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Vehicle Intrusion Detection in Highway Work Zones Using Inertial Sensors and a Lightweight Deep Learning Model

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ABSTRACT

Highway work zones are prone to intrusion events that threaten workers' safety and disrupt operations. Existing intrusion detection systems often produce high false alarms, causing alarm fatigue and reduced responsiveness. To address this, a data-driven intrusion detection method is proposed to distinguish real vehicle intrusions from non-hazardous events using inertial measurement unit (IMU) sensors attached to traffic cones. Acceleration and angular velocity data were collected through field experiments involving vehicle collisions, manual handling, and wind displacement. After preprocessing and data augmentation, a lightweight Long Short-Term Memory (LSTM) model was trained and optimized for real-time performance on edge devices. Evaluation yielded a 96% accuracy and a 97% recall for actual intrusions. Resultant acceleration and angular velocity are recognized as key features. This cost-effective, scalable solution enhances safety by effectively identifying actual hazards, minimizing false alarms, and mitigating the negative impact of alarm fatigue in highway work zones.

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Keywords: Highway Work Zones; Intrusion Detection; False Alarms Reduction; Worker Safety; LSTM

1. INTRODUCTION

Highway work zones are critical for the ongoing maintenance, repair, and expansion of road infrastructure, yet they present substantial safety risks to both the workers operating in these areas and the drivers navigating through them. In the United States, in 2022 a total of 37,000 injuries occurred due to crashes in work zone, with 891 fatal injuries [1]. Recent statistics also show a rising trend in fatalities and injuries from these accidents. According to the Federal Highway Administration (FHWA), work zone-related fatalities increased by 10.8% between 2020 and 2021, with fatal work zone crashes involving commercial motor vehicles experiencing a substantial 39% increase during the same period [2]. The temporary and often rapidly changing nature of work zone environments makes them vulnerable to intrusion events—instances where unauthorized vehicles or objects enter restricted areas, endangering the safety of personnel and equipment. These intrusions not only disrupt the workflow but can have severe consequences, including posing life-threatening risks to workers and leading to property damage or, in the worst cases, fatalities. Intrusions into work zones constitute approximately 10% of all work zone traffic accidents and 8% of those resulting in serious injuries [3]. The proximity of fast-moving traffic, the presence of heavy machinery, and the often reduced visibility or signage in work zones amplify these risks. For these reasons, developing efficient and accurate intrusion detection systems is paramount to minimizing risks and enhancing overall safety in work zones.

Current work zone intrusion detection systems often rely on various sensor technologies such as infrare]d [4], radar [5], microwave [6], and kinematic [7] to monitor work zone perimeters and detect potential intrusions [8]. Among these, the kinematic models are recommended for deployment in work zones on major highways, due to their low life cycle cost and good coverage of the work zone [9]. This type, usually installed on cone or similar component, triggers an alarm when the cone's orientation angle changes as a sign of being flipped over [7]. Inertial measurement unit (IMU) sensors, along with GPS, are key motion tracking sensors that used in highway work zones [10]. IMUs are capable of tracking dynamic conditions with precision, which is crucial for environments like work zones where movement can vary significantly. Their ability to capture subtle changes in movement makes them highly effective in identifying potential intrusion events.

However, while these technologies have demonstrated utility in identifying potential threats, they significantly suffer from a common and critical issue, meaning high false alarm rates [11,12]. These false alarms typically arise from the inability of such systems to effectively differentiate between true vehicle intrusions and non-threatening events like wind-driven movements of traffic cones or normal worker activity [13]. This issue may stem from the sensitivity of motion sensors to an accidental impact to the cone (or other hardware such as barricade), without adequately analyzing the causes of the movement or recognizing distinct patterns generated by different events. The researchers suggested that the system be deactivated to prevent false alarms during handling and placement of the device [8]. False alarms not only create unnecessary interruptions which reduce operational efficiency, but also contribute to "alarm fatigue," where frequent false positives lead to diminished responsiveness over time. It is reported that the wind and semi-trucks have blown the cones over, and after a few incidents, the workers simply stop utilizing or listening to it because they do not have time to deal with it [14]. As a result, there is a growing need for advanced, intelligent systems that can more accurately interpret sensor data and discern between genuine threats and non-hazardous events.

To address the limitations of existing intrusion detection systems, this research proposes an approach to accurately distinguish between real vehicle intrusions and non-hazardous events. The study uses data from IMUs attached to traffic cones to identify distinct movement patterns, which are then used to develop a deep learning model capable of enabling real-time detection of intrusion events. By analyzing these patterns, the model aims to determine whether an intrusion is occurring or if the detected event is non-threatening, such as movements caused by workers or wind. By addressing the limitations of current systems and presenting a sensor-based approach to intrusion detection, this research contributes to the ongoing efforts to improve safety in highway work zones. Unlike previous studies that primarily focus on threshold-based or traditional machine learning methods [15], this research leverages deep learning to capture complex temporal dependencies in sequential IMU data. By integrating an LSTM-based model with field-collected sensor data from realistic intrusion and non-intrusion events, this study offers a real-time intrusion detection approach specifically designed to reduce false alarms. Furthermore, the lightweight architecture enables deployment on edge devices, such as Raspberry Pi, making it practical for real-world highway work zones where centralized processing may not be feasible. This research contributes to developing an accurate, scalable, and deployable solution for protecting workers and infrastructure in high-risk environments.

This paper is organized as follows: Section 2 provides a detailed review of the research background, including existing approaches to intrusion detection in highway work zones and the challenges associated with their implications. Section 3 describes the methods used in this study, focusing on data collection and model development. Section 4 outlines the experimental setup and the implementation of the proposed method. Section 5 presents the results of the experiments and discusses their implications. Finally, Section 6 concludes the paper by summarizing the findings and outlining potential future research directions.

2. LITERATURE REVIEW

This section provides a comprehensive review of existing research related to intrusion detection in highway work zones, focusing on traditional passive measures, active systems, and emerging technologies. It also highlights the critical challenge of false alarms, which can undermine system reliability and user trust, and motivates the need for more intelligent and context-aware detection frameworks.

2.1. Intrusion Detection in Highway Work Zones

Highway work zones are high-risk areas that require robust safety measures due to their exposure to fast-moving traffic and operational machinery. The necessity for intrusion detection mechanisms stems from the need to protect both the workforce and equipment in these temporary, often unpredictable environments [3]. Intrusion events are particularly dangerous in work zones because unauthorized entries can cause severe injuries and disrupt the operational flow, highlighting the need for reliable detection systems that enhance safety without interfering with ongoing work [16,17].

Typical intrusion incidents in highway work zones often involve vehicles unintentionally entering restricted areas, either due to driver inattention, unfamiliar road layouts such as temporary detour routes, sudden lane merges, or unclear signage, or temporary traffic shifts [3]. Existing intrusion mitigation measures include passive strategies, which rely on static solutions to guide traffic and enhance safety; active systems, which detect and respond to potential threats through sensors, alarms, and communication devices; and emerging technologies, which integrate advanced sensing and communication methods to address the limitations of existing approaches.

2.1.1. Passive Measures

Passive measures have long been the foundation of safety management in highway work zones, providing non-interactive solutions to guide traffic and enhance worker safety. These measures are static by nature and primarily aim to warn and direct drivers, relying on their compliance to mitigate risks. Traffic control devices such as cones,

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barricades, and channelizing devices are widely deployed to demarcate work zones and redirect traffic. These tools are particularly effective in urban and rural work zones, as they help delineate restricted areas and provide visual cues to drivers. Research by Garber and Woo [18] demonstrated that such devices significantly reduced accident rates in urban work zones, emphasizing their role in improving safety during maintenance and construction activities. High-visibility signage plays a critical role in alerting drivers to upcoming work zones. Static signs, such as "Road Work Ahead" warnings, and dynamic systems, including flashing arrow boards, are commonly used to inform drivers of lane closures and detours. Bai et al. [19] evaluated the effectiveness of various signage types and found that portable changeable message signs (PCMS) were particularly effective in reducing vehicle speeds, especially for heavy vehicles such as trucks.

To address the issue of driver inattentiveness, portable rumble strips have been introduced as a tactile and auditory feedback mechanism. These strips are placed across the road to create vibrations and noise when vehicles pass over them, thereby alerting drivers to the presence of a work zone. A study by Yang et al. [20] demonstrated that portable rumble strips significantly reduced vehicle speeds and the proportion of speeding drivers in short-term work zones. This reduction in speed enhances safety for workers and drivers alike, particularly in high-risk environments. Worker visibility is another key aspect of passive safety measures. High-visibility clothing, such as reflective vests, ensures that workers are noticeable even in low-light or high-speed conditions. Turner [21] highlighted the effectiveness of such equipment in reducing accidents in work zones by improving driver awareness of workers' presence. However, these measures are limited by their reliance on driver attentiveness and compliance.

Despite their benefits, passive measures face inherent limitations. Their static nature prevents them from adapting to dynamic situations, such as sudden lane changes or driver errors, reducing their effectiveness in high-risk environments. Environmental factors, such as poor visibility due to weather or nighttime conditions, further diminish their utility [10]. Additionally, studies have noted that driver complacency can lead to reduced compliance with these measures over time, posing risks to both workers and motorists [26].

2.1.2. Active Systems

Active systems offer dynamic and real-time solutions to address safety concerns in highway work zones. These systems enable continuous monitoring, early detection, and alert mechanisms to mitigate risks of intrusion effectively. Active intrusion detection technologies are designed to detect and respond to potential threats in real-time, utilizing sensors, alarms, and communication devices to enhance worker safety and mitigate the impact of errant vehicles. By providing immediate alerts, these technologies address the limitations of passive measures [15].

One well-known system is the Advanced Warning and Risk Evasion (AWARE) system, which utilizes a combination of radar and position sensors to continuously monitor vehicle movements near work zones. By assessing vehicle trajectories and speeds, the AWARE system can detect potential intrusions and provide immediate warnings to workers. Studies have shown that such real-time detection significantly improves response time and reduces the likelihood of accidents [23–26]. The system is particularly effective in high-speed work zones, where rapid decision-making is crucial. Additionally, the system integrates GPS tracking to provide geofencing capabilities, ensuring more precise location-based alerts [24]. However, challenges such as high implementation costs and the need for robust communication infrastructure in remote work zones have been noted as barriers to widespread adoption [16].

Another system is the SonoBlaster, a mechanical device that triggers an audible alarm upon impact. The system is designed to be attached to traffic control devices such as cones or barricades and activates a high-decibel alarm when struck by an errant vehicle. The immediate acoustic alert serves as a crucial warning for workers, allowing them to take evasive action. Studies have shown that SonoBlaster alarms can reduce worker reaction times by up to 40%, making them particularly effective in noisy environments where visual alerts may not suffice [14]. However, limitations include the system's dependence on physical impact detection and prevalence of false alarms, which means that near-misses or slow intrusions may not always trigger the alarm, potentially reducing effectiveness in certain scenarios [27].

The Intellicone system enhances traditional traffic control devices by incorporating wireless communication and impact detection technology. Unlike SonoBlaster, which relies solely on sound-based alerts, Intellicone transmits signals to a remote alarm unit, enabling broader alert coverage. Research suggests that this system significantly improves work zone safety by providing layered warnings, ensuring that even workers distant from the point of impact receive timely alerts [12] The ability to integrate with existing traffic management systems also enhances adaptability, allowing for real-time modifications to work zone configurations based on detected intrusion patterns [28].

Another effective solution is the Traffic Guard Worker Alert System (WAS), which employs pneumatic sensor technology to detect vehicle intrusions. The system consists of a compressed air hose placed across work zone entry points, which, when compressed by an unauthorized vehicle, activates a wireless signal that transmits alerts to workers

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via wearable vibration devices. Studies indicate that WAS reduces the likelihood of worker injury by ensuring direct, personalized alerts, making it highly effective in areas with high background noise where traditional alarms may be drowned out [29]. However, false alarms due to non-threatening interactions with work zone equipment remain a challenge, as routine vehicle movements within the work zone can sometimes trigger unintended alerts [30].

Although these active systems have significantly improved safety, false alarms remain a major challenge. Many systems, including SonoBlaster and WAS, are susceptible to accidental activations caused by non-hazardous movements, such as wind-displaced cones or cones moved by workers. Research indicates that false alarms contribute to "alarm fatigue," where repeated non-critical alerts cause workers to become desensitized, potentially leading to missed warnings when real threats occur [23].

2.1.3. Emerging Technologies

Emerging technologies offer innovative solutions that enhance safety and operational efficiency. These technologies address the limitations of existing systems by integrating advanced sensing and communication methods. LiDAR technology has emerged as a pivotal tool in developing smart work zone systems. Its ability to create detailed, real-time maps of vehicle movements enables precise detection and early warnings of potential intrusions. Darwesh et al. [24] highlighted the integration of roadside LiDAR to improve situational awareness in work zones, emphasizing its potential to enhance safety with minimal false alarms. Jumari et al. [31] proposed the Signal Warning Detector (SWAD) system as another promising innovation in work zone safety. The system combines distance sensors and radar technology to detect approaching vehicles and activate alerts, such as vibration feedback devices worn by workers. This integration provides real-time warnings to enhance situational awareness and worker safety in high-risk traffic environments. Their study demonstrated the system's practicality in real-world scenarios and highlighted its potential to reduce accidents during highway emergency operations.

Similarly, systems utilizing wireless sensor networks (WSNs) create virtual perimeters around work zones to detect approaching vehicles and activate alarms, significantly reducing response times [13]. WSNs consist of interconnected sensor nodes deployed throughout the work zone, enabling real-time communication and automated decision-making. These networks can detect intrusions, track vehicle speeds, and identify unauthorized access, relaying the information to both on-site workers and centralized monitoring centers. WSN-based systems offer scalable and cost-effective solutions, enabling rapid deployment in dynamic work zone environments while maintaining reliable real-time intrusion detection [10].

Balancing safety and operational efficiency in work zones presents significant challenges. False alarms, which are prevalent in many detection systems, disrupt workflows and may lead to "alarm fatigue," where repeated alerts cause workers to lose sensitivity to potential threats [18]. Additionally, work zones are often fast-changing, with vehicles and equipment continuously moving, making it difficult to maintain strict intrusion detection without causing frequent, unnecessary interruptions [19]. Thus, effective systems must provide accurate, real-time alerts while minimizing unnecessary disruptions to maintain both safety and productivity [5].

IMU-based systems offer a compelling alternative due to their ability to capture precise movement patterns through accelerometers and gyroscopes, which are widely used in applications like navigation, motion tracking, and robotics [20]. Unlike visual or radar systems, IMU sensors are less affected by visibility conditions and can directly measure physical interactions, enabling them to differentiate between benign movements and genuine threats with higher accuracy [21]. This reduces false alarms and enhances reliability in real-time detection scenarios.

2.2. Factors Causing False Alarms

Numerous studies have investigated the reliability of sensor-based intrusion detection systems in highway work zones, particularly regarding the persistent challenge of false alarms. As noted by [36], sensors on traffic cones and other safety devices frequently generate false alarms, making them unreliable indicators of intrusions. This issue is compounded by broader operational and safety concerns. Research by [28] identifies key barriers to the adoption of work zone alert technologies, including perceived ineffectiveness, technical complexity during deployment, and high false alarm rates, which collectively contribute to stakeholder skepticism. A critical consequence of frequent false alerts, as highlighted in [37], is "alarm fatigue," where workers, exposed to numerous non-critical alerts, become less responsive over time. This desensitization is particularly hazardous, as it may lead workers to overlook or ignore genuine alerts, increasing the risk of accidents in high-risk work zone environments [5]. Gambatese et al. [14] further emphasize that false alarms disrupt work efficiency, as unnecessary interruptions can slow down operations and diminish workers' trust in the system's reliability. Consequently, studies consistently emphasize that false alarm rate has been always a critical parameter for evaluating the effectiveness and adaptability of work zone intrusion detection systems.

These systems often misinterpret benign environmental events as intrusions, leading to unnecessary alerts. This misinterpretation occurs because current sensors primarily rely on detecting movement or changes in position, without the ability to discern the underlying cause of the motion. For example, wind can shift cones slightly, inadvertently triggering intrusion alarms. Martin et al. [13] highlighted that such non-threatening movements frequently activate alerts, contributing to high false alarm rates. Additionally, Nnaji et al. [12] stated that routine interactions, such as workers moving or adjusting cones, are a common source of false positives, as these movements are often indistinguishable from actual intrusions by the detection system. In a system evaluation test experiment conducted by Novosel [36], it was observed that one of the traffic cones moved when a fast-moving truck went by near it, as a result of which the alarm was activated. The author discussed that although this did not represent an actual intrusion, the sensor did react upon movement. This indicates that solely relying on sensors being affected by an impact, and inability to analyze causing event or movement patterns could possibly lead to misinterpretation. Therefore, it is crucial for systems that can distinguish between movements caused by different events and realize if the impact is due to hit by a vehicle (real intrusion) or is generated by other non-hazardous events.

3. METHODS

In this section, we outline the methodology employed to address the challenge of automatically distinguishing real intrusion events from non-hazardous scenarios in highway work zones. Figure 1 presents the methodological framework of our study, including the key steps from data collection to model evaluation. To achieve the objective of the study, the first step involves collecting a comprehensive dataset from field test experiments, capturing both genuine vehicle intrusion events and non-hazardous scenarios. This data collection is critical, as it enables the system to recognize and differentiate the wide range of movement patterns associated with hazardous and non-hazardous events. Once collected, the data undergoes preprocessing, including noise reduction, data balancing, and labeling, to ensure the dataset is clean and representative. These steps are essential to minimize errors that could arise from sensor noise or data imbalance, which are common challenges in real-world applications. Finally, a deep learning model is developed and trained on the preprocessed dataset. This model is designed to be compatible with characteristics required for efficient deployment on edge devices in highway work zone intrusion detection systems. The model is intended to learn the unique movement patterns associated with vehicle impacts, and by identifying these distinct patterns, distinguish between hazardous events and non-intrusive scenarios, such as wind or manual handling.

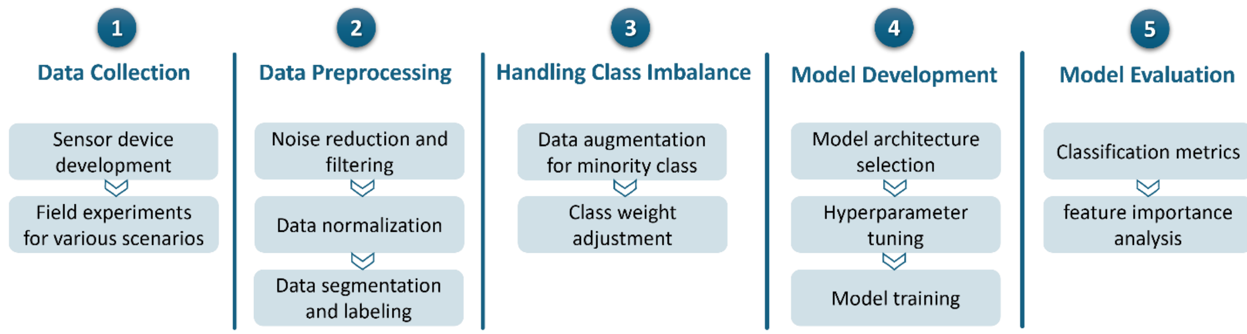

Figure 1. Overall framework of the proposed intrusion detection model.

3.1. Dataset Preparation

The first step in developing the proposed intrusion detection system involves collecting comprehensive data from highway work zones and providing a structured dataset of highway work zone intrusion-related events information. This data is essential for distinguishing between hazardous events, such as vehicle impacts, and non-intrusive scenarios, such as wind displacement or manual handling of cones. To ensure that the system can recognize and differentiate between these events, we utilize IMU sensors to capture detailed acceleration and angular velocity data. This sensor data provides the foundation for further processing and model development.

3.1.1. Sensory Data

For this study, we developed a custom data collection device, equipped with an IMU, a Raspberry Pi 4 processor, and a battery for mobile power. These devices were mounted on traffic cones and designed to wirelessly transmit real-time acceleration and angular velocity data to a computer using Wi-Fi. Field tests demonstrated that the system maintained consistent performance with minimal data loss or latency, even under high-impact conditions. To ensure reliability, we conducted tests under various conditions, including environments with potential Wi-Fi interference and physical obstructions. The system maintained stable communication over distances up to 25 meters. In cases of disconnections, a buffering mechanism on the device prevented data loss by queuing measurements for transmission once the connection was re-established. Given that the cones would be impacted by vehicles during the experiments, it was essential to protect the device components from potential damage caused by hard impacts and hits. To address this,

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we designed and 3D-printed a lightweight protective case using durable material. The case has separate compartments for the battery, and the processor and elements connected to it, to keep them secure and tight in place.

The device records both linear acceleration and angular velocity along the x, y, and z axes. The acceleration data captures the force applied to the cones during various events, while angular velocity provides insight into the rotational movements of the cones. By collecting data in real-time, the system captures dynamic movements that reflect the different types of events commonly seen in highway work zones.

In addition to the raw sensor data, two additional features are computed, which are resultant acceleration and resultant angular velocity. As defined in Eq. (1), resultant acceleration is calculated as the square root of the sum of the squared acceleration values across the three axes, representing the total force acting on the cone. Similarly, resultant angular velocity is computed to summarize the overall rotational movement (Eq. (2)). These features provide a more intuitive representation of the cone's movements, simplifying the analysis of complex events.

$$R_{Acc} = \sqrt{Acc_x^2 + Acc_y^2 + Acc_z^2} \qquad \text{Eq. (1)}$$

$$R_{AngVel} = \sqrt{Anglvel_x^2 + Anglvel_y^2 + Anglvel_z^2} \qquad \text{Eq. (2)}$$

Where Acc_x, Acc_y, Acc_z are the acceleration components along the x, y, and z axes, respectively. Similarly, $Anglvel_x$, $Anglvel_y$, $Anglvel_z$ are the angular velocity components along the x, y, and z axes, respectively.

3.1.2. Event Definition

To effectively detect and classify events in highway work zones, the system must account for two primary categories of events, meaning intrusion events and non-intrusion events. Intrusion events, caused by vehicle impacts, pose a direct threat to the safety of workers and equipment, and intrusion detection technologies are developed mainly to detect and prevent this type of accident. This event reflects the most critical use case for an intrusion detection system, where the safety of workers and equipment is at risk. The IMU's accelerometer and gyroscope data are particularly relevant here, as vehicle impacts generate distinct, high-force acceleration and angular velocity patterns. Capturing these high-impact movements allows the model to learn to recognize the unique signatures associated with genuine vehicle intrusions. Non-intrusion events, on the other hand, include movements that do not pose a direct threat to work zone safety. The main causes of false alarms in impact-based intrusion detection devices are identified as traffic cones that mistakenly knocked over, wind, passing cars, and other factors [14]. By analyzing highway work zone environment, in this research events that can result in non-intrusion events are defined as wind displacement, manual handling by workers, and even stationary conditions where no movement occurs. Manual handling by workers often triggers false alarms in conventional systems. Workers frequently lift, move, or reposition cones, resulting in movement detected by motion sensors. However, these movements exhibit more controlled, lower-magnitude impact compared to vehicle intrusions. Data from this event provides the model with information about non-hazardous human activity, helping it learn to distinguish between routine worker interactions and actual hazardous events. In addition to the manual handling, the wind displacement event is defined in this research to account for movements caused by wind, whether from passing vehicles or natural conditions. Wind-induced movements are often subtle but can be mistaken for vehicle intrusions by current systems. By providing IMU data of this event, which is typically characterized by lower acceleration and gradual angular velocity changes, the model can learn to differentiate between wind-related cone movements and genuine intrusions. Finally, stationary conditions, where there is no movement at all, are also considered in the model under non-intrusion events category.

Altogether, the specific sensory data explained in section 3.1.1, gathered from the aforementioned events, comprises a comprehensive dataset that covers the most occurring events likely to impact or trigger an intrusion detection system, and hence is required to develop a generalized and functional intrusion detection model.

3.2. Data Preprocessing

Effective preprocessing of IMU data is critical to ensure that the deep learning model can accurately detect and classify intrusion events. The raw IMU data collected from the field experiments must be filtered, normalized, segmented, and enriched with additional features before being fed into the model. This section outlines the key preprocessing steps applied to the acceleration and angular velocity data collected from the IMU sensors.

3.2.1. Noise Reduction and Filtering

IMU sensors are susceptible to various sources of noise, like all sensor data. The raw accelerometer and gyroscope data collected during experiments may contain high-frequency noise, sensor drift, or environmental interference. To mitigate these issues and ensure cleaner data, based on preliminary data analysis, both low-pass and high-pass filters are applied.

It is widely acknowledged that the selection of filter parameters should be based on the intrinsic characteristics of the recorded signals rather than relying on predetermined assumptions or default values [32]. To

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achieve this, a data-driven, frequency-domain analysis was conducted to determine appropriate filter parameters for both low-pass and high-pass filters. This method ensured that the chosen cutoff frequencies accurately reflect the frequency characteristics of the recorded signals. We converted the raw acceleration and angular velocity data into the frequency domain using the Fast Fourier Transform (FFT), which allowed for a detailed analysis of the cumulative energy distribution across the frequency spectrum. For low-pass filters, the 99% cumulative energy (E99) criterion was employed [32]. This approach identifies the cutoff frequency where 99% of the total signal energy is captured to ensure that meaningful motion content is preserved while predominantly noise-related frequencies are attenuated. The analysis revealed that the majority of the informative motion content for acceleration data was contained below approximately 22 Hz, while angular velocity data demonstrated dominant frequencies with most meaningful content below 8.5 Hz. Accordingly, Butterworth low-pass filters with these cutoff frequencies were applied to effectively retain slow-to-moderate dynamics and fundamental rotational movements while suppressing high-frequency noise. Butterworth filters were chosen for this study due to their well-established efficacy in noise reduction and signal preservation in digital signal processing [33].

In addition to addressing high-frequency noise, the removal of low-frequency noise, such as sensor drift, was accomplished using a high-pass filter. The 1% cumulative energy (E1) method was adopted for determining the high-pass cutoff frequency. This criterion ensures the removal of negligible low-frequency components while preserving essential baseline information. The analysis indicated that a 1st-order Butterworth high-pass filter with a cutoff frequency of 0.1 Hz sufficiently reduced gradual sensor drift without compromising low-frequency information critical for detecting subtle movements. Figure 2 demonstrates the effects of noise reduction on a randomly selected portion of the resultant acceleration.

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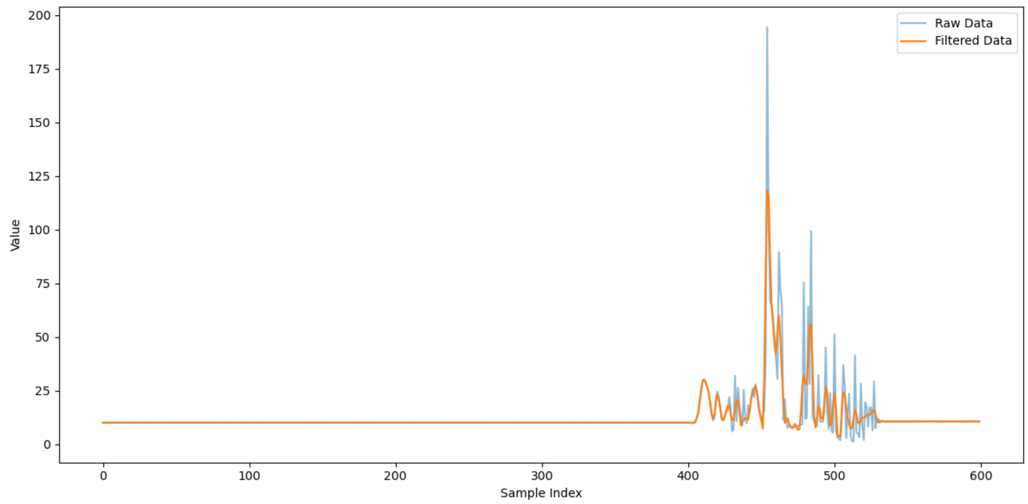

Figure 2. Comparison of resultant acceleration from raw (blue) and filtered (orange) IMU data, demonstrating the impact of noise reduction implementation.

3.2.2. Data Normalization

Since the raw IMU data from the x, y, and z axes can vary in range, normalization is performed to scale the data to a consistent range. Each axis of the accelerometer and gyroscope data is normalized individually using min-max normalization, as successfully implemented in previous IMU-based deep learning models [34]. The formula for normalization is presented in Eq. (3).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad \text{Eq. (3)}$$

Where x is the original data value, and x_{min} and x_{max} are the minimum and maximum values of the feature, respectively. This scaling brings all values into the range [0, 1] to ensure consistent feature magnitude across axes.

3.2.3. Data Segmentation and Labeling

Since the IMU data collected during the field experiments is continuous and time-series in nature, an essential preprocessing step is to segment this data into manageable and meaningful units. This segmentation enables the model to process the data effectively and associate specific time intervals with particular events, such as vehicle intrusions, wind displacement, or manual cone handling. The data segmentation process also involves selecting appropriate segments for the incident and stationary conditions. For each incident (e.g., vehicle collision, wind displacement, or manual handling), the onset of the event is determined by detecting the "first significant change" in sensor readings. To achieve this, the absolute difference between consecutive readings is computed separately for each sensor channel

(3 channels of acceleration and 3 channels of angular velocity). If the difference in any one of these channels exceeds a threshold value of 1, that timestamp is marked as the first significant change. This threshold was chosen based on preliminary analysis to capture sudden changes indicative of an event (e.g., a vehicle intrusion or other movement) . In other words, we observed in the collected sensor data patterns that a threshold of 1 reliably distinguished the onset of actual cone movements (vehicle collisions, wind-induced shifts, or manual handling) from minor fluctuations or sensor noise, while lower thresholds occasionally flagged non-events, and higher thresholds sometimes missed milder movements. Therefore, we found that 1.0 struck an effective balance between detecting all meaningful movements and minimizing false positives due to baseline noise.

Once this first significant change is identified, an adjustable lookback window of 50 timesteps is applied to include the pre-event context, ensuring that the complete movement (both preceding and during the event) is captured. The IMU data is collected at a sampling frequency of 50 Hz, meaning that 50 data points are recorded per second for each of the axes (x, y, z) of both the accelerometer and gyroscope. The complete segment is then extracted with a fixed target length of 100 timesteps (2 seconds). In addition, stationary data is obtained by extracting a segment of 500 timesteps immediately preceding the event window, representing the still condition before any interaction with the cone. To further process the continuous data, we employ a sliding window technique. Each window contains 100 timesteps, and consecutive windows overlap by 50%, meaning that each new window starts 50 timesteps (1 second) after the start of the previous one. Choosing this value is for providing a balance by maintaining sufficient overlap to capture temporal dependencies while avoiding excessive duplication of data. The use of a 50% overlap means every data point is included in at least two windows, which ensures that important transition points are captured, and no critical information is lost, particularly for events occurring across window boundaries.

After segmentation, each data window is labeled according to the corresponding event scenario: vehicle intrusion, wind displacement, manual handling by workers, or stationary condition. To create a binary classification problem, both wind, manual handling, and stationary conditions are labeled as non-collision events, while vehicle intrusion is labeled as a collision event.

3.2.4. Handling Imbalanced Data

The dataset consists of significantly fewer vehicle intrusion events compared to non-collision events. This imbalance occurs because in the dataset generated from experiment, vehicle intrusion events are expectedly rare compared to

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non-hazardous movements such as wind displacement, manual handling by workers, or stationary conditions. If left unaddressed, this imbalance can lead to a biased model [41] that is more likely to predict non-collision events. This could significantly reduce the ability to correctly identify true hazards. To address this class imbalance, two key approaches are employed: Data augmentation, and Class weight adjustment.

To increase the number of vehicle intrusion samples, data augmentation is applied. This approach involves generating synthetic variations of existing data by adding small random Gaussian noise to the vehicle intrusion windows. Incorporating Gaussian noise into IMU data for data augmentation is a well-established technique in time-series analysis and has been widely applied to IMU data for training Long Short-Term Memory (LSTM) and other neural networks, demonstrating improved estimation accuracy model robustness [35,36]. The noise simulates slight differences in sensor readings, such as those caused by minor measurement inaccuracies or environmental variations. By augmenting each vehicle intrusion sample multiple times, the size of the minority class increases, which improves the model's ability to generalize and recognize intrusion events more effectively. This process helps the model become more robust by exposing it to a wider variety of scenarios.

In addition, during model training, class weights are adjusted to give more importance to the minority class (vehicle intrusion). This approach encourages the model to pay more attention to vehicle intrusion samples during the training phase. By using the “class weight” utility from scikit-learn library, the class weights are computed inversely proportional to the class frequencies in the input data. Specifically, the weight for each class i is calculated using Eq. (4).

$$weight_i = \frac{n_{samples}}{n_{classes} \times n_i} \qquad \text{Eq. (4)}$$

Where $n_{samples}$ is the total number of samples in the dataset, $n_{classes}$ is the number of unique classes, and n_i is the number of samples in class i. This adjustment ensures that classes with fewer samples (the minority class) receive a higher weight, as a result of which the model does not become biased towards the majority class and helps mitigate the adverse effects of data imbalance by giving equal importance to both classes during the learning process.

3.3. Model Development

The primary objective of the model development phase is to create an effective model capable of distinguishing between real vehicle intrusions and non-hazardous cone movements in highway work zones. First, the frequency distributions for acceleration and angular velocity were analyzed to establish effective threshold values to distinguish

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between the incidents. Histograms of acceleration and angular velocity for all scenarios were plotted together, as shown in Figure 3, with the probability density function (PDFs) of these values provided in Figure 4. Based on this analysis, while intrusion and non-intrusion events do exhibit differences in average resultant acceleration and angular velocity, these metrics alone do not yield a clear or general cutoff for all scenarios. For instance, Figure 3 indicates that the histograms of resultant acceleration for vehicle intrusions and manual lifting overlap in certain ranges. A single threshold (e.g., 125 m/s²) might detect high-impact intrusions yet still fail to detect lower-intensity intrusions or falsely trigger on abrupt but harmless cone movements. Similarly, wind-induced movements vary widely depending on wind strength and direction, sometimes producing peak accelerations that approach intrusion-level values. These observations highlight that any fixed threshold must be carefully tuned to a specific environment or event profile to avoid missed detections or excessive false alarms. Additionally, simple statistical methods fail to capture the temporal dependencies inherent in intrusion events. For example, a quick spike caused by a worker's sudden lift may resemble a mild intrusion if only peak magnitude is considered; but subsequent deceleration and rotational pattern, which could be captured over a certain time window, could differ significantly between a non-hazardous lift and a true vehicle impact. Therefore, deep learning models are well-suited for this problem because they can learn hidden patterns in sequential IMU data.

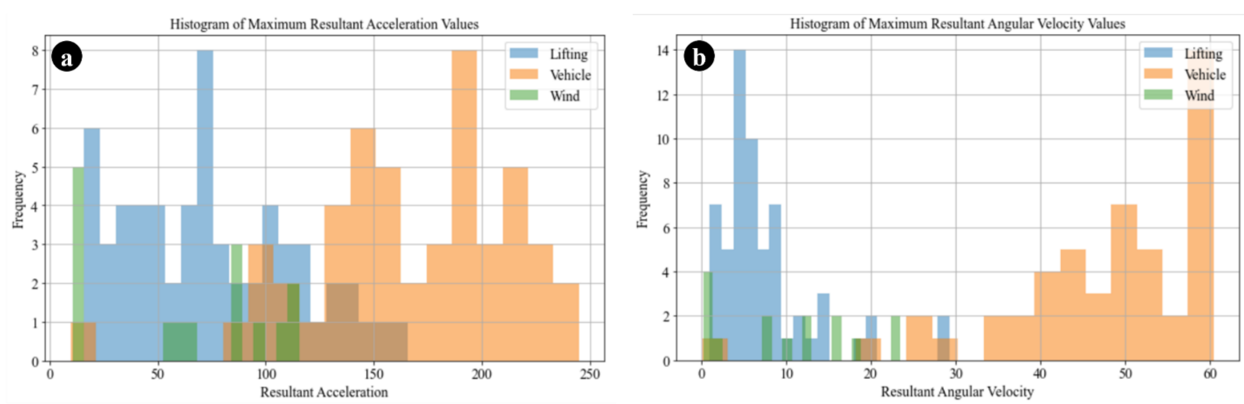

Figure 3. Histogram for vehicle intrusion, wind, and lifting by hand incidents: (a) Resultant acceleration; (b) Resultant angular velocity.

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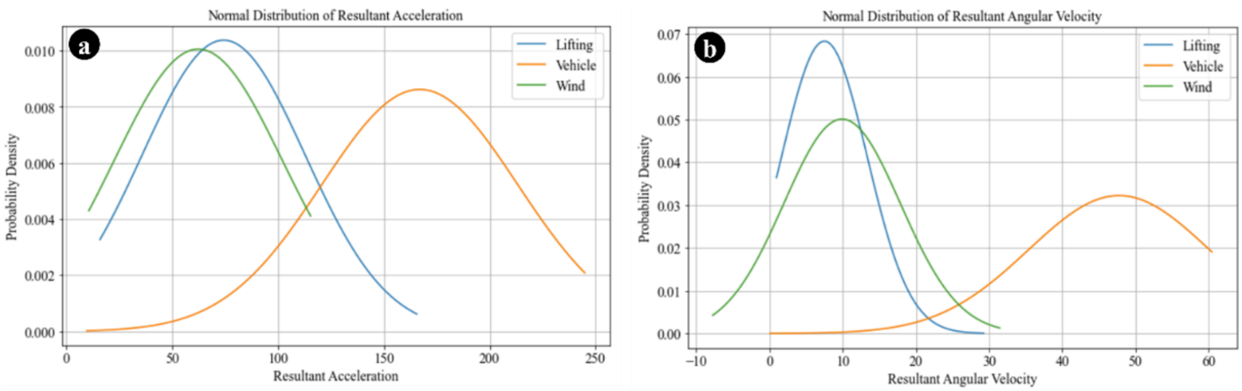

Figure 4. PDFs for vehicle intrusion, wind, and lifting by hand scenarios (a) Resultant acceleration; (b) Resultant angular velocity.

An LSTM network was chosen as the core model for this project due to its proven ability to handle time-series data and capture temporal dependencies. The IMU data collected during the experiments is inherently sequential, with each event (e.g., vehicle intrusion, wind displacement) unfolding over time. LSTM networks are particularly well-suited to process such time-series data, as they can retain information about previous timesteps, which enables the model to recognize patterns that develop across the duration of an event. One of the key benefits of LSTM is its gating mechanism, which allows the network to selectively retain or forget information from previous timesteps [37]. This ability to capture long-range dependencies makes LSTM a better fit for our task compared to traditional feedforward networks or other time-series models like simple Recurrent Neural Networks (RNNs), which may suffer from vanishing gradient issues when dealing with long sequences. It is worth mentioning that transformer-based models, such as Temporal Fusion Transformer (TFT), have also been shown to be promising for processing sequential data because of their self-attention mechanism, and could be a potential replacement for RNN-LSTM for the purpose of this study. However, they typically come with higher computational demands and increased complexity, and therefore need more memory and processing power. Given that the model needs to run on an edge device (e.g., a Raspberry Pi 4) with limited computational resources, model complexity and size were critical considerations [38]. Since the model needs to be deployed on an edge device for real-time processing, it is essential that the model remains lightweight to accommodate the limited processing capacity and memory of such devices. Therefore, the model network should be designed to balance accuracy with computational efficiency so that it can operate within the hardware constraints of the edge platform. To ensure the model remains lightweight, the number of LSTM units and

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layers was constrained, developing a compact architecture that delivers high classification accuracy without excessive computational overhead.

The model takes as input the processed IMU data, which has been segmented into 2-second windows. Each window contains a sequence of 100 timesteps, with each timestep corresponding to the readings from the IMU sensors. The input features for the model include the accelerometer and gyroscope data across the x, y, and z axes, plus the resultant acceleration and resultant angular velocity. The output of the model is a binary classification that indicates whether the event within the specified window is a real vehicle intrusion or a non-hazardous event (e.g., wind displacement, manual handling, or stationary). The choice of binary classification is aligned with the primary goal of distinguishing between hazardous and non-hazardous events in real-time. The output size is a single unit with a sigmoid activation function, which outputs a probability between 0 and 1. A threshold (typically 0.5) is applied to determine the final binary classification.

4. EXPERIMENTAL SETUP AND MODEL IMPLEMENTATION

This section outlines the comprehensive process of developing and validating the proposed vehicle intrusion detection framework. First, the field experiments conducted to collect sensor data under realistic highway work zone conditions are described. Following that, the implementation of the lightweight deep learning model used to classify these events based on IMU signals is explained. The section concludes with the evaluation procedures and metrics used to assess model performance.

4.1. Field Experiment

To develop a robust dataset for training and evaluating the intrusion detection model, we designed field experiments that reflect realistic highway work zone conditions. The experiments simulated three key event types, including vehicle intrusion, wind-induced cone displacement, and manual cone handling by workers. The following subsections describe the test sites, sensor setup, and procedures used for experiments.

4.1.1. Field Site Description

The field experiments were conducted at two distinct locations to simulate real-world highway work zone conditions. The first location, the Minnesota Department of Transportation (MnDOT) Road Research Facility (MnROAD), was used for two scenarios: vehicle intrusion and wind displacement. MnROAD is a dedicated pavement test track located

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in Monticello, MN and consists of various research materials and pavements. The site provides the necessary space and safety measures for vehicle experiments, including high-speed simulations of vehicles passing through work zones. The third scenario, manual cone handling by workers, does not require a dedicated road or vehicle, as it focuses on simulating human interaction with traffic cones, such as lifting and repositioning. Therefore, for diversity and generalization purposes, it was conducted on two fields, the MnROAD and the North Dakota State University (NDSU) campus. The NDSU site provided a controlled environment to capture data on cone movements caused by manual handling. Figure 5 shows both field sites.

Figure 5. Two field test sites used for data collection. Left) MnROAD pavement test track, used for vehicle-intrusion and wind-induced experiments; Right) NDSU campus, used for manual handling experiment.

4.1.2. Sensor Device Configuration and Attachment

To capture detailed data on cone movements during the experiments, custom devices with IMUs were mounted on traffic cones. Figure 6 displays the custom data collection device used in this study. Each IMU sensor was configured to measure both acceleration and angular velocity in three axes (x, y, z), capturing the linear and rotational movement of the cones. All IMU devices were connected to Raspberry Pi 4 processors powered by batteries, allowing real-time wireless data transmission to a central computer. This setup enabled continuous monitoring of cone movements during each experiment, with data recorded at a frequency of 50 Hz. In addition, custom-designed and 3d-printed protective casings, made from PLA (Polylactic Acid) filament, were used to ensure that the sensors and their connections remained intact during high-force impacts.

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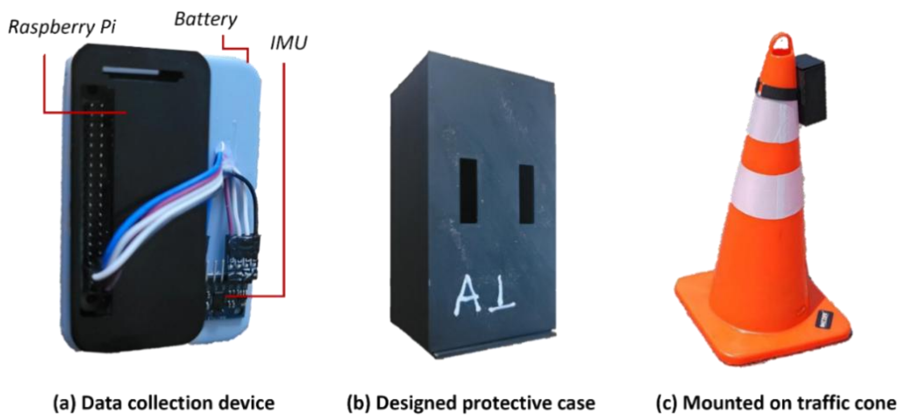

Figure 6. Custom data collection setup: (a) IMU device with a Raspberry Pi and battery, (b) 3D-printed protective case, and (c) the mounted cone configuration.

For the vehicle intrusion scenario, three cones were equipped with sensor devices and positioned to capture the impact from different angles—front, back, and side—relative to the direction of vehicle impact, as depicted in Figure 7. This is to ensure that impacts from various orientations are represented in the dataset, and a generalized dataset is provided for model development. The devices were securely attached to the cones using straps. In the wind displacement and manual handling scenarios, sensor devices were similarly mounted on the cones, with the same sensor configuration. The cones were positioned in a way that replicated real highway work zones, ensuring that the sensors could accurately capture the full range of motion resulting from wind forces and human interaction.

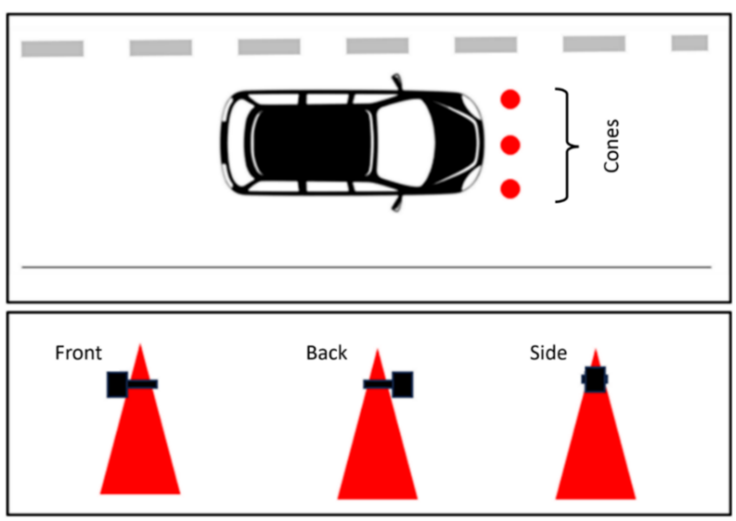

Figure 7. Top) Schematic representation of traffic cone placement in a highway work zone to capture vehicle intrusion scenarios; Bottom) Sensor device placement on cones at different impact angles.

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4.1.3. Data Collection

The vehicle intrusion scenario simulated a real vehicle intrusion into a highway work zone. A heavy-duty truck equipped with a front-mounted plow blade was driven at speeds ranging from 5 to 35 mph toward cones equipped with sensor devices. Table 1 presents the distribution of speeds and trials for the vehicle intrusion experiment. We selected speeds ranging from 5 mph to 35 mph in 5 mph increments to reflect typical slow-to-moderate travel speeds near work zones. Maintaining smaller increments (e.g., 1–2 mph steps) is impractical for the driver to sustain, so 5 mph intervals offered a balance between experimental precision and operational feasibility. A total of 20 distinct impact events were conducted, with each speed repeated at least once to ensure coverage of various collision intensities. In each event, three sensor-equipped cones were arranged to capture impacts from different angles (front, back, and side, as depicted in Figure 7), thus generating 60 total trials (3 trials per event). In each trial, acceleration and angular velocity data were collected during the collision. These trials captured the high-impact movements associated with vehicle intrusions. This setup ensures a statistically significant dataset that captures a wide range of possible movements. Figure 8 shows the vehicle intrusion experiment, specifically at the moment of vehicle hitting the cones.

Table 1. Trials and vehicle speed for vehicle intrusion experiment

Trial	Speed	Trial	Speed
1	5 mph	11	20 mph
2	5 mph	12	25 mph
3	5 mph	13	25 mph
4	10 mph	14	25 mph
5	10 mph	15	30 mph
6	10 mph	16	30 mph
7	15 mph	17	30 mph
8	15 mph	18	35 mph
9	15 mph	19	35 mph
10	20 mph	20	35 mph

Figure 8. Vehicle intrusion experiment. Left) Truck moving at a certain speed toward the cones; Right) The moment of impact, where the truck collides with the cones.

To simulate wind-induced cone movements, vehicles were driven close to the cones at varying speeds to generate significant wind forces. A digital anemometer was used to measure wind speed generated by the truck's movement (as depicted in Figure 9). The experiment included 15 trials to provide a representative sample of wind-induced cone movements under varying conditions, and address the need for sufficient data diversity, including different truck speeds and distances from the cones. Measured wind speed ranged from approximately 5 to 14 mph. To ensure the highest possible impact on the cones, the vehicle driver was instructed to drive as close to them as safely possible. The intent was to create a realistic replication of a real-world situation where vehicles pass close to cones and extreme wind forces are generated, causing the cones to move, or even fall. The setup ensured that the cones were exposed to realistic wind forces, in order to collect data on the subtle movements caused by wind without direct vehicle contact.

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Figure 9. Wind-induced movement experiment. Left) Vehicle passing by traffic cones to generate wind disturbance; Right) An anemometer measuring wind speed to quantify its impact on cone displacement

In the manual handling scenario, cones were lifted, moved, and repositioned by three participants with varying attributes (two males, one female) to simulate typical human interactions with traffic cones. A total of 60 trials were conducted. During these trials, participants were asked to perform various random actions, such as dropping the cone from a height (typical waist or chest level when holding a cone), gently placing the cone on the ground, throwing the cone, collapsing it, and other similar tasks. These diverse actions were designed to capture a wide range of possible human interactions with the cones. As with the previous experiments, the IMU sensors recorded acceleration and angular velocity data during these actions. Images of this experiment are provided in Figure 10.

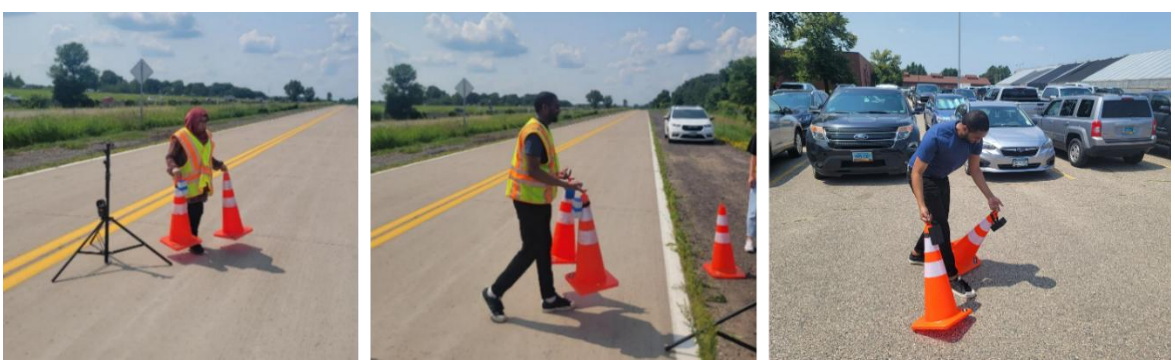

Figure 10. Manual handling experiment. Different scenarios, including lifting, repositioning, and placing cones, were tested.

4.2. Model Implementation

The LSTM model implementation is carried out with a focus on efficiently processing the segmented IMU data for real-time intrusion detection. The model takes as input the processed IMU data, segmented into 2-second windows, each containing 100 timesteps. This window size was selected after testing various durations, finding that 2-second window provided the optimal information model needs. Each timestep corresponds to sensor readings from the IMU sensors, including acceleration and angular velocity values across the x, y, and z axes. A representative snippet of the final labeled dataset, illustrating how IMU features and classification labels are organized, is presented in Figure 11.

=== Collision (Vehicle Intrusion) SAMPLE (showing 5 rows) ===

Acc_x	Acc_y	Acc_z	Resultant_Acc	Anglvel_x	Anglvel_y	Anglvel_z	Resultant_Anglvel	Window_ID	Label
0.639633	0.580119	0.169911	0.880078	0.467246	-0.756014	0.175253	0.905864	5	1
0.752376	0.393923	0.558256	1.016315	-0.256709	0.499293	0.145710	0.580021	33	1
0.308694	0.327139	0.707218	0.838135	0.106296	0.029059	-0.180536	0.211510	30	1
0.429268	0.803196	0.655055	1.121825	0.074598	-0.121168	-0.038142	0.147314	29	1
0.812574	0.957600	0.833829	1.507496	0.520953	-0.498640	0.485001	0.869057	0	1

=== Non-collision (Wind/Lifting/Stationary) SAMPLE (showing 5 rows) ===

Acc_x	Acc_y	Acc_z	Resultant_Acc	Anglvel_x	Anglvel_y	Anglvel_z	Resultant_Anglvel	Window_ID	Label
0.379113	0.517949	0.305079	0.710683	-0.136059	-0.125818	-0.115094	0.218148	549	0
0.631897	0.771181	0.448414	1.093201	-0.082781	-0.157768	-0.276072	0.328572	175	0
0.398588	0.666753	0.131004	0.787778	-0.139166	0.123	0.020823	0.187002	1586	0
0.367647	0.184898	0.401069	0.574638	0.145966	0.030758	-0.086317	0.172344	959	0
0.684620	0.395891	0.517481	0.945103	-0.018230	0.109254	0.099931	0.149181	1507	0

Figure 11. Example snippet from the final labeled dataset illustrating five random samples each from collision (vehicle intrusion) and non-collision (wind, lifting, and stationary) windows.

During training, class weights are adjusted to handle the imbalance in the dataset. The weights are computed using the class weight utility from the scikit-learn library to ensure that the minority class (vehicle intrusion) is given greater importance during model training, encouraging the model to correctly classify collision events. Specifically, the class weights are adjusted based on the frequency of each class, with higher weight assigned to the vehicle intrusion class to address the imbalance. This ensures that the model gives adequate importance to the minority class without introducing arbitrary values. To further address the class imbalance, data augmentation is applied to the vehicle intrusion data. Each sample from the minority class is augmented by adding random Gaussian noise with a mean of 0 and a standard deviation of 0.01, with each original sample being augmented two times. This effectively increases the number of samples available for training and improves the model's generalizability by simulating variations in sensor readings. As a result of applying this on vehicle intrusion class, samples increased from 793 to 2379, compared to 2809 non-intrusion samples. Figure 12 indicates the class distribution before and after data augmentation applied.

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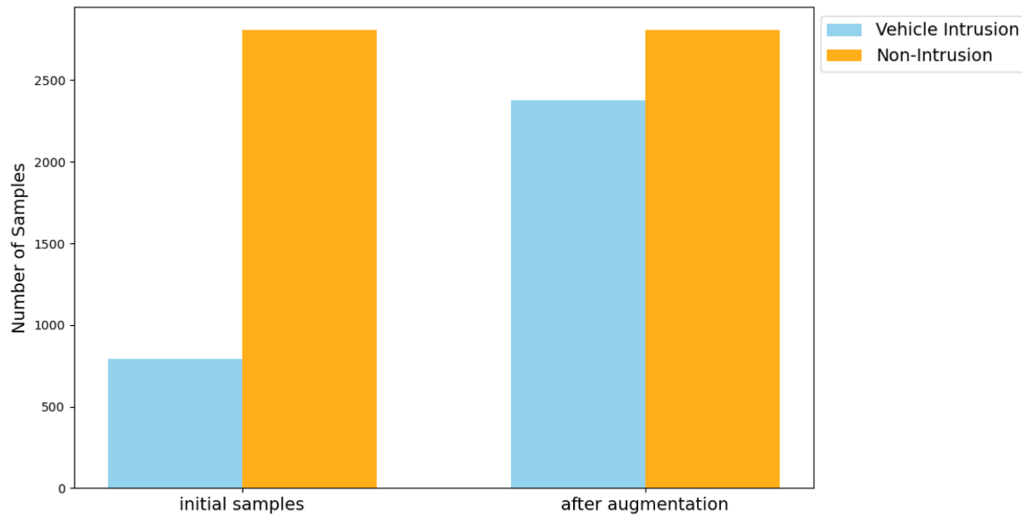

Figure 12. Class distribution of samples before and after data augmentation (training data), to increase the number of vehicle intrusion samples to address class imbalance.

In order to find the best parameters for the model network, hyperparameter tuning was conducted using the Keras Tuner's RandomSearch method to identify the optimal combination of hyperparameters for the model [39]. Specifically, the optimal number of LSTM units, dense units, dropout rate, and learning rate were determined to maximize model performance. However, to keep the model lightweight as intended, only two LSTM and one dense layers are used, and the range for LSTM and dense units are defined between 6 to 16 for the hyperparameter tuning algorithm. Also, Dropout layers are added to prevent overfitting. The tuning process explored various values for each parameter, ultimately finding that the best configuration included 16 and 8 LSTM units, 10 dense units, dropout rate of 0.3, and a learning rate of 0.0001. The output layer consists of a single unit with a sigmoid activation function, providing a binary classification output indicating whether the event in the given window is a real vehicle intrusion or a non-hazardous event. To ensure optimal model performance. The model is trained on the augmented dataset using early stopping to prevent overfitting. A validation split of 20% is used to monitor model performance during training [47]. The loss function used is binary cross-entropy, suitable for binary classification tasks, and the Adam optimizer is chosen for its adaptive learning rate capabilities. Model network schematic is presented in Figure 13. The model is trained for 200 epochs on a computer with a 13th Gen Intel(R) Core (TM) i7-1355U 1.70 GHz processor, 32 GB RAM, and Python 3.10.

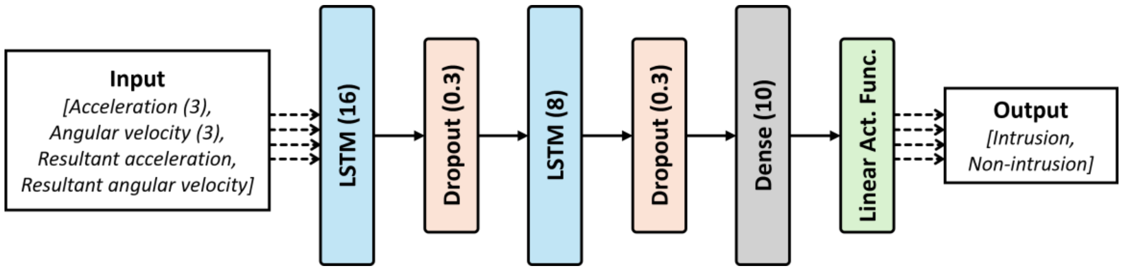

Figure 13. Deep learning model architecture for intrusion detection. The final activation function classifies events as either vehicle intrusions or non-intrusions.

4.3. Performance Evaluation

To evaluate how effectively the LSTM model distinguishes between real vehicle intrusions and non-hazardous events, we employed accuracy, precision, recall, and F1-score, which are standard metrics widely used in classification [48–51]. While accuracy provides a quick overview of overall correctness, precision and recall offer deeper insights into how well the model minimizes false alarms (false positives) and how reliably it identifies actual intrusions (true positives). Because both aspects are critical for worker safety and operational efficiency, the F1-score, the harmonic mean of precision and recall, provides a balanced single-metric view of performance. These metrics are defined in Eq. (5) to (8). In addition, we present a confusion matrix to illustrate the distribution of correct and incorrect predictions across the classes. This offers a clear view of where misclassifications occur and guides further improvements to reduce missed intrusions (false negatives) or unnecessary alarms (false positives).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{Eq. (5)}$$

$$Precision = \frac{TP}{TP + FP} \quad \text{Eq. (6)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{Eq. (7)}$$

$$F1\text{-}score = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \quad \text{Eq. (8)}$$

Where:

TP is True Positives, which in this context means real intrusions correctly classified,

TN is True Negatives, here means non-intrusions correctly classified,

FP is False Positives, here means non-intrusions incorrectly classified as intrusions,

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FN is False Negatives, here means real intrusions incorrectly classified as non-intrusions.

5. RESULTS AND DISCUSSION

This section presents the evaluation of the proposed intrusion detection framework and discusses the implications of findings. It begins by evaluating the model's ability to differentiate between true vehicle intrusion events and non-hazardous movements. Subsequently, the impact of key input features on model performance is investigated. A detailed discussion of performance limitations, implementation challenges, and future directions is also provided to guide further development and adoption.

5.1. Model Performance

The proposed LSTM model was evaluated on its ability to distinguish between real intrusion events (i.e., collisions caused by vehicles) and non-hazardous events (e.g., wind, manual handling, and stationary conditions). The results of the model's performance are presented using multiple evaluation metrics, including accuracy, precision, recall, and F1-score. The confusion matrix, training-validation accuracy graph, and key performance metrics are discussed in this section.

The model achieved an overall test accuracy of 96%. As indicated in the classification report (Table 2), the model achieved a precision of 0.87, a recall of 0.97, and an F1-score of 0.92. These metrics indicate that the model performs well in detecting intrusion events with a high degree of reliability while minimizing false positives and false negatives. With a high recall value (0.97) the model is effective at identifying real intrusion events, which is essential for safety-critical applications. The precision score (0.87), also, shows that the model was able to minimize false alarms and trigger alerts that are more likely to correspond to actual threats. Finally, the combined F1-score of 0.92 demonstrates a balanced performance in detecting intrusion events with both accuracy and reliability. From a practical standpoint, high precision is essential in real-world deployment, since excessive false positives may lead on-site personnel to lose confidence in the alerts and ultimately undermine the system's safety benefits. On the other hand, the high recall also affirms the effectiveness of the LSTM model in capturing subtle temporal patterns in the IMU data, ensuring minimal false negatives even under variable field conditions. At 0.97, the system identifies nearly all true vehicle intrusions, which is critical for a safety-focused application where each missed hazard could result in severe risks to highway workers.

Table 2. model performance metrics

Precision	Recall	F1-Score	Accuracy
0.87	0.97	0.92	0.96

The confusion matrix (Figure 14) provides additional insights into the model's performance on test data. This confusion matrix is based on a total of 811 instances, where 610 (75.2%) were non-intrusion events and 201 (24.8%) were intrusion events. The significant higher number of non-intrusion samples is because data augmentation applied only on train dataset. As shown in the confusion matrix, the model correctly classified 582 out of 610 non-intrusion events and 195 out of 201 intrusion events. However, it also misclassified 28 non-intrusion events as intrusions and 6 intrusion events as non-intrusions. The false negatives (missed intrusion events) are particularly critical in this context, as they represent cases where actual hazards are not detected. Despite these, the small number of false negatives highlights the model's reliability in identifying real intrusion events. Similarly, the relatively low number of false positives indicates that the system maintains a balance between minimizing unnecessary alerts and ensuring safety. The results show that combining high-resolution IMU data with a sliding window approach not only captures peak values (such as resultant acceleration and angular velocity), but also the way each event unfolds over time. Vehicle intrusion events often begin with an abrupt rise in signal magnitude and then slow down in a distinct pattern. In contrast, wind-induced or manually handled events sometimes reach similar peak values but tend to do so more gradually, followed by a swift return to normal. Because our model analyzes 2-second time windows, it can learn these different movement patterns, making it easier to tell a genuine intrusion from a harmless disturbance.

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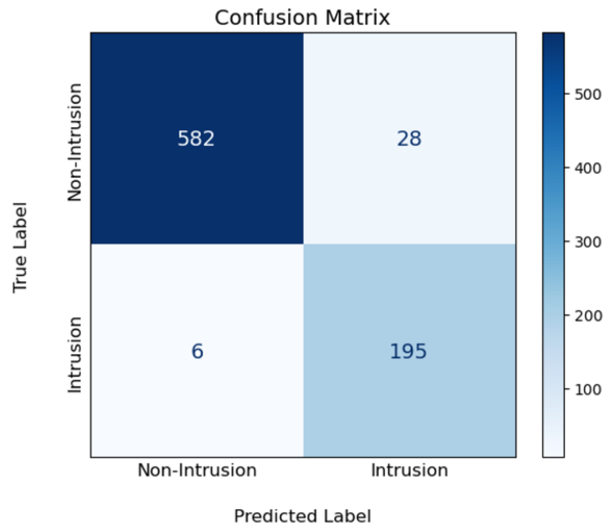

Figure 14. Intrusion detection model confusion matrix.

The training and validation accuracy graph (Figure 15) shows the model's training progress over 200 epochs. Training accuracy increased rapidly in the initial epochs and eventually stabilized around 95%, indicating successful learning. The validation accuracy exhibited fluctuations, especially in the early epochs, but converged to values more than 90% in later epochs. These fluctuations may be due to the variability in the dataset, such as the diversity of non-intrusion events (e.g., wind, manual handling, and stationary conditions). Despite these variations, the model successfully converged, and no significant overfitting was observed, suggesting that the combination of dropout layers and data augmentation was effective in preventing overfitting. The high training accuracy coupled with similar validation accuracy implies that the model has generalized well to unseen data. The use of data augmentation and class weight adjustment appears to have played a significant role in this outcome. Data augmentation was used to generate synthetic samples for the minority class (vehicle intrusion), increasing its representation in the dataset. This approach effectively improved the model's ability to learn and identify collision events, as evidenced by the increase in recall for the intrusion class. Additionally, class weight adjustment helped the model prioritize the minority class, reducing the impact of class imbalance and enabling better detection of intrusion events.

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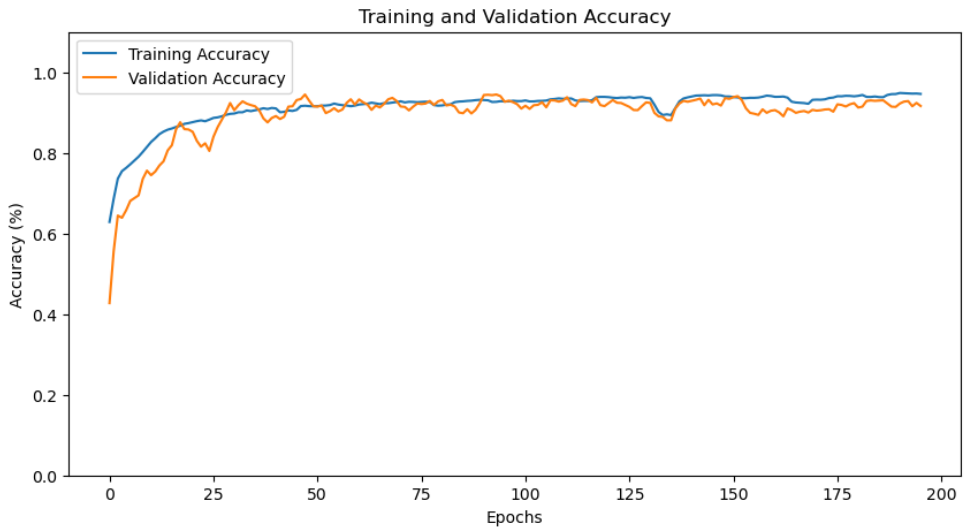

Figure 15. Training and validation accuracy of the intrusion detection model over 200 epochs.

To better understand the model's performance, particularly the areas where results were less than ideal, it is important to consider the factors that may have influenced these outcomes. When developing a deep learning model, two main aspects that play a crucial role are the network architecture, and the dataset used for training the model.

The choice to use a lightweight network architecture, consisting of a single LSTM layer with 16 units and a dense layer with 8 units, was made to ensure the model could run efficiently on edge devices with limited processing capabilities. This decision contributes to the feasibility of deploying the model in real-world scenarios, such as highway work zones, where edge devices are often required for real-time intrusion detection. However, the reduced model complexity may have impacted the model's ability to capture more intricate patterns in the data, potentially contributing to the lower precision observed for the intrusion class. A more complex model with additional layers or higher unit counts could potentially improve performance, but at the cost of increased computational requirements.

On the other hand, the dataset used for training and evaluation exhibited significant class imbalance, with far fewer intrusion events compared to non-intrusion events. This imbalance is an inherent challenge due to the rarity of vehicle intrusions compared to other activities like manual handling or stationary periods. Addressing this imbalance was crucial, as training without handling it could lead to a model biased towards predicting non-intrusion events, thereby failing to detect critical hazards. Although data augmentation and class weight adjustment helped mitigate this issue, the imbalance likely still affected the overall model performance, particularly the lower precision in detecting intrusion events. Future work could further explore advanced techniques, such as synthetic data generation or adaptive

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resampling, to better balance the dataset and improve the model's robustness. The model's precision for the intrusion class was lower than desired (77%), indicating that the model tends to produce false positives when detecting collision events. In the context of highway work zones, false positives may lead to unnecessary alerts, potentially affecting workers' trust in the system. However, false positives are preferable to false negatives in this safety-critical application, where failing to detect an actual intrusion could lead to severe consequences. Future work could further explore advanced techniques, such as synthetic data generation or adaptive resampling, to better balance the dataset and improve the model's robustness.

In addition, to quantitatively assess how noise reduction affects the proposed intrusion detection model, we conducted an ablation study comparing results with and without data filtering. To achieve this, the model was further trained on raw (unfiltered) data, with the whole architecture and configuration remaining the same. The filtered-data model demonstrated substantial improvements across all key metrics (Figure 16). It improved accuracy by 2.1%. Precision, recall and F1-score are also relatively increased between 4.3% to 20.8%.

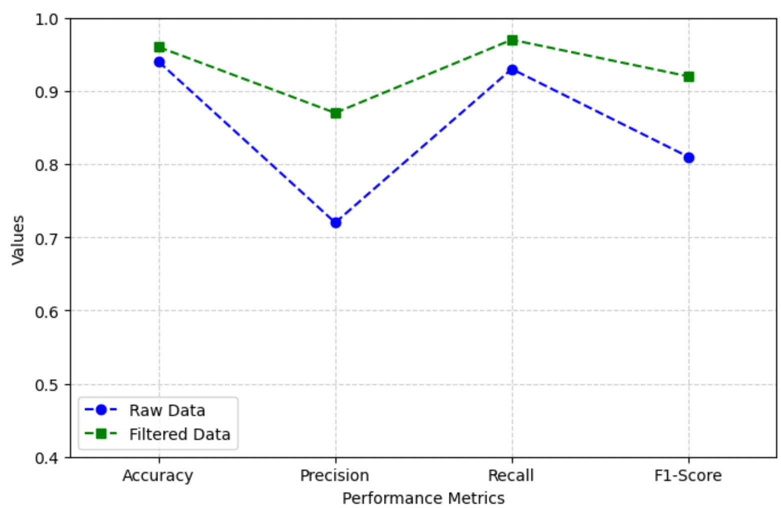

Figure 16. Comparison between performance metrics of models trained on raw or filtered data.

These results confirm that filtering suppresses sensor noise and sharp signal spikes in raw IMU data, thereby enabling the model to recognize collision-related patterns more effectively. The 20.8% precision gain indicates a significant reduction in false alarms (non-intrusions misclassified as collisions), while the 4.3% recall improvement reflects fewer missed intrusions. These are both critical for safety in highway work zones. The balanced F1-score enhancement further highlights the model’s improved reliability after noise reduction. These analysis and insights from the ablation study, while aligning with previous research [52,53], indicates that applying noise reduction methods on raw sensory data is a necessity for more effective use of data and enhance model reliability. In real-world conditions, noise filtering is especially impactful in busy highway environments prone to vibrations or electromagnetic interference from heavy equipment. While our results highlight the efficacy of a standard filtering approach, future deployments in varying climates or topographies might benefit from adaptive filters—tuned automatically to account for recurring low-frequency disturbances (e.g., continuous rumble from passing trucks).

Last but not least, to verify that our LSTM model is lightweight enough for real-time use on edge devices, we obtained its parameter count and file size after training. The model summary indicates a total of 7,505 parameters, of which 2,501 are trainable. This translates to an on-disk size of approximately 75 KB when saved in HDF5 format, which is notably small compared to large-scale deep neural networks. Additionally, no non-trainable parameters were present, highlighting the simplicity of our architecture. These figures confirm that our approach aligns well with edge constraints: a memory footprint of under 100 KB is typically negligible on devices such as the Raspberry Pi 4, which has up to 4 GB of RAM. In future deployments, we can further reduce the file size and inference latency by converting the model to TensorFlow Lite or applying quantization techniques. Overall, the modest parameter count and compact file size indicates the feasibility of deploying the proposed intrusion detection system in real-world highway work zones that demand quick response times and limited hardware resources.

5.2. Features Impact Analysis

We analyzed the importance of features extracted from the IMU data using SHapley Additive exPlanations (SHAP), a widely used method for interpreting machine learning models. SHAP values quantify each feature's contribution to the model's predictions by evaluating the marginal impact of each feature across various samples [54,55]. In this study, SHAP analysis was applied to a Random Forest model trained on IMU data features to identify the most influential factors in distinguishing between intrusion and non-intrusion events. The Random Forest model was trained on flattened IMU data segments, represented by features including accelerometer and gyroscope values along the x, y, and z axes, as well as resultant acceleration and angular velocity. We used TreeExplainer from the SHAP library to calculate SHAP values, which were then averaged to determine overall feature importance.

The feature importance analysis results are presented in Figure 17. Higher SHAP values indicate a greater impact on the model's decision-making process. The results indicate that Resultant Acceleration (Resultant_Acc) and

Resultant Angular Velocity (Resultant_Anglvel) were the most important features in distinguishing between intrusion and non-intrusion events. These features capture the overall magnitude of acceleration and angular velocity, respectively, suggesting that changes in overall motion and rotational dynamics are key indicators for identifying intrusion events. The individual accelerometer axes (Acc_x, Acc_y, Acc_z) and angular velocity axes (Anglvel_x, Anglvel_y, Anglvel_z) also contributed to the model's performance, but to a lesser extent. Among these features, movements in the y-axis (likely corresponding to lateral motion) played a more critical role in distinguishing different types of cone movements.

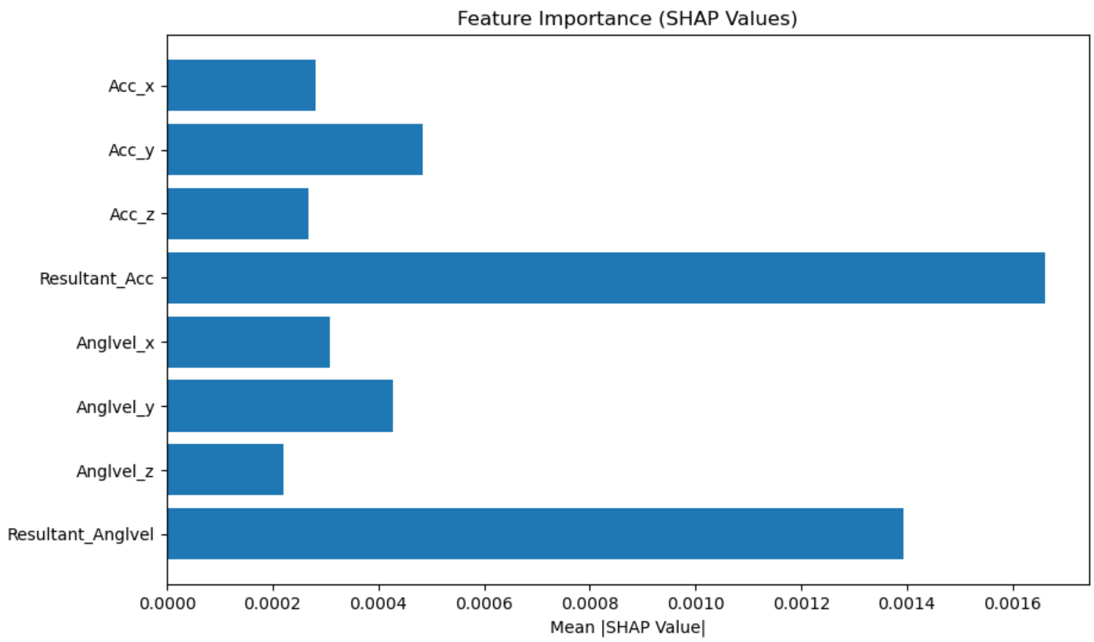

Figure 17. Model inputs feature important analysis using SHAP values.

The SHAP analysis provides valuable insights into which features were the most informative for the intrusion detection task. The high importance of resultant features aligns with expectations, as these metrics effectively summarize the overall magnitude of acceleration and angular velocity, making them robust indicators for differentiating between complex movements. In contrast, the individual axes may capture more specific or subtle movements, which might be less consistent across different intrusion scenarios, thereby contributing less overall to the classification decision. The feature importance analysis highlights that the model relies heavily on general movement patterns rather than individual axis-specific variations. This suggests that focusing on resultant features could lead to more efficient feature selection in future models, potentially simplifying the data preprocessing stage

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while retaining effective model performance. However, it also points to the possibility that the model might overlook certain subtle but significant axis-specific changes that could help in edge cases or nuanced scenarios. Future research could explore combining resultant features with more advanced, axis-specific features to improve detection performance further.

5.3. Practical Implications, Limitations, and Future Directions

The findings of this study have significant practical implications for enhancing safety in real-world highway work zones, where intrusion events pose serious threats to both worker safety and operational efficiency. Highway work zones are inherently high-risk environments due to the proximity of moving traffic, heavy machinery, and often limited visibility. The proposed deep learning model for intrusion detection, implemented with a lightweight LSTM architecture, demonstrates that it is feasible to deploy a real-time intrusion detection system on edge devices such as a Raspberry Pi. The system can effectively distinguish between vehicle intrusions and non-hazardous events (e.g., wind or manual handling of cones), which can help alert workers in a timely manner and thereby reduce the risk of accidents. This addresses a critical need to minimize false alarms, which are a common issue in current intrusion detection systems and can lead to alarm fatigue and reduced responsiveness. By reducing unnecessary alarms, the model ensures that workers are only interrupted when a real threat is detected, thereby maintaining operational efficiency and improving overall safety. The different scenarios considered in this study, including vehicle intrusions, wind, and manual handling of cones, contribute to making the model generalizable to various potential events that may occur in highway work zones.

From the practical point of view, it is also important to note that in safety-critical applications such as highway work zones, managing the trade-off between false positives and false negatives is important. In our system, a false positive occurs when a non-intrusion event (e.g., wind-induced cone movement or manual handling) is erroneously classified as a vehicle intrusion, whereas a false negative happens when a genuine vehicle intrusion is missed. Adjusting the classification threshold directly impacts these error rates. For instance, increasing the threshold tends to reduce the number of false positives and therefore, minimizes unnecessary alarms and alarm fatigue among workers. On the other hand, this stricter threshold can also result in an increase in false negatives, since more subtle intrusion signals might fall below the detection cutoff.

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Additionally, the use of IMU sensors attached to cones provides a practical and cost-effective solution for monitoring work zone safety, as these sensors are relatively inexpensive and can be easily deployed across multiple work sites. By automating the detection of potential hazards, the proposed system can enhance worker safety without requiring constant human monitoring. This system can be integrated into existing work zone safety technologies to provide an additional layer of safety. For instance, it can complement traditional camera-based surveillance systems by providing reliable, sensor-based data that reduces the likelihood of false alarms. The ability to deploy this model on portable and cost-effective edge devices like the Raspberry Pi also ensures scalability across different work zones without incurring high costs. The integration of this system into work zone safety protocols can significantly enhance worker awareness and response time, providing alerts in the event of a potential intrusion and mitigating the risks associated with unauthorized vehicle entries.

The proposed method is readily applicable for real-case deployments in highway work zones through a clear workflow. First, system setup and sensor attachment involve installing robust IMU sensors on traffic cones and calibrating them on-site to account for local conditions, such as baseline noise or sensor drift. Next, real-time data processing takes place on an edge device (e.g., Raspberry Pi), which filters the incoming IMU signals, segments them into short windows, and runs the lightweight LSTM model continuously to classify each window as either an intrusion event or a non-hazardous movement. In the next step, alerting and event handling, any detected intrusion automatically triggers an immediate notification (either visual, auditory, or both) that can be relayed to workers on-site or safety supervisors remotely. Finally, post-event checks ensure ongoing optimization and reliability. all data and model outputs are recorded for refining sensor thresholds as conditions change, and periodic maintenance (including battery checks and routine sensor inspections) ensures minimal downtime. By following these steps, transportation agencies and contractors can seamlessly integrate the proposed intrusion detection system into existing safety protocols and substantially improve worker protection in highway work zones.

Despite the promising results, there are several challenges that may arise when implementing this system in real-world scenarios. Although our experiments were conducted in field environments, real-world highway work zones may present additional variables, including varied weather conditions (e.g., heavy rain, snow, or extreme heat), electromagnetic interference from nearby equipment, and different vehicle interactions. These factors can introduce additional noise or signal disturbances into the IMU sensor data, potentially affecting the model’s robustness. To mitigate these challenges, future deployments would benefit from collecting training data under a wide range of environmental scenarios. Incorporating adaptive filtering methods could also help maintain signal quality in the presence of erratic noise sources. Additionally, expanding the dataset with varied vehicle speeds, turning maneuvers, and lane-change patterns could improve the model's generalizability, particularly in more complex traffic conditions. Real-time processing on edge devices may also pose limitations, especially when multiple sensors are deployed simultaneously, as edge devices have limited computational power. Ensuring that the system can operate effectively under varying conditions and with minimal latency will be crucial for successful deployment. Additionally, the robustness of the system against false positives, such as distinguishing between legitimate vehicle intrusions and non-threatening movements caused by environmental factors, needs to be further validated.

This study has certain limitations that must be acknowledged. First, the scenarios included in the experiments were limited, and the model may need further adaptation to handle a wider range of potential events, such as different vehicle types, speeds, and environmental conditions. Additionally, while IMU sensors provide valuable data for detecting cone movements, their accuracy may be affected by sensor drift or other factors, which could introduce noise into the system. The dataset also exhibited an imbalance between intrusion and non-intrusion events, which required careful handling through data augmentation and class weight adjustments; however, the impact of this imbalance on model performance may still be present. Another potential limitation is the vulnerability of the system to hardware failure, particularly in harsh impact scenarios. If the IMU sensor or edge device malfunctions or is damaged upon impact, real-time intrusion detection may be compromised.

To address the limitations and improve the scalability of the proposed system, several future directions are suggested. First, expanding the dataset to include a more diverse set of scenarios, including different vehicle types, weather conditions, and work zone configurations, will help enhance the model's robustness. Moreover, further optimization of the model, including hyperparameter tuning and experimentation with other lightweight architectures, could improve its performance while maintaining low computational requirements. Future research could also explore the scalability of the proposed approach to other types of work zones, such as urban construction sites or railway maintenance areas, where similar safety challenges exist. Finally, to improve system resilience, redundancy strategies should be explored, such as integrating multiple IMU sensors on different cones within a work zone. A distributed sensing approach could help maintain detection capability even if one device fails.

6. CONCLUSION

This paper presented a deep learning-based intrusion detection system for highway work zones using IMU sensor data to improve worker safety by accurately distinguishing between real vehicle intrusions and non-hazardous cone movements. The proposed approach addresses the shortcomings of existing intrusion detection systems, which often suffer from high false alarm rates. An important part of the proposed method included providing a comprehensive dataset of various possible events and conditions typically occur in highway work zones and affect the intrusion detection systems. This dataset was collected through field tests, including vehicle intrusion, manual handling, and wind-induced movements. For each test, acceleration and angular velocity of devices were recorded. The data underwent preprocessing steps, such as noise reduction filtering, data augmentation, and class weight adjustment to handle data imbalance. Then, a lightweight LSTM model, capable of implementing on an edge device, was developed to recognize an event as a real intrusion case or a non-intrusion event.

The experimental results indicate that the system achieved a test accuracy of 96%, with a recall of 97% for intrusion events, showcasing its capability to detect most genuine threats while reducing false alarms. Moreover, feature importance analysis was performed using SHAP method, and “resultant acceleration” and “resultant angular velocity” were shown to be the most important features in differentiating between intrusion and non-intrusion events. By integrating IMU sensors and leveraging the lightweight LSTM architecture, the proposed solution is feasible for real time deployment on edge devices, and thus scalable for deployment on different highway work zones.

Despite the promising results, the study has some limitations to be acknowledged. The dataset used for model training was limited to specific scenarios, which may not represent all potential conditions in highway work zones. Moreover, environmental variability, such as weather and road conditions, could impact sensor performance and model accuracy [56]. Future research could focus on expanding the dataset to include a broader range of scenarios, further optimizing the model architecture, and improving its robustness in diverse work zone conditions. In addition, exploring advanced techniques like synthetic data generation and adaptive resampling could help mitigate the effects of class imbalance and may lead to even more accurate intrusion detection.

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