pedestrian safety.

Our smart robot, CrossBot, integrates advanced sensors and artificial intelligence (AI) to assist pedestrians and cyclists in crossing streets safely. Using a combination of LiDAR sensors and video cameras, the robot monitors traffic conditions and autonomously decides when it is safe to guide pedestrians across. It also detects hazardous situations during crossings and issues warnings to pedestrians and drivers. The robot operates both day and night, ensuring consistent performance.

The CrossBot project, developed with funding from the Fresno State Transportation Institute, has garnered national and international media attention. It has been featured on platforms such as KTVU Fox 2, NBC Bay Area, and East Bay Times, with global coverage in countries such as Germany, Italy, and Japan [10]. This widespread recognition underscores CrossBot's societal relevance and its potential to address critical pedestrian safety concerns at the international level.

This project aims to pioneer a comprehensive, real-time pedestrian safety system that surpasses traditional traffic infrastructure, offering a robust solution to reduce pedestrian fatalities and injuries at crosswalks.

The rest of the paper is organized as follows. In Section II, we provide the system overview, followed by the machine learning object detection for pedestrian safety in Section III. In Section IV, we present the traffic light chassis design and methodology followed by the software system architecture in Section V. The CrossBot framework implementation and prototype experimentation are presented in Sections VI and VII followed by the conclusion in Section VIII.

II. System Overview

The smart robot designed to assist pedestrian road crossings integrates advanced software, machine learning neural networks, and hardware subsystems, working together to execute its intended function effectively.

The robot operates continuously to manage pedestrian and vehicular traffic at crosswalks. Upon detecting pedestrians waiting to cross, the system scans for incoming traffic. If no vehicles are approaching, the robot activates a red light for both directions of traffic, moves to the center of the street, and initiates a pedestrian walking signal. Throughout the crossing, the system monitors the situation to ensure all pedestrians cross safely. Once no more pedestrians are detected, the robot deactivates the walking signal, moves back to its starting position on the pavement, and signals a green light for vehicles to proceed.

In its monitoring state, the system constantly checks for pedestrian and traffic activity. If both pedestrians and vehicles are present, the robot assesses the speed of oncoming traffic. When it determines that stopping is unsafe, the system allows vehicles to continue. However, if a safe stopping distance is available, it signals a red light, stopping vehicles at the smart traffic light to allow pedestrians to cross safely.

III. Machine Learning-Driven Object Detection for Pedestrian Safety

A. YOLO Algorithm for Object Detection

A key component in the development of the CrossBot system is its robust object detection capability, which allows the smart robot to dynamically adapt to its environment in real-time. To achieve this, advanced machine learning algorithms are essential, particularly for classifying and tracking pedestrians, vehicles, and cyclists. After evaluating several alternatives, the YOLO (You Only Look Once) algorithm was selected for its superior performance in real-time object detection, high accuracy, and minimal false positives.

YOLO is a state-of-the-art deep learning algorithm that uses a convolutional neural network (CNN) to predict bounding boxes and class probabilities for multiple objects within a single pass of the image. Its end-to-end architecture enables accurate detection of multiple objects in complex environments, making it well-suited for applications such as pedestrian safety systems. YOLO is particularly effective in scenarios where objects overlap, as it processes the entire image at once, generating fast and reliable detection outcomes.

YOLO divides an input image into a grid of S x S cells, where each grid cell is responsible for predicting bounding boxes and associated confidence scores for objects it contains. This approach streamlines the detection process, allowing for efficient and accurate real-time analysis of traffic conditions at crosswalks.

B. YOLO Algorithm Implementation

To implement YOLO, we leveraged Python's OpenCV2 library, which simplifies the integration of multiple pre-trained YOLO models for vehicle and pedestrian detection in video feeds. OpenCV2 provides built-in functions that allow for seamless bounding box generation around detected objects, offering real-time visualization and analysis. These capabilities, combined with YOLO's high-speed performance, make it ideal for traffic monitoring and ensuring pedestrian safety in urban environments. The implementation of the YOLO models within CrossBot ensures quick and accurate detection of both vehicles and pedestrians, allowing the system to make intelligent decisions about when it is safe for pedestrians to cross.

C. Bounding Boxes and Object Labeling

In the context of pedestrian and vehicle detection, YOLO generates bounding boxes around detected objects and assigns class labels to each object within the frame. By analyzing each frame of a video feed, the system ensures that both pedestrians and vehicles are tracked and labeled accurately. The algorithm applies non-maximum suppression to eliminate overlapping bounding boxes, ensuring that only the most accurate predictions are retained. This process is critical for enabling the CrossBot system to respond effectively to real-world traffic conditions.

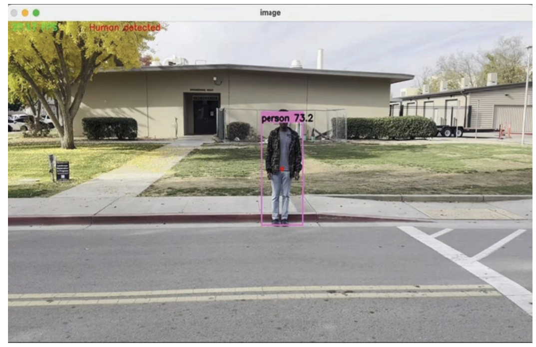

Fig. 1: Pedestrian detection algorithm in action for person detection crossing the street.

As demonstrated in Fig. 1, the system highlights pedestrians crossing the street with bounding boxes and displays percentage accuracy for the detection, ensuring precise identification of individuals during crossing events.

D. Curb Detection Implementation

To enhance the system's functionality, curb detection is integrated to track whether pedestrians successfully complete their crossing and reach the sidewalk. The system uses edge detection to define the sidewalk boundary and monitors pedestrian movement as they step onto the street. If a pedestrian intersects with the detected curb line, the system registers the event, allowing for continuous monitoring of pedestrian traffic. This feature ensures that pedestrians are safely guided across the street, further enhancing CrossBot's safety capabilities.

IV. Traffic Light Chassis Design Methodology

The development of the CrossBot system required a carefully engineered CAD model to integrate key components such as the LED matrix and LiDAR seamlessly. This section outlines the design considerations that ensured the structural integrity and functionality of these elements, aligning them with the system's overall requirements.

A. Designing for Functionality

The primary design approach focused on ensuring the robot's core functionality, guiding decisions such as sensor placement, LED matrix configuration, and overall system dimensions. Each design choice was optimized to enhance the robot's operational efficiency while maintaining structural balance.

B. Traffic Light Design

To provide clear and consistent signals for pedestrians and vehicles, the LED matrix panels were arranged in a box-like formation, as shown in Fig. 2. Two panels face

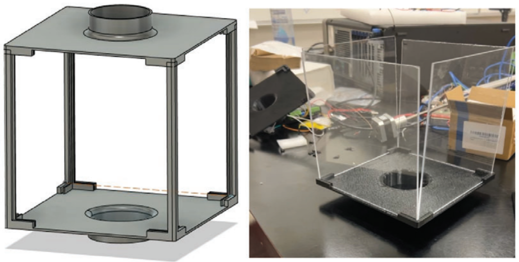

Fig. 2: CAD model, 3D printed case for LED matrix panels.

Fig. 3: Final prototype.

pedestrians, and two panels face inbound and outbound traffic, respectively. The enclosure design accommodates these panels, ensuring their protection from external elements.

The design includes four columns supporting an acrylic glass cover, protecting the LED panels and wiring from environmental factors. Gaps were incorporated into the columns and base to allow easy assembly of the LED matrix and protective glass.

The LED matrix is mounted on a PVC pipe, which serves to elevate the structure and also provides mounting support for the LiDAR sensor. Wiring for the LED panels, LiDAR, and cameras run through the hollow PVC pipe, connecting to the Raspberry Pi and Jetson Orin at the base.

A low-profile tray was designed to securely house the onboard computers, including the Raspberry Pi and Jetson Orin to facilitate efficient wiring and power management.

After the 3D printing and assembly process, the final robot design shown in Fig. 3, standing approximately 6 feet 1 inch tall, successfully met the required specifications.

V. Software System Architecture

A. Overview

The foundation of the CrossBot system is built on the Robot Operating System 2 (ROS2) architecture, widely regarded as an industry standard for developing advanced robotic applications. ROS2 offers a robust set of software libraries and tools, following a publisher-subscriber model to manage data flow efficiently through nodes and topics, as shown in Figure 4.

The ROS2 publisher-subscriber model simplifies data handling by allowing multiple nodes to access data concurrently without the need for complex multi-threading. This modular and scalable design promotes flexibility and system expansion, making it easier to integrate new functionalities and facilitating rapid development.

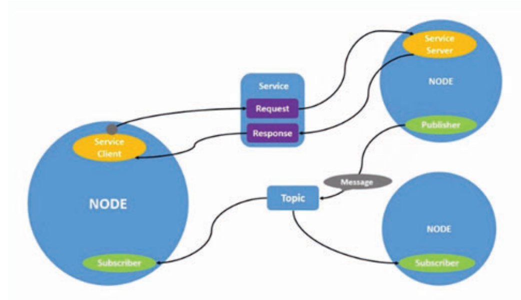

Fig. 4: ROS2 Node publisher and subscriber architecture.

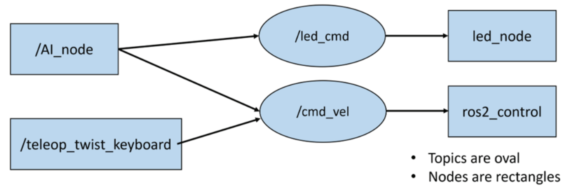

Fig. 5: Block diagram of the ROS2 node architecture.

B. Control Software Design and ROS2 Integration

Our control software is built on ROS2 Humble, a middleware specifically designed for complex robotic systems. ROS2 Humble adopts a distributed architecture based on the publisher-subscriber model, enabling smooth communication between individual nodes via topics. This decentralized approach enhances modularity and flexibility, allowing for a more adaptive control software design that can easily accommodate the dynamic nature of our system.

C. ROS2 Packages for Control Software

The control software leverages various ROS2 packages, such as the *ros2_control* package for navigation and motor control, as well as sensor integration packages like *Velodyne* for 3D LiDAR and the camera package for the USB camera. Figure 4 illustrates the architecture of the ROS nodes, highlighting the interaction between control nodes, sensor integration, and the LED matrix for traffic signals.

D. ROS Node Architecture for Traffic Control System

Figure 5 demonstrates the node architecture for the traffic control system. Two key nodes, */AI_node* and */teleop_twist_keyboard*, publish velocity commands to the common */cmd_vel* topic. The */AI_node* handles pedestrian detection and controls traffic flow based on AI-driven logic, while the */teleop_twist_keyboard* node allows for manual robot control via a keyboard interface.

The *ros2_control* node subscribes to the */cmd_vel* topic, processing input commands from either the AI or manual control for hardware interface management. Additionally, the */AI_node* manages traffic light logic, publishing commands to the *led_cmd* topic, which the *led_node* uses to control the LED matrix and display traffic signals.

This architecture ensures efficient coordination between AI, control, and hardware interaction within the ROS2 framework, optimizing the system for real-time traffic management.

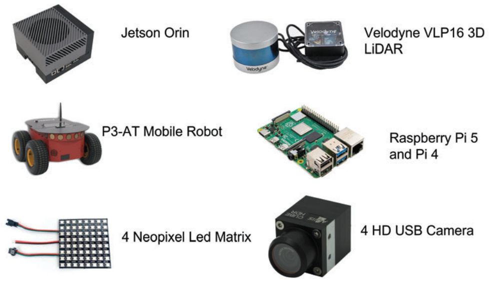

Fig. 6: CrossBot hardware system, including Velodyne LiDAR, NVIDIA Jetson AGX Orin, Raspberry Pi 5, and P3-AT Mobile Robot.

Fig. 7: CrossBot experimentation on a street at Fresno State.

Fig. 8: The fully built and functional CrossBot experiments in Fresno State school and streets.

VI. Robot Framework Implementation

The implementation of the CrossBot robot framework integrates multiple advanced hardware components, designed to work in concert to enhance pedestrian safety at crosswalks. Figure 6 presents an overview of the system's hardware components, which include the Velodyne VLP-16 LiDAR sensor, NVIDIA Jetson AGX Orin Developer Kit, Raspberry Pi 5, Pioneer 3-AT Mobile Robot, and a robust power distribution strategy.

At the core of the robot's sensing capabilities is the Velodyne VLP-16 LiDAR, which provides 360-degree real-time 3D distance measurements. This sensor plays a pivotal role in detecting vehicles, pedestrians, and cyclists, offering high-density point clouds that allow for precise object tracking and environmental mapping. The LiDAR's data is processed by the NVIDIA Jetson AGX Orin, a high-performance computing platform specifically tailored for AI applications. This module handles real-time data from LiDAR and onboard cameras, executing machine-learning models for object detection, classification, and decision-making.

The system's traffic management functionality is supported by a Raspberry Pi 5, which controls the LED matrix panels mounted on the robot. These panels are designed to display pedestrian and traffic signals, providing clear guidance for both road users and pedestrians.

The robot is built on the Pioneer 3-AT platform, a versatile mobile base that supports the integration of additional hardware components while enabling smooth navigation. Power distribution is managed by the P3AT Mobile Robot Power Distribution Board, ensuring stable and efficient power supply to all the subsystems, including the 3D LiDAR and Raspberry Pi.

The final system prototype, depicted in Figure 6, integrates all these components, offering a robust solution for autonomous pedestrian traffic control at crosswalks.

VII. Prototype Experimentation

The development of the smart robot designed to assist pedestrians in crossing streets has been successfully completed, with all hardware and software components fully integrated and tested. The prototype integrates Velodyne's VLP-16 LiDAR sensor and multiple high-resolution cameras on the smart traffic light robot, enabling robust autonomous control and functionality. The implementation of advanced machine learning algorithms, including the YOLO object detection models, has proven effective in detecting pedestrians, cyclists, and vehicles with a high degree of accuracy.

The prototype underwent extensive testing on the Fresno State campus and surrounding streets to evaluate its performance in real-world conditions. Figure 7 shows the experimentation setup during live tests at Fresno State roads, while Figure 8 presents the fully built and functional smart traffic light robot in action on Fresno State streets and school zones. These tests demonstrated the robot's capability to autonomously detect traffic conditions and make real-time decisions for pedestrian safety.

The deep learning models developed for this project achieved remarkable performance. The classification deep neural networks for pedestrian and cyclist detection reached an average validation accuracy of 90.48%, while vehicle and cyclist detection models achieved an average validation accuracy of 90.1%. Figures 9 and 10 illustrate the training and validation results for pedestrian, cyclist, and vehicle detection models.

In real-time testing, the system successfully utilized the LiDAR sensor for point cloud visualization, combined with the machine learning models for object detection. Figures 11 and 12 show live captions from the LiDAR sensor, where the model identifies pedestrians in crosswalks and vehicles on the road with associated confidence scores. These results demonstrate the system's ability to analyze real-time data and make decisions based on environmental conditions.

The experimental results validate the system's effectiveness in detecting and responding to pedestrian and traffic conditions, ensuring safety at crosswalks. This system offers a comprehensive, autonomous solution for pedestrian traffic control, with potential applications in school zones, busy

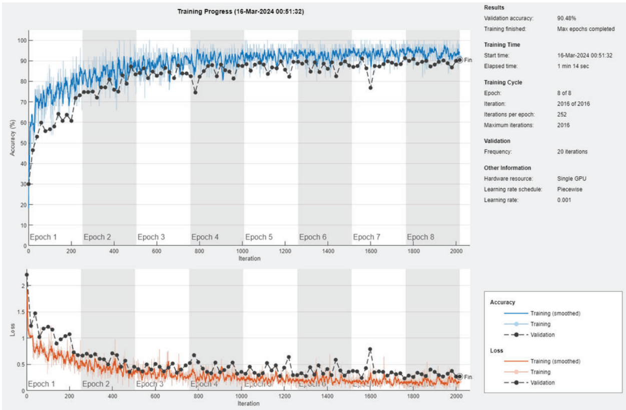

Fig. 9: Training results of the classification deep neural network for optical images of pedestrians and cyclists detection.

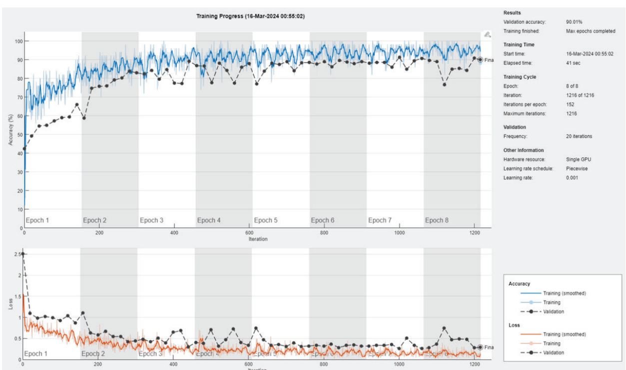

Fig. 10: Training results of the classification deep neural network for vehicles and cyclist detection.

intersections, and other high-risk areas.

VIII. Conclusion

In conclusion, this project addresses the urgent need for innovative pedestrian safety solutions, particularly at road crossings where vulnerable populations are at higher risk. By combining machine learning algorithms with LiDAR and video camera sensors, the smart robot system achieves accurate, real-time detection and intelligent decision-making, significantly enhancing pedestrian and cyclist safety.

This proactive approach to traffic management fosters safer road-crossing environments, demonstrating meaningful potential to reduce pedestrian-related accidents. The global media coverage, including features on KTVU Fox 2 and NBC Bay Area, highlights the societal relevance and impact of this initiative. For a closer look at CrossBot in action, a video demonstration is available through news coverage [10].

IX. Acknowledgment

Support and funding for this effort was partly provided by the Fresno State Transportation Institute (FSTI) [10].

References

[1] National Highway Traffic Safety Administration (NHTSA), "Traffic safety facts: 2020 data," https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813053, December 2020.

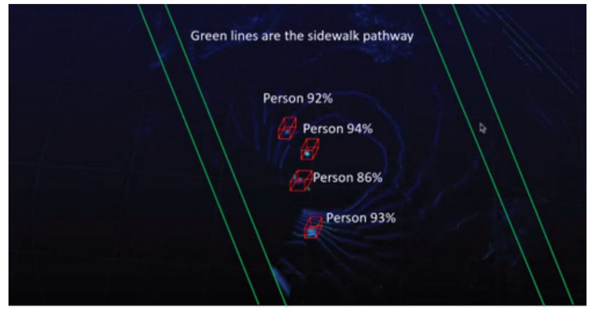

Fig. 11: Live caption of the LiDAR sensor point cloud with the ML model predicting the pedestrians in the crosswalk.

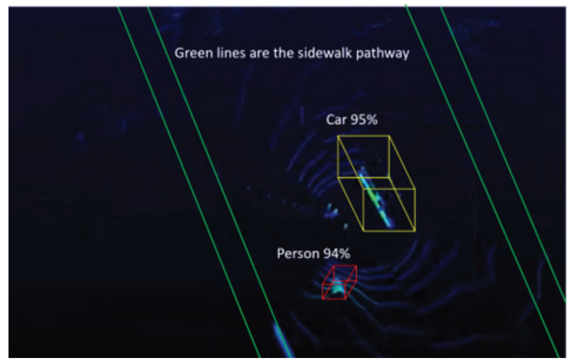

Fig. 12: Live caption of the LiDAR sensor point cloud with the ML model identifying a car and a pedestrian on the street.

[2] National Center for Statistics and Analysis (NCSA), "Pedestrians: 2021 data (traffic safety facts. report no. dot hs 813 458)," National Highway Traffic Safety Administration, Washington, DC, Tech. Rep., June 2023, available at: https://www.nhtsa.gov.

[3] CBSLA News, "Many los angeles elementary schools surrounded by dangerous streets," https://www.cbsnews.com/losangeles/news/many-los-angeles-elementary-schools-surrounded-by-dangerous-streets/, February 13 2017, available at: https://www.cbsnews.com/losangeles/news/many-los-angeles-elementary-schools-surrounded-by-dangerous-streets/.

[4] J. P. Wann, D. R. Poulter, and C. Purcell, "Reduced sensitivity to visual looming inflates the risk posed by speeding vehicles when children try to cross the road," *Psychol. Sci.*, vol. 22, no. 4, pp. 429–434, 2011.

[5] G. Pau, T. Campisi, A. Canale, A. Severino, M. Collotta, and G. Tesoriere, "Smart pedestrian crossing management at traffic light junctions through a fuzzy-based approach," *Future Internet*, vol. 10, no. 2, p. 15, 2018.

[6] W. K. Saad, Y. Hashim, and W. A. Jabbar, "Design and implementation of portable smart wireless pedestrian crossing control system," *IEEE Access*, vol. 8, pp. 106 109–106 120, 2020.

[7] H. Kulhandjian, J. Barron, M. Tamiyasu, M. Thompson, and M. Kulhandjian, "Pedestrian detection and avoidance at night using multiple sensors and machine learning," in *Proc. of IEEE International Conference on Computing, Networking and Communications (ICNC)*, Honolulu, Hawaii, February 2023.

[8] H. Kulhandjian, "AI-based Pedestrian Detection and Avoidance at Night using an IR Camera, Radar, and a Video Camera," California State Transportation Consortium, Tech. Rep., March 2022, project No. 2127, pp. 1-42.

[9] H. Kulhandjian, J. Barron, M. Tamiyasu, M. Thompson, M. Kulhandjian, and L. Aslanyan, "AI-Based Pedestrian Detection and Avoidance at Night Using Multiple Sensors," *Journal of Sensor and Actuator Networks*, vol. 13, no. 3, p. 34, 2024.

[10] Fresno State Transportation Institute, "Crossbot for safer pedestrian crossings," https://engineering.fresnostate.edu/institutes/fsti/news/crossbot.html, n.d.