

PLENARY SESSION

Trustworthy edge intelligence in engineering today: Applications in industrial control, robotics and transport engineering

Žarko Čojbašić^{1*}, Goran Petrović¹

¹ University of Niš, Faculty of Mechanical Engineering, Niš, Serbia

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* Correspondence: zcojba@ni.ac.rs

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ABSTRACT

Artificial intelligence is rapidly transforming modern engineering systems, enabling unprecedented levels of autonomy, adaptability, and real-time decision-making in industrial automation, robotics, and intelligent transportation systems. However, the increasing deployment of complex machine-learning models in safety-critical applications introduces significant challenges related to transparency, interpretability, reliability, and trustworthiness. This invited plenary paper presents a synthesis of the authors' recent research results focused on trustworthy edge intelligence for engineering applications, with particular emphasis on explainable artificial intelligence (XAI), edge computing, and resource-constrained intelligent systems. The paper presents recent developments in explainable AI approaches for industrial automation and robotics, including hybrid deep-learning and ANFIS-based architectures for interpretable industrial decision support and machine-vision applications. Recent results in TinyML- and Industrial Internet of Things (IIoT)-based intelligent edge systems for low-cost industrial quality control are also discussed. In transport engineering, special attention is devoted to edge-AI implementations for intelligent transportation systems based on YOLO and Grad-CAM approaches deployed on embedded platforms such as NVIDIA Jetson devices and Raspberry Pi systems equipped with AI accelerators. Comparative analyses of performance, explainability, energy efficiency, and deployment suitability are presented. Finally, future directions toward human-centered, explainable, and trustworthy intelligent engineering systems are discussed in the broader context of engineering today and emerging Industry 5.0 paradigms.

KEYWORDS

Trustworthy Artificial Intelligence, Explainable Artificial Intelligence, Edge Computing, Industrial Automation, Robotics, Intelligent Transportation Systems.

1. INTRODUCTION

Artificial intelligence (AI) is increasingly transforming modern engineering systems by enabling autonomous operation, adaptive decision-making and intelligent data processing across a broad range of applications. Recent advances in machine learning, computer vision and intelligent data analytics have significantly expanded the capabilities of engineering systems operating in dynamic and complex environments [1, 2]. Such developments have accelerated the adoption of AI technologies in industrial automation, robotics and transport engineering, where intelligent systems are expected to support reliable operation, improved efficiency and enhanced decision-making under real-world conditions [3, 4]. Furthermore, the growing availability of embedded computing platforms has facilitated the deployment of intelligent algorithms directly within engineering systems, bringing computational intelligence closer to sensors, actuators and end users [5, 6].

Despite their remarkable predictive capabilities, many contemporary AI models remain difficult to interpret due to their inherent complexity. This limitation is particularly important in safety-critical and mission-critical engineering applications, where understanding the rationale behind automated decisions is often as important as achieving high predictive performance [7, 8]. In industrial automation, robotics and intelligent transportation systems, engineers and operators increasingly require transparent and trustworthy decision-support mechanisms capable of providing insight into the reasoning process of intelligent systems [9, 10]. Consequently, explainable artificial intelligence (XAI) has emerged as an important research direction aimed at improving model interpretability, transparency and user trust while maintaining the advantages of modern machine-learning approaches [8, 9].

At the same time, the growing demand for real-time processing, reduced communication latency, privacy preservation and increased operational autonomy has accelerated the development of Edge AI solutions [5, 6]. By performing inference directly on embedded and resource-constrained devices, Edge AI enables intelligent operation without continuous dependence on cloud infrastructure. Recent advances in TinyML - a class of machine-learning approaches designed for execution on microcontrollers and other resource-constrained edge devices, Industrial Internet of Things (IIoT) technologies and specialised AI accelerators have further expanded the applicability of Edge AI across diverse engineering domains, supporting the deployment of intelligent systems in industrial environments, robotic platforms and transportation infrastructure [11, 12].

While XAI addresses the need for transparency and trust, and Edge AI addresses the requirements of efficient deployment and real-time operation, their simultaneous implementation remains a significant challenge. The convergence of these two paradigms gives rise to Edge Explainable Artificial Intelligence (Edge XAI), where explainability mechanisms are integrated directly into edge-deployed intelligent systems [13, 14]. Such an approach enables trustworthy edge intelligence capable of combining computational efficiency, real-time responsiveness and interpretable decision-making within practical engineering environments. As engineering systems become increasingly autonomous and interconnected, Edge XAI is emerging as a promising framework for balancing performance, transparency and trustworthiness.

This invited plenary paper presents a synthesis of the authors' recent research results in Edge AI, XAI and intelligent engineering systems [15, 16, 17, 18, 19, 20, 21, 22]. Particular attention is devoted to the emerging concept of Edge Explainable Artificial Intelligence (Edge XAI) and its application in industrial control, robotics and transport engineering. Through representative examples and experimental studies conducted on embedded platforms, the paper highlights the role of Edge XAI in enabling trustworthy edge intelligence and discusses future directions aligned with Engineering Today and the evolving paradigms of Industry 4.0 and Industry 5.0 [1]. The convergence of Edge AI and Explainable AI, referred to here as Edge XAI, provides a practical framework for achieving trustworthy edge intelligence in contemporary engineering applications and represents a promising pathway towards the development of trustworthy engineering systems operating under real-time and resource-constrained conditions.

2. EDGE EXPLAINABLE ARTIFICIAL INTELLIGENCE (EDGE XAI)

2.1. Edge AI Foundations

The rapid development of embedded computing technologies has significantly expanded the deployment possibilities of artificial intelligence in engineering applications. While conventional AI solutions often rely on cloud-based computation, many industrial and transportation systems require local processing capabilities capable of supporting real-time operation and autonomous decision-making. Consequently, increasing attention has been devoted to Edge AI approaches, where machine-learning and computer-vision algorithms are executed directly on embedded platforms located close to the data source [5, 6]. Such architectures reduce communication latency, improve operational reliability and facilitate intelligent operation in environments where cloud connectivity may be limited or undesirable [5].

Recent advances in embedded machine learning have demonstrated that intelligent algorithms can be successfully deployed across a wide spectrum of edge platforms, ranging from highly resource-constrained microcontrollers to more capable embedded computing systems. TinyML represents an important example of this trend, showing that machine-learning models can be implemented even on devices with very limited computational resources, memory and power consumption [11, 12]. Such approaches facilitate intelligent sensing, monitoring and decision-support functionalities directly at the data source while reducing communication overhead and enabling distributed intelligence. At the same time, the growing availability of low-cost embedded platforms and dedicated AI accelerators has expanded the range of Edge AI applications, allowing increasingly sophisticated machine-learning and computer-vision algorithms to be deployed in practical engineering environments [6]. As a result, modern Edge AI systems can be implemented using a variety of hardware and software solutions tailored to the performance, cost and operational requirements of specific applications.

The practical deployment of Edge AI increasingly relies on heterogeneous computing architectures combining general-purpose processors, graphics processing units and dedicated AI accelerators [6]. Such platforms enable the execution of increasingly sophisticated machine-learning and computer-vision algorithms while satisfying constraints related to computational resources, energy consumption and deployment cost. Recent developments in embedded AI hardware have therefore created new opportunities for implementing advanced intelligent systems in industrial automation, robotics and intelligent transportation applications [17, 19, 20].

2.2. Principles of Explainable Artificial Intelligence (XAI)

The growing adoption of machine-learning and deep-learning methods in engineering systems has highlighted the need for greater transparency in automated decision-making. Although state-of-the-art models frequently achieve high predictive accuracy, their internal decision processes often remain difficult to interpret [8, 9]. This limitation is particularly important in engineering environments where safety, reliability and accountability represent essential operational requirements. Consequently, understanding the factors that influence model predictions has become an important prerequisite for the successful deployment of intelligent systems in practice [7, 8].

Explainable Artificial Intelligence (XAI) encompasses a broad range of methods aimed at improving the transparency and interpretability of machine-learning models [8, 9]. By providing insights into model behaviour and decision-making processes, XAI supports validation of intelligent systems and facilitates the identification of potential errors, biases and unexpected behaviour. Furthermore, explainability contributes to the development of trustworthy AI systems by enabling engineers and operators to better understand, verify and evaluate automated decisions before they are applied in real-world environments [10].

Different explainability approaches have been proposed for engineering applications, ranging from inherently interpretable models to post-hoc explanation techniques applicable to complex deep-learning architectures [8, 9]. Figure 1 presents a taxonomy of representative XAI approaches and illustrates the diversity of methods available for improving transparency and interpretability in intelligent engineering systems [15]. In computer-vision applications, gradient-based methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) have attracted considerable attention due to their ability to provide intuitive visual explanations while maintaining compatibility with high-performance convolutional neural networks [23, 24, 25]. Such approaches enable visual interpretation of model predictions and support the practical adoption of explainable AI in engineering systems.

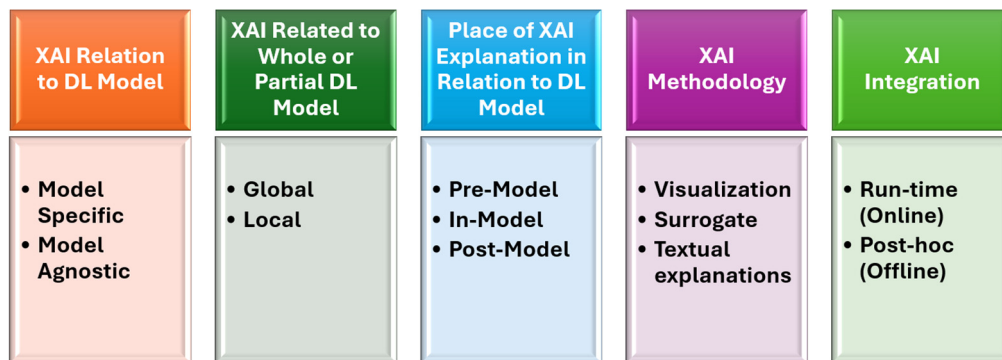


Figure 1: An approach to the taxonomy of XAI approaches [15]

2.3. Edge XAI as an Enabler of Trustworthy Intelligence

The increasing complexity of modern engineering systems has created a need for intelligent solutions that are not only computationally efficient but also transparent and interpretable. While Edge AI addresses deployment and real-time processing requirements, and XAI addresses transparency and trustworthiness requirements, many practical engineering applications require both capabilities simultaneously. As mentioned before, this convergence has led to the emergence of Edge Explainable Artificial Intelligence (Edge XAI), in which explainability mechanisms are integrated directly into edge-deployed intelligent systems [13, 14].

Unlike conventional explainability frameworks that are frequently executed offline or within cloud-based environments, Edge XAI aims to generate explanations within the operational environment itself. Such an approach enables continuous monitoring of model behaviour and supports real-time verification of automated decisions. The ability to combine local inference with local explainability is particularly relevant for example in industrial automation, robotics and intelligent transportation systems, where rapid decision-making and operational reliability are critical requirements [17, 18, 21].

By integrating explainability directly into embedded intelligent systems, Edge XAI supports the development of human-centred engineering solutions in which AI technologies function as collaborative decision-support tools rather than opaque black-box models. Through enhanced transparency, interpretability and operational trust, Edge XAI provides a practical framework for achieving trustworthy edge intelligence and represents an important step towards the next generation of intelligent engineering systems aligned with the evolving paradigms of Industry 4.0 and Industry 5.0 [1], while simultaneously emerging as an increasingly important cornerstone of Engineering Today.

3. APPLICATIONS IN INDUSTRIAL CONTROL AND ROBOTICS

This section presents representative examples from the authors' recent research illustrating how Edge XAI concepts can be applied to practical engineering problems. The selected case studies cover intelligent quality control in industrial control systems and gesture-based human–robot interaction, demonstrating different aspects of trustworthy edge intelligence in industrial and robotic environments.

3.1. Edge XAI for Industrial Quality Control

The increasing availability of low-cost embedded hardware has enabled the deployment of intelligent quality-control systems directly within industrial production environments. Among such applications, apple variety classification in the food industry represents an important quality-control task that has recently attracted increasing attention due to the growing demand for automated inspection and sorting systems. Recent advances in machine vision, Edge AI and Industrial Internet of Things (IIoT) technologies have created new opportunities for implementing automated inspection systems

capable of performing classification and monitoring tasks close to the data source [12, 25, 13]. Such approaches reduce communication requirements, improve responsiveness and support distributed intelligence, making them attractive for modern manufacturing systems [27].

To investigate the feasibility of intelligent quality control on embedded platforms, our recent research explored the integration of the TinyML framework, computer vision and IIoT technologies within an industrial inspection framework [20]. The developed system utilised embedded machine-learning models to perform real-time product classification while operating under the computational constraints typical of industrial edge devices. The proposed architecture demonstrates how intelligent inspection capabilities can be deployed directly within production environments without dependence on cloud-based processing.

The left side of Figure 2 shows the main elements of the industrial experimental setup developed in our previous research [29] and based on heavy duty industrial equipment, including the Siemens Simatic S7-1500 PLC with TM NPU artificial intelligence module, Basler camera and FlexLink conveyor. In contrast, the right side of Figure 2 shows the alternative low-cost Edge AI device for the same quality-classification task, based on an ESP32 platform. Experimental results demonstrated that compact machine-learning models can achieve satisfactory classification performance while maintaining the computational efficiency required for edge deployment on resource-constrained devices [20]. Beyond predictive accuracy, the study highlighted the importance of understanding model behaviour and assessing the suitability of deployed algorithms for practical industrial environments. From the perspective of this invited plenary paper, the presented framework represents an illustrative example of how explainability considerations can complement Edge AI and contribute to more transparent and trustworthy quality-control processes.

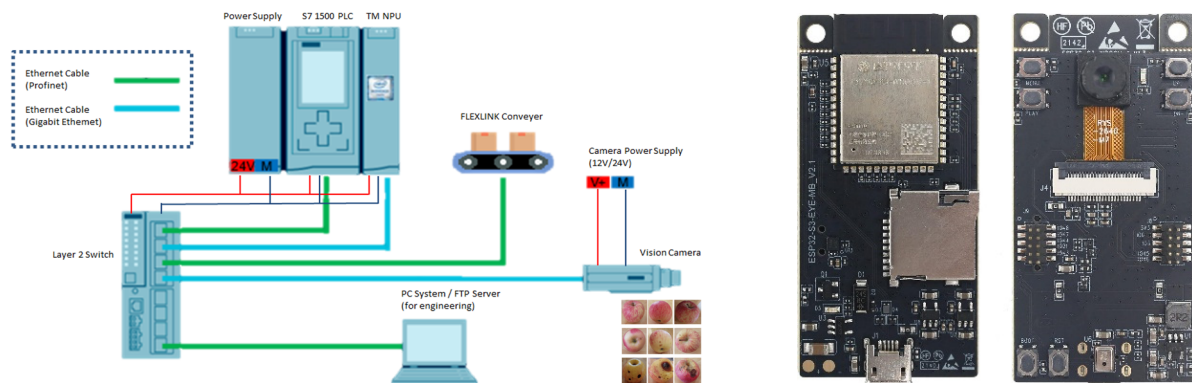


Figure 2: Elements of the experimental setup based on Siemens Simatic 1500 PLC with TM NPU artificial intelligence module, Basler 25 FPS 2 MP Camera and FlexLink conveyor (left) and ESP32-S3-EYE Main Board (right) [20]

It is further worth noticing that industrial control systems increasingly require intelligent functionalities capable of supporting monitoring, prediction and decision-making directly on embedded devices. However, the limited computational resources available on many industrial platforms impose significant constraints on the complexity of deployable machine-learning models [11, 28]. Consequently, TinyML has emerged as a promising approach for bringing machine-learning capabilities to resource-constrained industrial environments [5].

In further recent expansion of our previously mentioned results, several TinyML implementation strategies were investigated and compared within the context of an industrial control application [19]. Particular attention was devoted to analysing the trade-offs between predictive performance, computational requirements and deployment feasibility. Table 1 summarises the TinyML implementation strategies investigated and their performance characteristics. The comparison highlights the trade-offs between computational requirements, memory consumption and predictive performance that must be considered when deploying intelligent algorithms on industrial embedded platforms. The obtained results demonstrated that practical machine-learning functionality can be achieved even on highly constrained embedded platforms, confirming the potential of TinyML for intelligent industrial control.

In addition to TinyML-based approaches, our recent research also investigated a hybrid Convolutional Neural Network (CNN)–Adaptive Neuro-Fuzzy Inference System (ANFIS) framework for the same considered industrial automation problem in the food industry [26]. In the proposed architecture, CNN models were employed to extract discriminative features relevant for apple quality classification, while ANFIS provided interpretable fuzzy-rule-based reasoning capable of relating extracted features to quality classes through linguistic rules. Applied to apple classification and defect detection tasks, the hybrid approach demonstrated how predictive performance and explainability can be combined within a single intelligent system. From the perspective of trustworthy Edge XAI, such inherently interpretable models complement post-hoc explanation techniques by improving transparency, trustworthiness and understanding of AI-assisted decision-making in industrial environments.

Table 1: Model size, accuracy and inference time [19]

Model variant	Size (kB)	Accuracy (%)	S3-EYE Inference time (ms)	WROVER Inference time (ms)
<i>MilliMobileNet</i>	44	82	34.347	/
<i>MicroMobileNet</i>	16	79	29.161	/
<i>NanoMobileNet</i>	5.8	73	6.080	6.595
<i>PicoMobileNet</i>	2.7	68	2.610	2.875

The presented study illustrates that Edge AI deployment on highly resource-constrained devices involves more than achieving satisfactory predictive performance alone. Practical implementation also requires careful consideration of memory usage, computational efficiency and system responsiveness [19]. These factors directly influence the feasibility of deploying intelligent algorithms in industrial environments and therefore represent important design considerations for trustworthy edge intelligence systems.

3.2. Edge XAI for Gesture-Based Human–Robot Interaction

Human–robot interaction represents an important application domain for trustworthy intelligent systems, particularly within emerging Industry 5.0 environments where collaboration between human operators and robotic systems is becoming increasingly important [1, 29, 30]. In our recent work, a vision-based gesture-recognition framework was developed to support intuitive communication between human users and robotic systems [18]. By recognising hand gestures in real time, the proposed approach provides a natural interaction mechanism without requiring specialised control interfaces.

The developed framework combined Edge AI and explainability techniques within a gesture-recognition application deployed on embedded hardware platforms [18]. Experimental evaluation demonstrated that reliable gesture recognition can be achieved under realistic operating conditions while maintaining the computational efficiency required for edge deployment. The results further confirmed the feasibility of implementing intelligent perception algorithms directly on resource-constrained systems intended for practical robotic applications.

The left side of Figure 3 presents representative Grad-CAM and LIME explanations illustrating the image regions contributing most strongly to gesture-recognition decisions, whereas the right side of Figure 3 shows the computational time as a function of batch size for SHAP, LIME and Grad-CAM. Unlike many industrial applications where intelligent systems primarily support machine-centred processes, gesture recognition directly involves interaction with humans. Consequently, transparency and explainability become particularly important for establishing trust and user acceptance [23, 31]. The presented framework therefore represents a compelling example of human-centred Edge XAI, where intelligent perception, embedded deployment and trustworthy decision-making converge within a single robotic application [18].

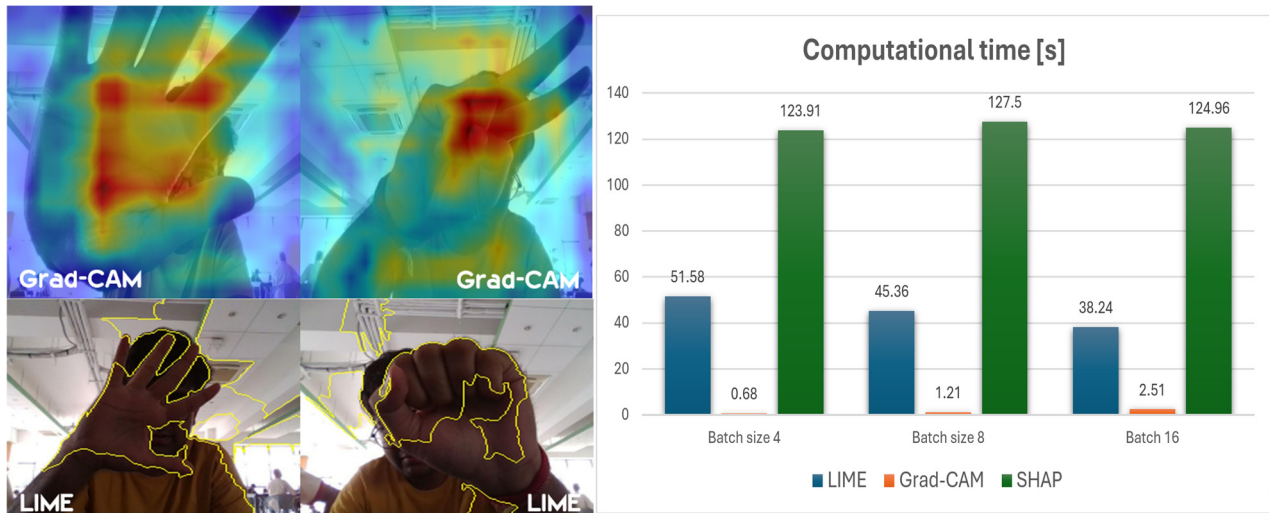


Figure 3: Grad-CAM heatmaps and LIME superpixel explanations illustrating key decision-making regions in sample images (left) and Computational time vs batch size for SHAP, LIME and Grad-CAM (right) [18]

Taken together, the presented case studies demonstrate how Edge XAI can support a broad spectrum of engineering applications ranging from industrial quality control in intelligent control systems to collaborative robotic environments. Although the investigated use cases differ substantially in their objectives and implementation details, they share common requirements for resource-efficient deployment, explainable operation and trustworthy decision-making. These characteristics collectively define the concept of trustworthy edge intelligence explored throughout this paper.

4. APPLICATIONS IN TRANSPORT ENGINEERING

This section presents representative examples from the authors' recent research demonstrating the application of Edge Explainable Artificial Intelligence (Edge XAI) concepts in intelligent transportation systems. The selected case studies address complementary aspects of trustworthy transportation intelligence, including explainable traffic monitoring, intelligent road-intersection management and the deployment of explainable deep-learning models on embedded edge platforms.

4.1. Explainable Artificial Intelligence for Trustworthy Road Intersection Management

Recent advances in computer vision and artificial intelligence have created new opportunities for intelligent traffic monitoring and road-intersection management [32, 33]. In particular, edge-deployed deep-learning systems can support automated vehicle recognition and traffic analysis while reducing dependence on cloud-based infrastructure [5, 6]. However, practical deployment of such systems requires not only accurate predictions but also transparent decision-making mechanisms capable of supporting user trust and operational reliability [8, 10].

To address these requirements, our recent research investigated the integration of explainable artificial intelligence techniques into edge-based road-intersection management systems [16]. By combining deep-learning-based vehicle recognition with visual explanation methods, the proposed framework enables both traffic analysis and interpretation of model decisions. Such an approach allows engineers and operators to verify whether classification outcomes are based on relevant visual features and therefore contributes to the development of trustworthy transportation intelligence.

The left side of Figure 4 presents representative Grad-CAM heatmaps and LIME superpixel explanations illustrating the key image regions contributing to vehicle-recognition decisions in road intersection management, whereas the right side of Figure 4 shows the computational time as a function of batch size for three comparative XAI methods - SHAP, LIME and Grad-CAM. The visual explanations identify image regions contributing most strongly to model predictions and provide insight into the internal reasoning process of the deep-learning model, while the computational performance comparison highlights the practical implications of selecting different explainability methods for deployment in resource-constrained transportation applications [34, 35]. The presented results illustrate how explainability can be incorporated into practical transportation applications and demonstrate an important example of Edge XAI in intelligent transportation systems [16].

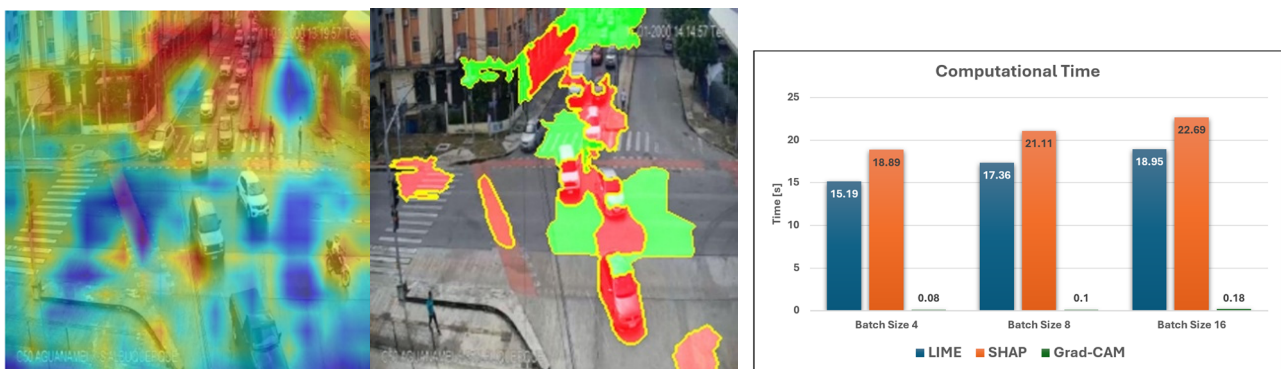


Figure 4: Grad-CAM heatmaps and LIME superpixel explanations illustrating key decision-making regions (left) and computational time vs batch size for SHAP, LIME and Grad-CAM (right) [16]

4.2. Real-Time Explainable Computer Vision for Intelligent Transportation Systems

Computer vision represents one of the most important application domains of artificial intelligence in transportation engineering [36, 37]. Recent developments in deep learning have significantly improved the performance of vehicle detection and classification algorithms, supporting applications such as traffic monitoring, emergency-vehicle recognition and intelligent infrastructure management [38]. In our recent work, YOLO-based deep-learning models were investigated as a foundation for efficient and accurate transportation intelligence systems [21].

Although deep-learning models can achieve high predictive performance, their decision-making processes often remain difficult to interpret [8, 9]. To address this challenge, Grad-CAM visualisation techniques were integrated into the vehicle-recognition framework, enabling visual interpretation of classification outcomes [24]. The resulting explanations facilitate validation of model behaviour and provide additional confidence regarding the correctness of automated decisions.

The left side of Figure 5 illustrates YOLO-based vehicle detection and classification results, whereas the right side of Figure 5 presents the corresponding Grad-CAM visual explanations highlighting the image regions contributing most strongly to the classification decisions. The results demonstrate that explainability can be incorporated into real-time transportation applications without compromising the practical usability of the system. The presented approach therefore represents a practical implementation of Edge XAI capable of combining predictive performance with transparent and interpretable decision-making [21].



Figure 5: (a) YOLO model annotated emergency and non emergency vehicles and (b) Grad-CAM generated heatmap illustrating key decision-making regions [17]

4.3. Embedded Edge XAI Platforms for Transportation Applications

The practical deployment of intelligent transportation systems requires computational platforms capable of supporting real-time inference under constraints related to energy consumption, hardware cost and operational reliability [6, 39]. Consequently, increasing attention has been devoted to embedded AI platforms that enable local processing and low-latency operation directly at the network edge [5, 6].

To investigate the practical feasibility of Edge XAI deployment, our recent research compared two representative embedded AI platforms: NVIDIA Jetson Orin Nano and Raspberry Pi 5 equipped with the Hailo-8L AI accelerator [17]. Both platforms were evaluated with respect to deep-learning inference performance, explainability support and suitability for intelligent transportation applications. The comparison provides valuable insight into the trade-offs associated with different deployment strategies for transportation intelligence systems.

Figure 6 presents the computational performance of the investigated platforms when executing the same deep-learning model with integrated explainability mechanisms. The presented results clearly indicate that platform selection depends strongly on application requirements. While Jetson-based solutions provide superior computational performance and native support for advanced AI frameworks, Raspberry Pi–Hailo systems offer attractive cost and energy-efficiency characteristics [17].

The comparative evaluation further demonstrated that NVIDIA Jetson Orin Nano generally provides higher computational performance and a more integrated CUDA/TensorRT software environment for DL + XAI transportation tasks, particularly when explainability mechanisms are incorporated into the processing pipeline. In contrast, Raspberry Pi 5 combined with the Hailo-8L accelerator offers lower power consumption, lower cost and attractive deployment flexibility, while still maintaining real-time capability for the investigated applications. Although the two platforms differ in computational characteristics, both produced meaningful and visually consistent Grad-CAM explanations, confirming their suitability for practical Edge XAI deployment in intelligent transportation systems. The inclusion of explainability mechanisms further influences overall system behaviour, highlighting the importance of simultaneously considering performance, transparency and deployment constraints.

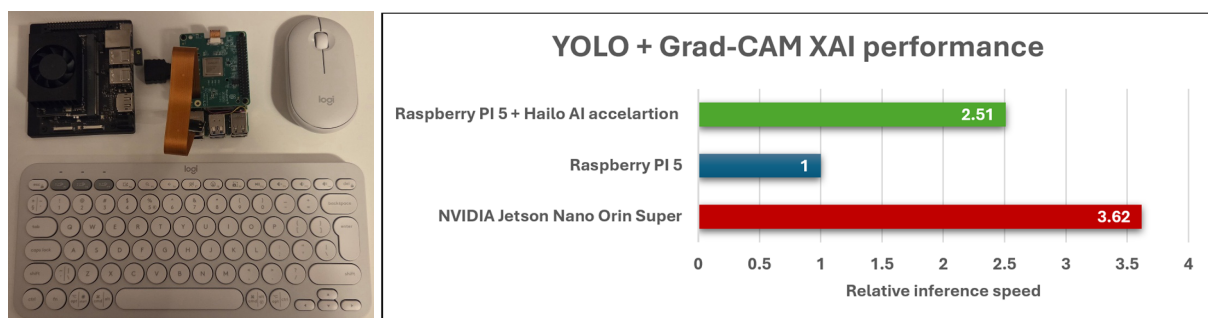


Figure 6: Experimental setup with two Edge AI devices (left) and computational performance of the same model with XAI integrated on two Edge AI devices, average from multiple runs and batch sizes (right) [17]

The presented transportation case studies demonstrate how Edge XAI can support intelligent transportation systems that are not only accurate and computationally efficient but also transparent and trustworthy. The combination of explainable deep learning, embedded deployment and practical performance evaluation illustrates a comprehensive framework for developing next-generation transportation solutions. Furthermore, the presented studies confirm that trustworthy transportation intelligence depends not only on advances in artificial intelligence algorithms but also on the ability to understand, validate and effectively deploy such algorithms in real-world operating environments. These observations reinforce the central thesis of this paper that Edge XAI represents a practical pathway towards trustworthy edge intelligence in transportation engineering.

5. CONCLUSIONS AND FUTURE DIRECTIONS

The presented industrial-control and robotics case studies demonstrate that Edge XAI can successfully support a diverse range of engineering applications, including industrial quality control, intelligent control systems and gesture-based human–robot interaction [18, 19, 20]. The investigated solutions showed that intelligent systems deployed on resource-constrained platforms can simultaneously achieve satisfactory performance and provide interpretable insights into their decision-making processes. The obtained results confirm the practical feasibility of integrating explainability into embedded intelligent systems operating in real-world industrial and robotic environments. Furthermore, the presented studies illustrate that Edge AI technologies can extend advanced machine-learning capabilities beyond cloud-based infrastructures and enable trustworthy intelligent operation directly at the point of use [5, 27].

The transport-engineering case studies further confirmed the potential of Edge XAI for intelligent transportation systems [16, 17, 21]. The combination of deep-learning-based vehicle recognition, Grad-CAM explainability and deployment on embedded AI platforms demonstrated that modern transportation solutions can benefit from both high-performance computer vision and transparent model behaviour. Comparative evaluation of different hardware architectures additionally highlighted the importance of balancing computational performance, energy efficiency and explainability requirements when designing practical transportation intelligence systems [17]. The presented results indicate that trustworthy transportation intelligence increasingly depends not only on predictive accuracy but also on the ability to understand and validate automated decisions in real-world operating conditions [16, 21].

A common observation emerging from all presented case studies is that explainability becomes increasingly important as artificial intelligence moves from laboratory environments towards practical deployment. While Edge AI provides the computational framework necessary for real-time operation [5, 6], explainability contributes transparency, interpretability and user trust [8, 10]. The convergence of these paradigms, referred to in this paper as Edge Explainable Artificial Intelligence (Edge XAI), therefore represents a practical framework for achieving trustworthy edge intelligence across diverse engineering domains. The presented examples demonstrate that the integration of explainability into edge-deployed intelligent systems is not merely a theoretical concept but a practical engineering approach capable of supporting trustworthy decision-making in industrial, robotic and transportation applications [16, 17, 18, 19, 20, 21].

Future research is expected to focus on increasingly integrated Edge XAI solutions capable of providing real-time explanations while operating under stringent resource constraints. Particular attention is likely to be devoted to human-centred intelligent systems, collaborative robotics, adaptive transportation infrastructures and emerging Industry 5.0 environments in which intelligent technologies operate in close cooperation with human users [1, 29]. Advances in embedded AI hardware, TinyML frameworks and explainability methods are expected to further expand the practical applicability of Edge XAI across engineering domains [6, 5, 27]. In this context, trustworthy artificial intelligence is likely to evolve from a desirable system characteristic into a fundamental design requirement, supporting the development of intelligent engineering systems capable of combining autonomy, transparency and human trust [1, 10]. Such developments are closely aligned with the vision of engineering today and the continuing transformation of engineering practice through intelligent technologies.

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