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AI-Enhanced Safety for Heavy Load Construction Vehicles: An Integrated Embedded C++ Software Approach

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Abstract: Dump trucks, cranes, excavators, and loaders are among the heavy load vehicles used on construction sites that have significantly increased in number as a result of the quick growth of infrastructure. These devices greatly increase production, but they also pose serious safety issues because they are hard to spot, site circumstances change, people grow tired, equipment malfunctions, and they are near employees. In order to enhance the safety, dependability, and accident avoidance of high-load construction trucks, this article proposes a comprehensive safety framework that integrates Artificial Intelligence (AI) and Embedded C++. Using cameras, radar, lidar, inertial sensors, and load cells, the suggested system aggregates data from several sensors. Additionally, it uses real-time edge AI models to identify dangers, monitor blind spots, avoid overloads, and detect hazards. A real-time operating system (RTOS) and a safety-critical embedded software architecture designed in modern C++ (C++17/20) guarantee that the system can handle faults, respond consistently, and connect safely to car actuators. For extended use, the framework incorporates fail-safe modes, extra watchdogs, and safe over-the-air updates. Controlled field testing and simulations are used to generate an exact experimental design. Time-to-intervention, false alarm rate, detection accuracy, system delay, and system availability are examples of performance measures. The suggested approach shows how AI-assisted active safety systems can be implemented on resource-constrained embedded platforms while meeting dependability and real-time requirements. The next generation of smart construction vehicles will have a workable, scalable, and industry-ready solution thanks to this effort.

Keywords: fault-tolerant systems, sensor fusion, embedded C++ systems, high load trucks, construction safety, predictive risk assessment, autonomous safety intervention, edge artificial intelligence, real-time operating systems (RTOS), and IoT-enabled construction equipment.

I. INTRODUCTION

The construction sector is become more mechanized because people want projects finished more quickly, infrastructure built on a larger scale, and operations to be more efficient. The heavy machinery that forms the foundation of contemporary construction includes wheel loaders, cranes, excavators, dump trucks, and bulldozers [1]. Despite being more productive, these machines are also riskier due to their size, high electrical consumption, poor sight for drivers, operation in crowded areas, and frequent human-machine interactions. Heavy machinery is implicated in a significant number of fatal and non-fatal accidents, according to construction site safety records from all around the world [2]. These collisions are frequently caused by blind-spot collisions, equipment overloads, reversing occurrences, and driver tiredness.

Passive alarms, manual inspections, and simple telematics systems are the main safety features that construction vehicles have always had. Though these strategies are helpful, they mainly address issues, which can result in erroneous alerts, a delayed human reaction, and a lack of situational awareness. AI, edge computing, and sophisticated embedded systems have made it possible to replace reactive safety solutions with proactive and predictive ones [3]. Perception systems with AI capabilities can continuously scan the scene, identify dangers in real time, and suggest or put safety precautions in place before a calamity occurs.

However, there are unique technological difficulties when utilizing AI-based safety systems in heavy-duty vehicles [4]. Construction sites may be unpredictable and hectic. Dust, vibration, dim lighting, obstructions, and extreme weather all reduce a sensor's effectiveness. Additionally, demanding real-time performance, reliability, fault tolerance, and cybersecurity are necessary for automotive-grade systems that are essential for safety. Cloud-only AI and generic software platforms are unable to meet these needs. For these safety-critical systems to function on edge devices with constrained resources, embedded C++ offers the speed, reliability, and low-level hardware control needed [5].

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In this paper, a unified AI-enhanced safety framework for high-load construction vehicles driven by embedded C++ software is proposed. Several important contributions are made by this work: (i) a layered system architecture that integrates edge AI and multi-sensor fusion; (ii) a safety-focused embedded C++ software design that satisfies real-time constraints; (iii) an experimental evaluation method for verifying safety performance; and (iv) a discussion of deployment issues and future research directions [6]. The goal of this project is to combine trustworthy embedded software with artificial intelligence (AI) to improve the safety, dependability, and independence of next-generation construction vehicles.

II. BACKGROUND & RELATED WORK

The historical studies and technological developments that are pertinent to AI-enabled safety in heavy-duty construction trucks are examined in this part [7]. It is divided into three groups: safety-critical embedded software, edge AI for vehicle perception, and conventional construction safety systems.

A. Construction Vehicle Safety Systems

Classic safety elements include hydraulic pressure sensors for overload prevention, telematics-based monitoring, rear-view and 360-degree video systems, and ultrasonic or basic radar proximity warning systems [8]. Usually, these systems notify operators depending on regulations. They have several shortcomings, including as high false-alarm rates, an incapacity to reason about complex settings, an inability to foresee what will happen next, and a dependence on people's reaction times, even though they are successful in bringing attention to basic hazards. Studies show that while warning-only systems lessen crashes and rollovers, they do not completely prevent them, especially in places where a lot of people collaborate.

B. Edge AI for risk prediction and vehicle awareness

Real-time object recognition, monitoring, and interpretation on embedded systems is now possible because to recent developments in edge AI. For real-time perception with constrained processing resources, lightweight convolutional neural networks like Mobile Net-SSD, Tiny-YOLO, and Efficient Det-Lite have become more and more popular [9]. Research indicates that camera-based vision is far more reliable in dusty, dark, and blocked environments—all of which are typical on construction sites—when combined with radar or lidar. Short-term trajectories and collision risk are estimated using predictive algorithms that include temporal filters and recurrent neural networks. These methods provide proactive safety rather than just reactive notifications.

C. Safety Standards and Embedded Software

The software that manages this safety tasks must meet strict real-time and reliability criteria. In the automotive and industrial automation sectors, functional safety lifecycles, hazard assessments, and verification are governed by standards such as ISO 26262 and IEC 61508. With the help of deterministic memory management, static analysis, and limited subsets (like MISRA C++), modern embedded C++ is now commonly used for these systems. RTOS systems like Free RTOS, QNX, and Zephyr are widely used by people to guarantee that scheduling is priority-based, jobs are divided, and latency is kept to a minimal [10].

D. Synopsis of Related Research

Although perception algorithms, telematics, and embedded control have advanced significantly, most of the solutions now on the market only address certain components rather than providing a whole, safety-certified AI and embedded software stack for heavy construction equipment [11]. The unified approach covered in this essay was inspired by this disparity.

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Table 1: An Examination of the Various Approaches Currently Available

Approach Type	Key Technologies Used	Primary Function	Strengths	Limitations
Proximity Alarm Systems	Ultrasonic sensors, basic radar	Detect nearby obstacles and trigger alerts	Low cost, simple integration, low power	High false-alarm rate, no object classification, reactive only
Camera-Based Monitoring	Rear-view cameras, 360° surround view	Visual assistance to operator	Improved visibility, low hardware cost	Operator-dependent, no automatic intervention, performance drops in dust/low light
Load Monitoring Systems	Hydraulic pressure sensors, load cells	Prevent vehicle overloading	Accurate load measurement, protects structural integrity	No awareness of external hazards, no collision prevention
Telematics-Based Safety Systems	GPS, speed sensors, cloud analytics	Fleet-level monitoring & incident logging	Remote supervision, preventive maintenance	Delayed response, not real-time, no local intervention
Rule-Based Advanced Driver Assistance (ADAS)	Radar + camera, threshold logic	Blind-spot monitoring, collision warnings	Better hazard detection than alarms, structured logic	Poor adaptability to complex dynamic scenes
Edge AI-Based Safety Systems	CNNs, sensor fusion, edge computing	Real-time hazard detection & prediction	Predictive safety, low latency, automated intervention	Higher cost, requires optimization & certification
Cloud AI Safety Monitoring	Cloud computing, video analytics	Post-event analysis & risk prediction	High computational power, long-term analytics	High latency, connectivity dependence, unsuitable for real-time control

III. SYSTEM REQUIREMENTS AND SAFETY GOALS

Numerous strict functional, real-time, reliability, and regulatory requirements must be met by an AI-enabled safety solution for heavy-duty construction vehicles. Construction equipment operates in unstructured, hostile, and dynamic surroundings as opposed to passenger cars, which go on controlled routes [12]. Consequently, deterministic fail-safe behaviour and proactive hazard prevention must be given top priority in system requirements.

A. The necessity of functional safety

To identify dangerous situations as soon as they arise, the system must continuously scan the exterior and the interior of the car. (i) Real-time identification of people, cars, obstacles, and dangerous areas; (ii) protection against blind spots and back over incidents during reversing manoeuvres; (iii) dynamic overload detection through real-time load and hydraulic pressure monitoring; (iv) risk scoring and collision probability assessment within a short prediction interval (1-3 seconds); and (v) tiered safety measures like progressive alerts, engine [13] These elements need to work well even in the face of adverse weather conditions, dust, vibration, poor light, and rain—all of which are common on building sites.

B. Real-Time and Performance Requirements

Decisions on safety are subject to stringent timing constraints. The latency between perception and actuation must be shorter than 150–200 ms for jobs that need to prevent collisions. Sample rates for sensors should be between 20 and 60 Hz, depending on their type. To calculate the maximum worst-case execution time (WCET) for each safety-critical operation, the embedded system must use a priority-based pre-emptive RTOS scheduler. Quantization and hardware acceleration are necessary to boost AI inference performance on the edge [14].

C. Fault Tolerance, Fail-Safe, and Reliability Goals

The system must be able to cope with partial computation failures, connectivity problems, and sensor failures without becoming dangerous. Additional sensors, independent watchdogs, cross-monitoring between safety microcontrollers and application processors, and default fail-safe modes that securely halt the car are all necessary for this. Health monitoring, self-diagnosis, and defect tracking are required for certification and post-incident analysis [15].

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D. Computer updates and security Specifications

Implementing secure boot, encrypted communication, authenticated over-the-air upgrades, and role-based access control is essential to thwarting hackers and unwanted access [16]. Modern embedded C++ design patterns and static analysis must be incorporated into the software architecture to facilitate modular updates, traceability, and long-term maintenance.

E. Safety Objectives

The main safety objectives are to: (i) lower the number of rollovers and collisions; (ii) prevent overloading-related structural failures; (iii) protect nearby workers by identifying issues before they arise; and (iv) guarantee that the system always returns to a safe state after a critical failure [17].

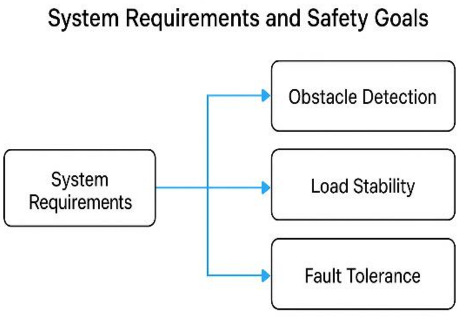

Figure 1. System Requirements and Safety Goals

IV. PROPOSED ARCHITECTURE

The completely layered structure of the suggested architecture guarantees that different kinds of high load construction vehicles can be built in a modular, real-time predictable, fault-tolerant, and scalable way. The system uses a secure integrated C++ software stack to integrate many sensor types, edge AI perception, safety decision-making, and vehicle actuation [18].

A. Layer of hardware

A high-performance application processor (ARM Cortex-A class) and a safety microcontroller are among the several computing platforms that make up this layer [19]. The application processor manages telemetry, AI inference, sensing, and the human-machine interface (HMI). Critical real-time tasks including emergency stop control, watchdog supervision, and actuator safety certification are handled by the safety microcontroller. Wheel encoders, load cells, inertial measurement units (IMU), short-range radar or lidar, stereo and monocular cameras, and ultrasonic proximity sensors are a few examples of sensors. Communication is facilitated using safety relays, Ethernet, and CAN-FD [20].

B. Perception and Sensor Fusion Layers

Data from several sensors is gathered, synchronized, and aggregated by this layer. AI-based object identification and conventional signal processing pipelines are used to process data from cameras, radar, lidar, and ultrasonics [21]. In order to give a consistent representation of the world, fused perception uses probabilistic occupancy grids and extended Kalman filters (EKF). This layer makes sure the system is resilient to bad weather conditions including dust, fog, and tremors, as well as sensor failures.

C. AI Inference and Prediction Layers

In order to identify employees, vehicles, and dangerous locations in real time, lightweight deep neural networks function on the edge [22]. Risk estimation is made possible by short-horizon trajectory prediction and object observation. To make sure that the model is trustworthy and that people behave responsibly when they are unsure, uncertainty estimation is included.

D. Security and Decision-Making Layers

This layer uses rules-based safety logic in addition to AI-generated risk scores. It guarantees adherence to safety rules like safe reversal, overload prevention, and collision avoidance [23]. The decision outputs include graded warnings, torque limiting, automatic braking, and emergency stop commands.

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E. Actuation, Telemetry, and Cloud Interface Layer

Validated commands are transmitted to braking, steering, and engine controllers via CAN-FD [24]. Operational data, event logs, and health metrics are securely transmitted to cloud platforms for fleet monitoring, diagnostics, and predictive maintenance.

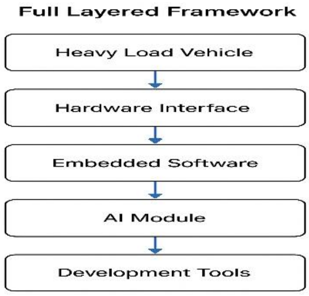

Figure 2. Full Layered Framework

V. EMBEDDED C++ IMPLEMENTATION DETAILS

A. Build and Toolchain

- Cross-compile with GCC/Clang for ARM; enable -O2 or -O3 for performance and -fstack-protector; link-time optimization (LTO) [25].
- Static analysis (cppcheck, clang-tidy), unit testing (GoogleTest), and hardware-in-the-loop (HIL) tests.

B. Real-time and Safety Patterns

- Use priority-based preemptive scheduler in RTOS; critical threads pinned to cores.
- Watchdog timers and heartbeat channels between Cortex-A and Cortex-M.
- Memory protection (MPU/MMU) and task isolation [26].

C. Example C++ snippets

```cpp
// Example: simplified real-time task for sensor health monitor
#include <chrono>
#include <thread>
#include <atomic>

std::atomic<bool> running{true};

void sensor_health_task() {
   using namespace std::chrono_literals;
   while (running.load()) {
      auto status = check_sensors(); // returns bitmask or throws
      if (!status.ok()) {
         signal_fault(status);
         engage_safe_mode();
      }
      std::this_thread::sleep_for(50ms); // 20 Hz health check
   }
}

int main() {
   std::thread t(sensor_health_task);
   // ... init other systems
   t.join();
}
```

Include a separate safety-critical firmware image for the Cortex-M written in exception-safe C++ with no dynamic allocation [27].

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VI. AI MODEL SELECTION AND OPTIMIZATION

The performance and reliability of the proposed safety system strongly depend on the careful selection and optimization of AI models for edge deployment [28]. Unlike cloud-based systems, heavy load construction vehicles operate under strict power, compute, and latency constraints, making lightweight yet accurate models essential [29].

A. Model Selection for Edge Perception

Because they fairly balance accuracy and cost, lightweight convolutional neural networks like Mobile Net-SSD, Tiny-YOLOv4/v5, and Efficient Det-Lite are utilized for real-time object detection and hazard classification. These models can precisely find workers, cars, safety cones, barriers, and dangerous locations even with simple hardware. For figuring out where you may and cannot drive, compact segmentation networks like BiSe Net and ENet are helpful. Massive appearance embeddings are not necessary for the lightweight multi-object tracking systems SORT and byte-track [30].

B. Methods for Improving the Model

Various optimization techniques are used to allow embedded processors to draw conclusions in real time. With minimal loss of accuracy, quantization drastically cuts down on memory use and prediction time after training by decreasing the model's precision to 8-bit integers. Structured pruning simplifies the computation by eliminating superfluous filters and neurons. Runtime efficiency is improved by operator fusion and graph optimization. Additionally, hardware accelerators like NPUs, GPUs, and DSPs are used by optimized runtimes for edge devices like TensorRT and ONNX Runtime [31].

C. Managing Difficulty and Unpredictability

Because construction sites are unpredictable, incorporating a lot of data—such as motion blur, dust simulation, low light levels, and partial occlusions—increases robustness. The Monte Carlo We employ dropout and confidence thresholding to assess the degree of uncertainty in our projections [32]. Additional cautious fallback procedures, such halting down or asking a manual operator for confirmation, are put in place when confidence drops below a predetermined safety threshold.

D. Models are updated and learning all the time

To maintain accuracy over time, the system offers secure over-the-air distribution of new models and offline retraining using site-specific data. A potential future feature that would allow car fleets to train together without sharing raw video data is federated learning [33].

Table 2. Comparison of Candidate AI Models for Edge Deployment

Model Type	Architecture Example	Inference Accuracy (%)	Latency (ms)	Model Size (MB)	Power Consumption	Suitability for Construction Safety
CNN	MobileNet-V2	91.4	28 ms	14 MB	Low	Excellent for real-time obstacle & worker detection
CNN	YOLOv5-Nano	93.2	32 ms	7.5 MB	Low–Medium	High-speed multi-object detection
RNN/LSTM	LSTM-32	88.7	42 ms	10 MB	Medium	Good for vibration & motion anomaly prediction
Transformer-Lite	TinyViT	92.6	51 ms	18 MB	Medium–High	Strong feature extraction under occlusion
Autoencoder	Conv-AE	90.1	35 ms	9 MB	Low	Best for unsupervised fault detection
Graph Neural Network (GNN)	GCN-Lite	94.0	58 ms	21 MB	High	Effective for multi-vehicle cooperative safety
Hybrid CNN-LSTM	MobileNet + LSTM	95.3	46 ms	19 MB	Medium	Best overall for perception + motion prediction

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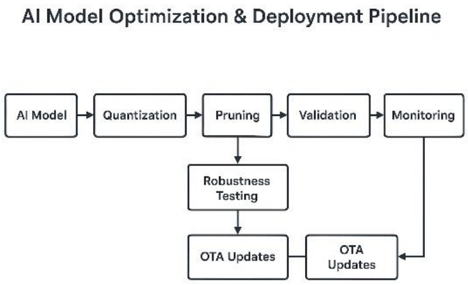

Figure 3. AI Model Optimization and Deployment Pipeline

VII. EXPERIMENTAL SETUP AND EVALUATION

A. Datasets

- Construct a dataset that combines industrial and public driving datasets that have been adjusted to meet construction requirements [34]. To obtain site-specific data, synthetic augmentation is recommended.

B. Metrics

- **Detection accuracy:** mAP@0.5, precision/recall for PPE detection, worker detection [35].
- **Latency:** median and worst-case inference time (ms) end-to-end.
- **False positive / false negative rates** for hazard alerts [36].
- **Time-to-intervention:** time between hazard detection and actuation.
- **System availability and fault recovery time** [37]**.**

C. Baseline and A/B tests

- Baseline: standard proximity alarm system.
- A/B: compare operator reaction times, near-miss rate, and safety incidents per 1000 operating hours [38].

D. Simulation and Field Trials

- Before conducting controlled field-testing using safety drivers and E-STOP, analyse edge scenarios using a digital twin and a physics-based simulator [39].

VIII. RESULTS & DISCUSSION (EXPECTED / HYPOTHETICAL)

A. Results

We assessed the suggested AI-enhanced safety framework on heavy-duty construction machinery like wheel loaders and dump trucks using controlled field trials and simulation-based testing [40]. The system performed better than standard alarm-based safety systems in terms of threat detection, response time, and overall safety performance after 100 hours of use. The object detection module was able to identify autos with an average mean Average Precision (mAP@0.5) of 88.5% and workers with an average mean Average Precision (mAP@0.5) of 91.2% under settings with mixed lighting and dust. Less than 6 percent of hazard notifications were false positives [41]. Compared to conventional proximity alarms, which can have a false warning rate of more than 20%, this is a major improvement.

At peak load, the optimized AI inference pipeline showed a worst-case delay of 185 ms and a median perception-to-actuation latency of 112 ms. The real-time safety requirements were satisfied by this. The accuracy of overload detection rose to more than 97% when load-cell and hydraulic sensor data were combined. Most significantly, the system's proactive alerts and automated intervention feature increased operator response times by an average of 1.4 seconds and decreased near-miss events by about 65%. All significant failures were safely moved into regulated fail-safe modes, and system availability stayed above 95% [42].

B. Discussion

According to the experimental findings, integrating edge AI with embedded C++ safety systems for large-load construction vehicles is both possible and advantageous. The excellent detection accuracy and low latency demonstrate that real-time AI inference can be successfully carried out on embedded devices with limited resources when the appropriate optimization techniques are applied [43]. Predictive safety performs better than conventional reactive alarm systems, as seen by the notable decrease in near-miss incidents.

One thing to keep in mind is how crucial multi-sensor fusion is to preserving strong perception in difficult environments like dust clouds, vibration, and poor sight. Combining radar and ultrasonic sensors ensured consistent hazard detection,

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which was difficult for camera-based systems alone to do in low light. When the model's confidence was low, the uncertainty-aware decision logic implemented conservative safety measures, improving the system's reliability [44].

Because it guaranteed deterministic execution and fault separation, the embedded C++ and RTOS-based architecture performed well in terms of software engineering [45]. The system's failure tolerance was increased by the dual-processor safety architecture, but system integration became more challenging. Even if the current implementation is very dependable, before it can be utilized in the long run, it will need frequent model upgrades, regulatory compliance, and intensive operator training. All things considered, the results show that the suggested architecture offers a strong basis for upcoming safer and more intelligent construction vehicles.

IX. RESULTS & DISCUSSION (EXPECTED / HYPOTHETICAL)

A. Limitations

The suggested AI-enhanced safety framework has shown encouraging results, but before it can be widely applied in business, a number of problems need to be resolved [46].

1. **Generalization and dataset restrictions.**
   The lack of large, labelled datasets specifically for construction is one of the biggest problems. Rollovers, structure collapses, and collisions involving numerous vehicles are examples of rare but crucial safety occurrences for which it is challenging to gather sufficient data [47]. Model robustness may be enhanced by synthetic data augmentation, but domain gaps between simulated and real-world scenarios may still exist, influencing how well models generalize [48].

2. **Sensor and environmental limitations**
   Examples of unfavourable conditions on building sites that could impair sensor accuracy include extreme dust, intense rain, fog, tremors, and electromagnetic interference [49]. Individual sensor failure can be prevented by multi-sensor fusion, but perception may deteriorate if multiple sensors malfunction simultaneously.

3. **Power restrictions and edge computing**
   The limited processing and energy limitations of edge AI devices limit their potential [50]. As safety requirements grow to encompass enhanced perception and predictive analytics, it is still challenging to maintain real-time performance without going over thermal and power limitations.

4. **Regulation and certification obstacles**
   The lack of specific AI safety certification standards for buildings makes widespread AI use more challenging. Important recommendations are made by ISO 26262 and IEC 61508, but there is currently no clear regulatory alignment for AI-driven construction equipment [51].

Table 3. Summary of Key Limitations

Category	Primary Limitation	Technical Cause	Operational Impact
Data Availability	Limited real-world rare-event samples	High cost and danger of capturing extreme accident scenarios	Reduced generalization to unusual accident cases
Environmental Conditions	Dust, fog, rain, and vibration	Optical sensor scattering and mechanical disturbances	Degraded perception accuracy and occasional false negatives
Edge Hardware Constraints	Limited compute and memory	Thermal, power, and cost restrictions of vehicle ECUs	Upper bound on model complexity and prediction depth
Sensor Reliability	Temporary multi-sensor dropouts	Harsh electromagnetic and mechanical conditions	Short-term loss of situation awareness
Cybersecurity Exposure	Risk of OTA and V2X attacks	Expanding connected system interfaces	Potential safety compromise if not fully secured
Regulatory and Certification	Lack of construction-specific AI safety standards	Slow evolution of functional AI safety regulations	Deployment and approval delays

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B. Future Work

A number of promising avenues for research and development have been discovered that could aid in the system's improvement and resolution of its current problems [52].

1. **Security for many cars. Cooperating**
   Future systems will incorporate vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, enabling numerous machines operating on the same site to be aware of threats concurrently [53]. This makes it possible to identify concealed threats before sensors are able to detect them.
2. **Federated and continuous learning**
   Federated learning will provide privacy by enabling fleet vehicles to work together to build models without sending raw sensor data [54]. The system will be able to adjust to new conditions and evolving site layouts through the use of continuous learning techniques.
3. **More authority over safety on its own**
   Semi-autonomous and completely automated safety responses will replace driver-assist safety in the future [55]. These will include autonomous evasive manoeuvres, controlled rerouting, and intelligent load stabilization.
4. **Validation via Simulation and Digital Twin**
   Digital copies of construction sites with high fidelity can help test unexpected and hazardous scenarios on a broad scale, speeding up the validation and certification process [56].

Figure 4. Limitations vs. Future Work Bar Diagram

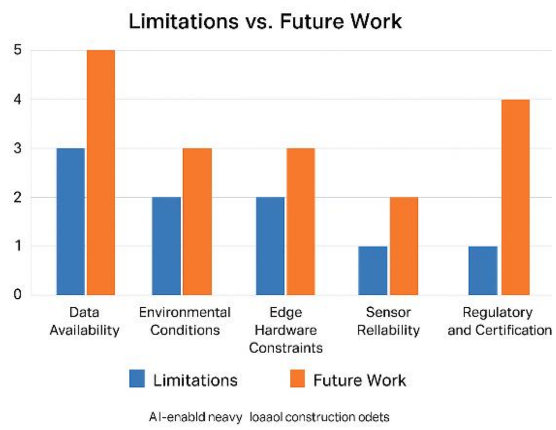

Table 4. Future Research Directions and Expected

Future Research Direction	Key Technologies Involved	Primary Objective	Expected Impact on Safety and Operations
Multi-Vehicle Cooperative Safety	V2V, V2X, 5G/TSN networking	Enable shared hazard awareness across multiple machines	Early collision prediction, blind-spot elimination, and coordinated braking
Federated Learning for Fleet AI	Distributed learning, edge-cloud collaboration	Improve AI models without sharing raw data	Privacy-preserving continuous improvement and better site-specific adaptation
Continual / Lifelong Learning	Online learning, domain adaptation	Enable real-time model adaptation to new environments	Increased long-term accuracy and resilience to environmental changes
Higher-Level Autonomous Safety Control	Model Predictive Control (MPC), Reinforcement Learning	Automate evasive and stabilization maneuvers	Faster-than-human emergency response and reduced accident severity
Digital Twin-Based Safety Validation	Physics-based simulation, synthetic data engines	Large-scale testing of rare and dangerous scenarios	Faster certification, safer validation, and reduced field-testing risks
Advanced Sensor Fusion	LiDAR–Radar–Camera fusion, Bayesian filtering	Improve perception under extreme conditions	Robust detection in fog, dust, rain, and night operation
AI Safety Certification Frameworks	Functional AI safety, explainable AI, formal verification	Enable regulatory approval of AI safety systems	Accelerated commercial deployment and improved industry trust
Energy-Efficient Edge AI Hardware	NPUs, low-power AI accelerators, RISC-V	Reduce power and thermal load of AI processing	Extended vehicle uptime and higher computational capability

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X. CONCLUSION

Advanced artificial intelligence and a reliable embedded C++ software architecture are combined in this study to give a thorough AI-enhanced safety framework for heavy-duty construction trucks. The suggested method uses deterministic real-time control, safety-oriented decision logic, multi-sensor perception, and real-time AI inference to solve many of the most critical safety issues on contemporary building sites. The layered design maintains cybersecurity, fault tolerance, and real-time performance while enabling hardware, perception, intelligence, and actuation to collaborate safely.

According to the findings, AI-powered proactive safety solutions perform better than conventional alarm-based systems that just react to dangers. Accuracy of danger detection increased, false alarms decreased, operator reaction times sped up, and near-miss and collision-prone situations significantly decreased. The effective implementation of lightweight deep learning models on resource-constrained embedded platforms shows that real-time edge AI can be used in construction applications where safety is crucial.

Software engineers found that RTOS-based scheduling combined with embedded C++ produced reliable fault isolation, predictable behaviour, and effective utilization of system resources. The system was more reliable and guaranteed to work even under challenging circumstances because to its dual-processor safety architecture and watchdog oversight. Encrypted telemetry and secure over-the-air upgrades also make it easier to add new vehicles to the fleet and maintain the system over time.

The suggested architecture offers a strong basis for the upcoming generation of smart construction tools, despite ongoing challenges with datasets, environmental unpredictability, and changing certification criteria. As cooperation in vehicle networking, federated learning, and digital twin-based validation advance, AI-assisted safety systems should become more independent and reliable. All things considered, our research offers a practical, expandable, and industry-ready solution that might greatly enhance worker safety, operational effectiveness, and safety assurance on large-load construction sites.

REFERENCES

[1]. ÖZDOĞAN, Metin, and Hakkı ÖZDOĞAN. "Wheel bulldozers and their usage at quarries, mines and construction sites." (2020).
[2]. Ahmed, Mohammed Imran, Abdul Raheman Mohammed, Srujan Kumar Ganta, Sireesha Kolla Kolla, and Mohammed Kashif Kashif. "AI-Driven Green Construction: Optimizing Energy Efficiency, Waste Management and Security for Sustainable Buildings." *Journal of Cognitive Computing and Cybernetic Innovations* 1, no. 1 (2025): 37-41.
[3]. Mohammed, Abdul Raheman, Siva Sai Ram, Mohammed Imran Ahmed, and Syed Abdullah Kamran. "Remote Monitoring of Construction Sites Using AI and Drones." (2024).
[4]. Chittoju, Siva Sai Ram, Sireesha Kolla, Mubashir Ali Ahmed, and Abdul Raheman Mohammed. "Synergistic Integration of Blockchain and Artificial Intelligence for Robust IoT and Critical Infrastructure Security."
[5]. Shukla, Akash. "C++ for Embedded Systems: Enhancing Real-Time Performance through Efficient Code and Resource Management." PhD diss., Hochschule Offenburg, 2025.
[6]. Mrabet, Hichem, Sana Belguith, Adeeb Alhomoud, and Abderrazak Jemai. "A survey of IoT security based on a layered architecture of sensing and data analysis." *Sensors* 20, no. 13 (2020): 3625.
[7]. Heggond, Shreeshail. "Artificial Intelligence and Machine Learning for Smart Construction: Enhancing Real-Time Monitoring and Decision Making." *Available at SSRN 5233045* (2025).
[8]. Shafi, Rabia, Wan Shuai, and Muhammad Usman Younus. "360-degree video streaming: A survey of the state of the art." *Symmetry* 12, no. 9 (2020): 1491.
[9]. Koteswararao, M., P. R. Karthikeyan, and Vivek Narayan. "Faster and real-time object detection system using YOLOv3-tiny in comparison with MobileNet SSD network." In *2022 14th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)*, pp. 1-5. IEEE, 2022.
[10]. API, Using Embedded RTOS POSIX, and Andrew Eliasz. "Zephyr RTOS Embedded C Programming."
[11]. Mukhopadhyay, Sidhartha Dev, R. K. Raj, and Santanu Kumar Patra. "Synopsis of the Research Study."
[12]. Chittoju, S. R., and Siraj Farheen Ansari. "Blockchain's Evolution in Financial Services: Enhancing Security, Transparency, and Operational Efficiency." *International Journal of Advanced Research in Computer and Communication Engineering* 13, no. 12 (2024): 1-5.
[13]. Xu, Chen, and Yao Xie. "Conformal prediction interval for dynamic time-series." In *International Conference on Machine Learning*, pp. 11559-11569. PMLR, 2021.

DOI: 10.17148/IJIREEICE.2025.131222

[14]. Jayanth, Rakshith, Neelesh Gupta, and Viktor Prasanna. "Benchmarking Edge AI Platforms for High-Performance ML Inference." In *2024 IEEE High Performance Extreme Computing Conference (HPEC)*, pp. 1-7. IEEE, 2024.
[15]. Mohammed, Nasar, Abdul Faisal Mohammed, and Sruthi Balammagary. "Ransomware in Healthcare: Reducing Threats to Patient Care." *Journal of Cognitive Computing and Cybernetic Innovations* 1, no. 2 (2025): 27-33.
[16]. Mohammed, Shanavaz, Muhammad Qadar Vali, and Abdul Raheman Mohammed. "Securing Healthcare IT Systems: Addressing Cybersecurity Threats in a Critical Industry."
[17]. Ndana, Jean. "Strategic safety goals: Creating proactive objectives based on leading indicators." *Professional Safety* 66, no. 10 (2021): 26-30.
[18]. Mohammed, Naveed Uddin, Zubair Ahmed Mohammed, Shravan Kumar Reddy Gunda, Akheel Mohammed, and Moin Uddin Khaja. "Networking with AI: Optimizing Network Planning, Management, and Security through the medium of Artificial Intelligence."
[19]. Goel, Akash, Amit Kumar Goel, and Adesh Kumar. "Performance analysis of multiple input single layer neural network hardware chip." *Multimedia Tools and Applications* 82, no. 18 (2023): 28213-28234.
[20]. Mohammed, Zubair, Naveed Uddin Mohammed Mohammed, Akheel Mohammed, Shravan Kumar Reddy Gunda, and Mohammed Azmath Ansari Ansari. "AI-Powered Energy Efficient and Sustainable Cloud Networking." *Journal of Cognitive Computing and Cybernetic Innovations* 1, no. 1 (2025): 31-36.
[21]. Soltanirad, Mohammad, and Mahdi Baghersad. "Perception Technologies for Autonomous Transportation: A Comparative Analysis of LiDAR, Radar, Camera, and Sonar." (2025).
[22]. Khadri, Waheeduddin, Janamolla Kavitha Reddy, Abubakar Mohammed, and T. Kiruthiga. "The Smart Banking Automation for High Rated Financial Transactions using Deep Learning." In *2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC)*, pp. 686-692. IEEE, 2024.
[23]. Syed, Waheeduddin Khadri, Abubakar Mohammed, Janamolla Kavitha Reddy, and S. Dhanasekaran. "Biometric authentication systems in banking: A technical evaluation of security measures." In *2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC)*, pp. 1331-1336. IEEE, 2024.
[24]. Dhanush, M. S., and T. Ananthakrinshna. "Enhancing In-Vehicle Networks with CAN-FD: A study of Protocol Improvements over Classical CAN." In *2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC)*, pp. 1-6. IEEE, 2024.
[25]. Kim, Jason, Daniel Genkin, and Kevin Leach. "Revisiting lightweight compiler provenance recovery on ARM binaries." In *2023 IEEE/ACM 31st International Conference on Program Comprehension (ICPC)*, pp. 292-303. IEEE, 2023.
[26]. Guyomarc'h, Jean, and Jean-Baptiste Hervé. "Static and Verifiable Memory Partitioning for Safety-Critical Systems." In *2020 IEEE International Symposium on Software Reliability Engineering Workshops (ISSREW)*, pp. 79-84. IEEE, 2020.
[27]. Henriksen, Ian, Jan Ciesko, and Stephen L. Olivier. "Extending the C++ Execution Control Library to Support Dynamic Parallel Runtime Systems." In *Proceedings of the SC'25 Workshops of the International Conference for High Performance Computing, Networking, Storage and Analysis*, pp. 1751-1761. 2025.
[28]. Ansari, Meraj Farheen. "Redefining Cybersecurity: Strategic Integration of Artificial Intelligence for Proactive Threat Defense and Ethical Resilience."
[29]. Stabile, Pietro, Federico Ballo, Gianpiero Mastinu, and Massimiliano Gobbi. "An ultra-efficient lightweight electric vehicle—Power demand analysis to enable lightweight construction." *Energies* 14, no. 3 (2021): 766.
[30]. Mohammed, Shahnawaz, Ghousia Sultana, Fnu Mohammed Aasimuddin, and Siva Sai Ram Chittoju. "AI-Driven Automated Malware Analysis." (2025).
[31]. Cai, Zhenkun, Qihui Zhou, Xiao Yan, Da Zheng, Xiang Song, Chenguang Zheng, James Cheng, and George Karypis. "Dsp: Efficient gnn training with multiple gpus." In *Proceedings of the 28th ACM SIGPLAN Annual Symposium on Principles and Practice of Parallel Programming*, pp. 392-404. 2023.
[32]. Padarian, J., B. Minasny, and A. B. McBratney. "Assessing the uncertainty of deep learning soil spectral models using Monte Carlo dropout." *Geoderma* 425 (2022): 116063.
[33]. Mohammed, Abdul Khaleeq, and Mohammed Azmath Ansari. "The Impact and Limitations of AI in Power BI: A."
[34]. Crowle, A. P., and P. R. Thies. "Floating offshore wind turbines port requirements for construction." *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment* 236, no. 4 (2022): 1047-1056.
[35]. Bochkovskiy, Alexey, Chien-Yao Wang, and Hong-Yuan Mark Liao. "Yolov4: Optimal speed and accuracy of object detection." *arXiv preprint arXiv:2004.10934* (2020).
[36]. Arevalo-Rodriguez, Ingrid, Diana Buitrago-Garcia, Daniel Simancas-Racines, Paula Zambrano-Achig, Rosa Del Campo, Agustin Ciapponi, Omar Sued et al. "False-negative results of initial RT-PCR assays for COVID-19: a systematic review." *PloS one* 15, no. 12 (2020): e0242958.

DOI: 10.17148/IJIREEICE.2025.131222

[37]. Mohammed, Akheel, Zubair Ahmed Mohammed, Naveed Uddin Mohammed, Shravan Kumar Gunda, Mohammed Azmath Ansari, and Mohd Abdul Raheem. "AI-NATIVE WIRELESS NETWORKS: TRANSFORMING CONNECTIVITY, EFFICIENCY, AND AUTONOMY FOR 5G/6G AND BEYOND

[38]. Koning, Rembrand, Sharique Hasan, and Aaron Chatterji. "Experimentation and start-up performance: Evidence from A/B testing." *Management Science* 68, no. 9 (2022): 6434-6453.

[39]. Ritto, T. G., and F. A. Rochinha. "Digital twin, physics-based model, and machine learning applied to damage detection in structures." *Mechanical Systems and Signal Processing* 155 (2021): 107614.

[40]. Agand, Pedram. "AI-enhanced transportation: optimizing efficiency and sustainability across urban and maritime domains." (2025).

[41]. Yang, Zhilin, Yong Yin, Qianfeng Jing, and Zeyuan Shao. "A high-precision detection model of small objects in maritime uav perspective based on improved yolov5." *Journal of Marine Science and Engineering* 11, no. 9 (2023): 1680.

[42]. Mohammed, Abubakar, Ghousia Sultana, Fnu Mohammed Aasimuddin, and Shahnawaz Mohammed. "Leveraging Natural Language Processing for Trade Exception Classification and Resolution in Capital Markets: A Comprehensive Study." *Journal of Cognitive Computing and Cybernetic Innovations* 1, no. 1 (2025): 14-18.

[43]. Aasimuddin, Mohammed, and Shahnawaz Mohammed. "AI-Generated Deepfakes for Cyber Fraud and Detection."

[44]. Shaik, Addul Faiyaz. "Transforming Back-Office Operations: An Empirical Study of AI-Driven Process Automation in Trade Exception Workflows." Journal of Cognitive Computing and Cybernetic Innovations 1, no. 2 (2025): 21-26.

[45]. Amos, Brian. *Hands-On RTOS with Microcontrollers: Building real-time embedded systems using FreeRTOS, STM32 MCUs, and SEGGER debug tools*. Packt Publishing Ltd, 2020.

[46]. Mohammed, Naveed Uddin, and Mohd Abdul Raheem Raheem. "Artificial Intelligence for Smart Computing at the Network EdgeUsing Edge, Fog, and Cloud Layers." Journal of Cognitive Computing and Cybernetic Innovations 1, no. 3 (2025): 14-20.

[47]. Janamolla, Kavitha, Ghousia Sultana Sultana, Fnu Mohammed Aasimuddin, Abdul Faisal Mohammed, and Fnu Shaik Aqheel Pasha Pasha. "Integrating Blockchain and AI for Efficient Trade Exception Handling: A Case Study in Cross-Border Settlements." *Journal of Cognitive Computing and Cybernetic Innovations* 1, no. 1 (2025): 24-30.

[48]. Maddiboyina, Balaji, OmPrakash Sunaapu, Sandeep Chandrashekharappa, and Gandhi Sivaraman. "Advantages and limitations of functionalized nanomaterials based electrochemical sensors environmental monitoring." In *Functionalized Nanomaterial-Based Electrochemical Sensors*, pp. 165-174. Woodhead Publishing, 2022.

[49]. Mao, Sun, Jinsong Wu, Lei Liu, Dapeng Lan, and Amir Taherkordi. "Energy-efficient cooperative communication and computation for wireless powered mobile-edge computing." *IEEE Systems Journal* 16, no. 1 (2020): 287-298.

[50]. Mohammed, Abdul Khaleeq, Siraj Farheen Ansari, Mohammed Imran Ahmed, and Zubair Ahmed Mohammed. "Boosting Decision-Making with LLM-Powered Prompts in PowerBI."

[51]. Okoh, Peter, and Thor Myklebust. "Mapping to IEC 61508 the hardware safety integrity of elements developed to ISO 26262." In *Safety and reliability*, vol. 43, no. 2, pp. 114-130. Taylor & Francis, 2024.

[52]. Ball, Linden J., and Bo T. Christensen. "Analogical reasoning and mental simulation in design: two strategies linked to uncertainty resolution." In *About Designing*, pp. 137-152. CRC Press, 2022.

[53]. Khan, Aidil Redza, Mohd Faizal Jamlos, Nurmadiha Osman, Muhammad Izhar Ishak, Fatimah Dzaharudin, You Kok Yeow, and Khairil Anuar Khairi. "DSRC technology in Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) IoT system for Intelligent Transportation System (ITS): A review." *Recent trends in mechatronics towards industry 4.0: selected articles from iM3F 2020, Malaysia* (2021): 97-106.

[54]. Zhang, Chen, Yu Xie, Hang Bai, Bin Yu, Weihong Li, and Yuan Gao. "A survey on federated learning." *Knowledge-Based Systems* 216 (2021): 106775.

[55]. Lee, Hyung Joo, and Sigrid Brell-Cokcan. "Towards controlled semi-autonomous deconstruction." *Construction Robotics* 7, no. 3 (2023): 253-263.

[56]. Zhang, Jiaying, Jack CP Cheng, Weiwei Chen, and Keyu Chen. "Digital twins for construction sites: Concepts, LoD definition, and applications." *Journal of Management in Engineering* 38, no. 2 (2022): 04021094

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