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Automatic Barrier Deployment Using Multimodal Machine Learning for Rapid Protective Response

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Abstract

Sudden violent incidents such as gunfire require a rapid protective response. Traditional protective barriers require cognitive processing to recognize the threat before physically closing the barrier. This end-to-end process takes approximately 30-60 seconds. Studies show that reducing protective response time to sub-second can reduce casualty risk significantly. The purpose of this research was to design, implement, and evaluate an automatic barrier deployment system triggered by machine-learning-based threat detection to reduce protective response time to sub-second levels. The system integrates gunshot acoustics and vision-based shooter detection using machine learning (ML) models that are executed on an edge computing platform. Audio signals are processed into log-mel spectrograms and classified using a convolutional neural network (CNN), while video frames from a USB camera are analyzed using another CNN-based object detection model. Upon threat detection, a wireless command is transmitted to ESP32, activating a relay to control the robotic system's motors and deploying a polycarbonate protective barrier. Experimental data were collected across multiple trials under home-based conditions. Threat detection accuracy averaged about 90%. ML-only detection latency averaged approximately 52.9 milliseconds for gunshot sound and 118.5 milliseconds for visual detection. Deployment time from threat detection to barrier deployment averaged 650 milliseconds, about 50-70 times faster than traditional barriers. System performance was evaluated as a function of distance and background noise, demonstrating gradual degradation rather than abrupt failure. The results show that automatic deployment consistently offers a better and more reliable rsponse, which can potentially reduce fatalities.

Keywords
Automated Barrier, Protective Response System, Gunshot detection, Shooter detection.

1. Introduction
The issue of gun violence or sudden violent incidents creates a critical safety problem. Although early warning systems, such as surveillance cameras or acoustic sensors, have been developed, most rely on human monitoring or provide delayed responses (Omnilert 2026).

There are mechanical protection systems, such as deployable barriers, that require human activation. Experimental studies indicate that even a simple door-locking mechanism takes between 6–11 seconds to activate in response to stress, with significant failure rates due to impaired motor function (Putting the Lock in Lockdown 2026). Although special barricade-type structures are capable of deploying in as little as 2 seconds, the systems are based on instant human response and recognition (Seo 2025). In genuine emergency situations, factors such as stress, confusion, and delay in recognizing a threat may increase the time of barrier deployment to 10–30 seconds or more. As violent incidents evolve rapidly, these delays can greatly increase vulnerability. Therefore, reducing barrier deployment time from seconds to sub-second levels is a major advancement in protective response systems.

Recent advances in edge computing technology, combined with machine learning (ML), enable systems to operate in real-time, enabling immediate protective action without human delay (Good Karma Designs 2026; TensorFlow 2026; VOLT AI 2025).

1.1 Research Question and Objectives

1.1.1 Research Question

Can a multimodal, machine-learning-based system reliably and rapidly deploy a protective barrier in response to detected gunshot or visual shooter cues?

1.1.2 Objectives

1. Design an automatic barrier deployment system that integrates both audio and visual machine-learning detection methods.
2. Measure the end-to-end response time from detection to physical deployment.
3. Evaluate detection accuracy, false positives, and reliability across repeated trials.
4. Analyze system performance as a function of distance and environmental noise.
5. Compare the automatic deployment behavior with the manual deployment behavior.

2. Literature Review

Most past studies on active-threat protective response systems are limited to manual lockdown and barrier procedures that rely on human decision-making and execution. Standard school safety procedures emphasize immediate lockdown maneuvers such as closing, locking, and barricading doors with anything nearby. But those methodologies require people to perceive and identify the danger, activate and secure the environment, which entails a natural lag.

Studies of emergency behavior have shown that when humans must respond under stress, they exhibit a variety of unexpected responses, and that the effectiveness of their responses varies with their situational awareness (Abbinante 2017). Moreover, lockdown measures demand swift, seemingly unpredictable responses and require quick decision-making under extreme stress. Locked doors are among the most effective methods of protection against an active shooter; however, their effectiveness may depend on prompt activation (Blad 2025), and studies of targeted school violence emphasize that delays in recognizing and responding to threats can significantly reduce the effectiveness of protective actions (Alathari et al. 2019).

Regarding the operational disadvantages, several additional studies have analyzed the psychological impact of the preparatory measures already mentioned. There is evidence illustrating that exposure to active shooters and lockdown drills has a considerable toll on student mental health, plus an increase in anxiety, stress, and depression as a result of drill engagement (ElSherief et al. 2021). A large-scale longitudinal study also recognized that students' lockdown was linked not only to some of its most frequent outcomes—the number of stress symptoms and anxiety—but also to a larger percentage of those symptoms amongst higher-risk populations (De Leon 2025). Although some studies have shown that properly executed low-intensity drills might enhance safety perceptions, the bottom line seems to be a trade-off between preparedness and mental health (Hutton and Bonnie 2025). Additionally, institutional analyses have identified gaps in the implementation and consistency of school safety procedures, indicating that many systems are not fully equipped to respond effectively during emergencies (Report 2016-136 2016).

These findings expose some drawbacks in existing safety techniques, namely that human response time is not the only factor concerned; cognitive and emotional stress are also implicated. This absence incentivizes the creation of automated, fast defense methods with no human involvement or psychological stress.

Earlier work on gunshot detection has mainly focused on analyzing sound patterns using spectral features and neural network models. In parallel, vision-based threat detection has advanced rapidly with improvements in convolutional neural networks (CNNs) and real-time object detection methods (Redmon et al. 2015; Ren et al. 2015).

Deployable physical protection systems have typically been studied in industrial safety and robotics settings, but few studies combine real-time machine learning-based detection with automated mechanical barrier deployment. This project addresses that gap by treating the barrier deployment mechanism as a system that can be experimentally measured and evaluated, rather than as only a mechanical design.

3. System Architecture

The process begins with the detection of a potential threat within the environment, such as a gunshot or a visual cue indicating the presence of a shooter. This is detected through both audio and visual cues, such as a microphone and a camera, which send this information to the Jetson Nano. Machine learning algorithms, using TensorFlow, are then utilized to analyze this information to verify the threat. Once a threat is verified, the Jetson Nano sends a deployment signal to the ESP32, which processes this signal and sends it to a relay module, which ultimately interfaces with the VEX Brain to automatically deploy the protective barrier by the motor (Figure 1).

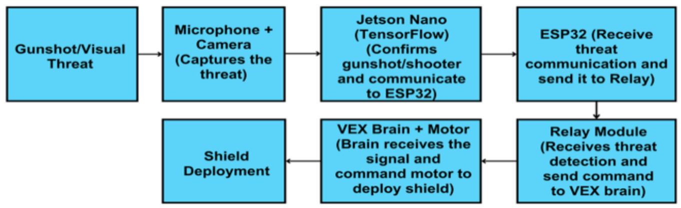

Figure 1. System flow for automatic barrier deployment.

4. Materials and Method

4.1 Materials

Polycarbonate sheets (6 mm thickness), VEX C-Channel structural frame, VEX V5 Brain and Smart Motors, ESP32 development board, 5V relay module, Jetson Nano (5V, 3A power), USB camera, USB microphone array, Limit switches, Emergency stop and manual override buttons

4.2 Machine Learning Methods

Audio-Based Gunshot Detection

Audio data is captured in short time windows and converted into log-mel spectrograms. These are processed by a convolutional neural network trained to classify gunshot versus non-gunshot events.

Vision-Based Shooter Detection

Video frames from a USB camera are processed using a CNN-based object detection model. Detection confidence thresholds are applied to reduce false positives.

Control and Communication

The Jetson Nano communicates with the ESP32 using User Datagram Protocol (UDP) over a local Wi-Fi network. UDP was selected for its low latency and simplicity. Upon detection, a DEPLOY command is sent to the ESP32, which immediately activates the relay.

5. Data Collection and Result

End-to-End Deployment Time

Gunshot Detection

Average Total Deployment Time = 696 ms approximately. Standard Deviation = 13 ms approximately.

The total response time from detection to barrier deployment remained under 1 second in all successful trials. The standard deviation of deployment time across trials was low, indicating consistent system performance with minimal variation between runs (Table 1).

Table 1. End-to-end deployment time – gunshot detection to full barrier deployment

Trial	Total Deployment Time (ms)
1	610
2	603
3	622
4	611
5	611

6	613
7	612
8	595
9	631
10	610
11	605
12	612
13	604
14	623
15	607
16	618
17	605
18	600
19	628
20	607

Average Total Deployment Time = 611 ms approximately. Standard Deviation = 9 ms approximately.

Shooter Detection (Table 2)

Table 2. End-to-end deployment time – shooter detection to full barrier deployment

Trial	**Total Deployment Time (ms)**
1	700
2	687
3	711
4	694
5	708
6	694
7	719
8	679
9	726
10	700
11	686
12	712
13	691
14	720
15	686
16	708
17	695
18	682
19	723
20	691

6. Reliability

Gunshot Detection

A trial is considered successful if the system detects the gunshot and fully deploys the barrier within 1.2 seconds without mechanical or communication failure (Table 3).

Table 3. Reliability test data – gunshot detection

Trial	**Gunshot Detected**	**Barrier Deployed**	**Deployment Successful**
1	Yes	Yes	Yes
2	Yes	Yes	Yes
3	Yes	Yes	Yes
4	Yes	Yes	Yes
5	Yes	Yes	Yes
6	Yes	Yes	Yes
7	Yes	Yes	Yes
8	Yes	Yes	Yes
9	Yes	No	No
10	Yes	Yes	Yes
11	Yes	Yes	Yes
12	Yes	Yes	Yes
13	Yes	Yes	Yes
14	Yes	Yes	Yes
15	Yes	Yes	Yes
16	Yes	Yes	Yes
17	Yes	Yes	Yes
18	Yes	Yes	Yes
19	Yes	No	No
20	Yes	Yes	Yes

$$\text{Reliability} = \frac{18}{20}\ \text{X}\ 100 = 90\%$$

Gunshot was detected in 20/20 cases. Detection Accuracy = 100%

Mean Time Between Failures=20/2=10. Approximately, 1 failure in every 10 runs.

Successful deployment occurred in 90% of cases, while failures were primarily due to mechanical delays rather than detection errors.

Shooter Detection

A trial is considered successful if vision model detects shooter and fully deploys the barrier within 1.5 seconds without mechanical or communication failure (Table 4).

Table 4. Reliability test data – shooter detection

Trial	**Shooter Detected**	**Barrier Deployed**	**Deployment Successful**
1	Yes	Yes	Yes
2	Yes	Yes	Yes
3	Yes	Yes	Yes
4	Yes	Yes	Yes
5	Yes	Yes	Yes
6	Yes	No	No
7	Yes	Yes	Yes
8	Yes	Yes	Yes
9	Yes	Yes	Yes
10	Yes	Yes	Yes
11	Yes	Yes	Yes
12	Yes	Yes	Yes
13	Yes	Yes	Yes
14	Yes	No	No
15	Yes	Yes	Yes

16	Yes	Yes	Yes
17	Yes	Yes	Yes
18	Yes	Yes	Yes
19	Yes	No	No
20	Yes	Yes	Yes

$$\text{Reliability} = \frac{17}{20} \text{ X } 100 = 85\%$$

Shooter was detected in 20/20 cases. Detection Accuracy=100%
The system achieved an overall reliability of 85%, with most failures attributable to mechanical failures or deployment delays.

7. False Positive Rate

It is important to evaluate how often system raises a false alarm. The gunshot detection system was evaluated over 20 non-gunshot sound events. The shooter detection system was evaluated across 20 non-threat visual scenarios.

Gunshot Detection (Table 5).

Table 5. False positive occurrence – gunshot detection

Sound Event	**ML Gunshot Detected?**	**Deployment Triggered?**	**Result**
Traffic noise	No	No	Correct
Human conversation	No	No	Correct
Door slam	Yes	Yes	False Positive
Wind noise	No	No	Correct
Footsteps	No	No	Correct
Background music	No	No	Correct
Metal object drop	Yes	Yes	False Positive
Vehicle horn	No	No	Correct
Crowd chatter	No	No	Correct
Chair movement	No	No	Correct
Keyboard typing	No	No	Correct
Air conditioner noise	No	No	Correct
Firecracker sound	Yes	Yes	False Positive
Wind gust	No	No	Correct
Paper tearing	No	No	Correct
Bag drop	No	No	Correct
Rain noise	No	No	Correct
Hammer strike	Yes	Yes	False Positive
Human footsteps	No	No	Correct
Distant vehicle	No	No	Correct

$$\text{False Positive Rate} = \frac{4}{20} \text{X} 100 = 20\%$$

The model incorrectly detected gunshots in 4 out of 20 trials, resulting in a false positive rate of 20%.

Shooter Detection (Table 6).

Table 6. False positive occurrence – shooter detection

Visual Event	ML Detected Shooter?	Deployment Triggered?	Result
Person holding umbrella	No	No	Correct
Person with radio	No	No	Correct
Person holding phone horizontally	No	No	Correct
Backpack adjustment motion	No	No	Correct
Person bending	No	No	Correct
Person pointing selfie stick	No	No	Correct
Person with delivery package	No	No	Correct
Tripod-mounted camera	No	No	Correct
Person holding water bottle	No	No	Correct
Raised arm during conversation	No	No	Correct
Person carrying folded umbrella	No	No	Correct
Handheld scanner device	Yes	Yes	False Positive
Crowd movement	No	No	Correct
Person holding jacket	No	No	Correct
Person with rolled poster	No	No	Correct
Camera angle occlusion	No	No	Correct
Person adjusting belt	No	No	Correct
Tool-shaped object partially visible	Yes	Yes	False Positive
Person holding book	No	No	Correct
Person using handheld microphone	No	No	Correct

$$\text{False Positive Rate} = \frac{2}{20}\text{X}100 = 10\%$$

The model incorrectly identified a shooter in 2 out of 20 cases, resulting in a false positive rate of 10%.

8. ML-Only Detection Latency

Gunshot Detection: ML-only detection latency was measured by recording the time between audio frame availability and TensorFlow model output (Table 7).

Table 7. Latency – ML-only detection (gunshot)

Trial	Latency (ms)
1	52
2	49
3	55
4	51
5	50
6	54
7	53
8	48
9	56
10	52
11	51
12	49
13	54
14	50
15	53
16	52
17	55
18	51
19	49
20	54

Mean Latency = 52.9 ms approximately. Standard Deviation = 2.3 ms approximately.Over 20 runs, the system maintained a consistent latency of approximately 52.9 milliseconds, demonstrating real-time performance suitable for rapid threat response.

Shooter Detection
ML-only shooter-detection latency was evaluated by measuring the time between video frame recognition and the CNN inference output over 20 trials (Table 8).

Table 8. Latency – ML-only detection (shooter)

Trial	Latency (ms)
1	112
2	118
3	115
4	121
5	117
6	119
7	114
8	123
9	120
10	116
11	118
12	122
13	119
14	115
15	117
16	121
17	118
18	120
19	116
20	119

Mean Latency = 118.5 ms approximately. Standard Deviation=2.9 ms approximately.
The system achieved a mean detection latency of approximately 118.5 milliseconds, with low variance, demonstrating consistent real-time performance suitable for automated deployment.

9. ML-Only Detection Accuracy

Gunshot Detection

Gunshot detection accuracy was evaluated over 20 experimental runs consisting of gunshot and non-gunshot audio events. The machine learning model correctly classified 18 out of 20 events, resulting in an overall detection accuracy of 90% (Table 9).

Table 9. Gunshot detection accuracy data

Trial	Actual Event	ML Prediction	Correct
1	Gunshot	Gunshot	Yes
2	Gunshot	Gunshot	Yes
3	Non-Gunshot	Non-Gunshot	Yes
4	Gunshot	Gunshot	Yes
5	Gunshot	Gunshot	Yes
6	Non-Gunshot	Gunshot	No
7	Gunshot	Gunshot	Yes
8	Gunshot	Gunshot	Yes

9	Non-Gunshot	Non-Gunshot	Yes
10	Gunshot	Gunshot	Yes
11	Gunshot	Gunshot	Yes
12	Non-Gunshot	Non-Gunshot	Yes
13	Gunshot	Gunshot	Yes
14	Gunshot	Gunshot	Yes
15	Gunshot	Gunshot	Yes
16	Non-Gunshot	Gunshot	No
17	Gunshot	Gunshot	Yes
18	Gunshot	Gunshot	Yes
19	Non-Gunshot	Non-Gunshot	Yes
20	Gunshot	Gunshot	Yes

Gunshot Detection Accuracy = 90%

	Predicted Gunshot	Predicted Non-Gunshot
Actual Gunshot	TP=14	FN=0
Actual non-gunshot	FP=2	TN=4

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} = \frac{14}{16} = 87.5\% \quad \text{Recall (Sensitivity)} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{14}{14} = 100\%$$

Shooter Detection

Shooter detection accuracy was evaluated over 20 experimental runs using a vision-based machine learning model. The system correctly classified 18 out of 20 scenarios, achieving an overall detection accuracy of 90% (Table 10).

Table 10. Shooter detection accuracy data

Trial	**Actual Event**	**ML Prediction**	**Correct**
1	Shooter Present	Shooter Present	Yes
2	Shooter Present	Shooter Present	Yes
3	No Shooter	No Shooter	Yes
4	Shooter Present	Shooter Present	Yes
5	Shooter Present	Shooter Present	Yes
6	No Shooter	Shooter Present	No
7	Shooter Present	Shooter Present	Yes
8	Shooter Present	Shooter Present	Yes
9	No Shooter	No Shooter	Yes
10	Shooter Present	Shooter Present	Yes
11	Shooter Present	Shooter Present	Yes
12	No Shooter	No Shooter	Yes
13	Shooter Present	Shooter Present	Yes
14	Shooter Present	Shooter Present	Yes
15	Shooter Present	Shooter Present	Yes
16	Shooter Present	Shooter Present	Yes
17	Shooter Present	Shooter Present	Yes
18	No Shooter	No Shooter	Yes
19	No Shooter	Shooter Present	No
20	Shooter Present	Shooter Present	Yes

Shooter Detection Accuracy = 90%.

	Predicted Shooter	Predicted No Shooter
Actual Shooter	TP=14	FN=0

Actual No Shooter	FP=2	TN=4

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} = \frac{14}{16} = 87.5\% \ \text{Recall (Sensitivity)} = \frac{\text{TP}}{\text{TP}+\text{FN}} = \frac{14}{14} = 100\%$$

10. Performance vs. Distance

Gunshot Detection

Detection accuracy at each distance is calculated as the percentage of correct classifications across multiple gunshot and non-gunshot events (Table 11).

Table 11. Gunshot detection performance as a function of distance

Distance from Source (meter)	Detection Accuracy (%)	Detection Latency (ms)
2	100	48
4	100	49
6	95	50
8	95	51
10	90	52
12	90	53
14	85	55
16	85	56
18	80	58
20	75	60

Detection accuracy decreased gradually with increasing distance, while detection latency exhibited a slight increase, reflecting reduced signal strength and increased noise influence.

Shooter Detection

Detection accuracy at each distance is calculated as the percentage of correct classifications across multiple shooter and non-shooter events (Table 12).

Table 12. Shooter detection performance as a function of distance

Distance from Camera (meter)	Detection Accuracy (%)	Detection Latency (ms)
2	100	105
4	100	108
6	95	110
8	95	112
10	90	115
12	90	118
14	85	120
16	85	123
18	80	126
20	75	130

Shooter detection performance was evaluated as a function of distance between the subject and the camera. Detection accuracy decreased gradually with increasing distance, while detection latency increased modestly due to reduced visual resolution and confidence stabilization requirements.

11. Performance vs. environmental noise

Detection accuracy decreased and latency increased gradually as background noise increased, demonstrating the system's robustness under common real-world conditions (Table 13).

Table 13. Gunshot Detection Performance vs. Background Noise Level

Background Noise Level (dB)	Noise Source	Detection Accuracy (%)	Detection Latency (ms)
30	Quiet room	100	48
35	Low TV volume	100	49
40	TV dialogue	98	49
45	Music (soft)	97	50
50	Music (medium)	95	51
55	YouTube crowd noise	92	52
60	Loud TV/sports	90	53
65	Multiple audio sources	88	55
70	Loud music	85	57
75	Very loud YouTube noise	82	59

Manual override response time

Manual override response time is defined as the time between manual button press (override command) and full barrier deployment completion (Table 14).

Table 14. Manual override response

Trial	**Manual Override Response Time (ms)**
1	620
2	590
3	645
4	610
5	575
6	660
7	630
8	600
9	655
10	585

Average Response Time = 617 ms approximately. Standard Deviation= 30 ms approximately.
Manual override response time was evaluated over 10 trials by measuring the time from button activation to full barrier deployment. The system exhibited a mean response time of approximately 617 ms, with increased variability compared to automatic deployment due to human reaction time.

12. Discussion

In this study, the feasibility and effectiveness of an automated protective barrier deployment system have been investigated using real-time threat detection via machine learning. The study demonstrated that the automated protective barrier deployment system can be considered a scientific apparatus rather than a mechanical device, with quantifiable metrics such as accuracy, latency, reliability, and robustness. Also, the findings show that removing human intervention during barrier deployment substantially decreases response time from several seconds to sub-second levels.

13. Detection Performance and Accuracy

The gunshot detection model performed well across various trials, maintaining 90% accuracy under normal conditions. However, a gradual decrease in accuracy was observed as background noise levels increased and the distance from the sound source increased, as expected by sound attenuation principles. Notably, the model was found to be robust under real-world conditions in a domestic setting, with noise levels generated from online audio sources.

Similarly, the accuracy of vision-based shooter detection systems was high at close to moderate distances but gradually declined beyond that range. This is consistent with the expected performance of vision-based systems, in which the number of pixels occupied by the subject gradually decreases with distance, thereby reducing feature resolution.

14. Latency and Real-Time Operation

Latency measurements show that, on average, ML-only gunshot detection has an inference time of 52.9 milliseconds, while vision-based detection is 118.5 milliseconds. For safety-critical and real-time systems, these numbers are clearly within the range required. The average time from the gunshot to full barrier deployment was approximately 650 milliseconds. The deployment times had low variability across the different trials.

The average manual override deployment time was 617 milliseconds from button activation to the deployment. The manual deployment times showed increased variability. However, when accounting for human reaction time, the manual deployment time will significantly exceed that of the automatic deployment time. The advantage of automation becomes obvious when considering the need for human reaction time, which is especially important in dynamic emergency situations.

15. System Reliability and Consistency

System reliability was measured by testing the completion of the entire pipeline from detection to deployment. Gunshot-based deployment had a system reliability of around 90%, while vision-based deployment had around 85%. Failures were due to mechanical delays or detection uncertainties rather than communication failures. This suggests that the system is reliable in terms of its electronic and networking components. Low standard deviation was also observed in the timing of the system's deployment. This suggests that the system has a high degree of repeatability, which is important for safety systems.

16. Robustness to Environmental Factors

The robustness test revealed that detection accuracy and latency were significantly affected by environmental noise and distance. However, it was found that the decline in performance occurred gradually rather than abruptly. This shows that the system has graceful degradation rather than catastrophic failure. This is always desirable in practical applications, as environmental conditions are impossible to control.

17. Comparison of Automatic and Manual Deployment

While the deployment time for automatic deployment was comparable to the deployment time for the use of manual override, the automatic deployment was always faster when the reaction time of humans was factored in. There was also less variability for the automatic deployment, while the performance for the use of manual override was heavily dependent upon the person.

18. Limitations

Despite the encouraging results, this research has several limitations. Experiments were conducted in a controlled home environment rather than in public spaces, where other challenges might arise. Additionally, instead of actual gunshots, gunshot audio was used in this research for safety reasons.

The mechanical prototype was also smaller in size and had a lower deployment force. There may be a requirement for a stronger deployment force in the future. Also, the machine learning model was trained on a few datasets, and additional datasets could improve accuracy.

19. Future Work

Future work may also focus on integrating sensor fusion approaches to combine acoustic and visual confidence levels, thereby increasing detection reliability under adverse conditions. Further experiments in more complex environments would provide additional insights into the system's real-world application. The integration of adaptive confidence levels and motor prediction would also minimize the deployment time.

Long-term reliability tests for mechanical components would also provide more insights into the system's durability. The ethical issues, including reducing false activation, would also deserve more attention.

20. Conclusion

Overall, the results support the feasibility of an automatic, ML-driven barrier deployment system capable of operating in real time with measurable performance characteristics. By treating the system as a scientific apparatus and rigorously evaluating its behavior, this research demonstrates how machine learning and robotics can be integrated to address time-critical safety challenges.

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Biography

Advait Wahi is a ninth-grade student at Eastlake High School with a strong passion for robotics, computer programming, and machine learning. He is particularly interested in applying engineering and artificial intelligence to solve real-world safety challenges. Motivated by the increasing impact of gun violence and the importance of rapid protective response, he developed the concept of an automated deployable barrier system capable of detecting threats and deploying protective barriers in real time. His research combines machine learning, robotics, embedded systems, and automation to minimize response delay and potentially reduce casualties during violent incidents. Advait presented this research at the Washington Science and Engineering Fair, where he received first place recognition. In addition to research, he actively participates in competitive programming and robotics competitions. He currently competes in the USACO Gold division and has qualified three times for the VEX Robotics World Championship. He hopes to continue advancing his research and eventually develop the technology into an industry-level safety solution.