IECON 2024 - 50th Annual Conference of the IEEE Industrial Electronics Society | 978-1-6654-6454-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/IECON55916.2024.10905565

Semantics for Enhancing Communications- and Edge-Intelligence-enabled Smart Sensors: A Practical Use Case in Federated Automotive Diagnostics

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***Abstract*—Modern edge artificial intelligence (AI) chipsets and edge-intelligence-enabled smart sensors frameworks support real-time data processing and event detection at the signal source. Beyond measuring local conditions and transmitting corresponding signals, AI-enabled smart sensors provide the capability to interpret and analyze signals through local analytical operations. Its well-known semantics provide an abstraction layer for better comprehension and self-descriptive applications. This paper identifies and explains the advantages of semantics and ontology engineering in integrating edge AI-enabled smart sensors and their applications into federated automotive systems. Building on demonstrated work using AudioSet for event detection, the application presented as an AI mechanic at the edge demonstrates how smart sensor integration necessitates the re-evaluation of how automotive diagnostic trouble codes (DTCs) are generated and processed. While DTCs and their logic are intended to facilitate correct assembly and repair, they do not always clearly indicate the underlying issue. This paper also underlines the need to review ontologies and semantic models for smart sensor standard specifications in light of AI-enabled smart sensors.**

Keywords— Artificial Intelligence, Automotive Industry, Edge Intelligence, Internet of Things, Ontology Engineering, Semantic Technologies, Smart Sensors.

I. INTRODUCTION

Semantic technologies are largely used in Web applications as developed and recommended by the World Wide Web Consortium (W3C) [1]. Semantics have demonstrated significant capacity for sharing and exchanging information across the Web by adding a data layer for improving knowledge-based services. With the advent of edge artificial intelligence (AI) chipsets and frameworks, semantics are penetrating edge-based technologies to enable real-time event detection at the signal source [2]. In current intelligent environments, new requirements emerge when multiple systems need to be orchestrated, and federated management systems are a solution that has potential for adopting advanced sensors with Edge AI [3][4][5]. The vision for AI-enabled intelligence relies on sensors that will possess the capability not just to transmit signals but also to interpret (knowledge-based) and analyze the aggregated information (semantics) to enable decisions and actions. These smart sensors have more capabilities including: 1) a set of physical sensors, 2) analog signal conditioning, analog-to-digital conversion, and sensor data processing using intelligent-powered algorithms, 3) timing and synchronization by an internal clock with an optional external time reference, and 4) network communications with the physical world [6]. Smart sensor integration will necessitate re-evaluating how semantics can improve actual market sensor communications.

This paper explores the potential of semantics with an automotive use case through a suggested update of the automotive diagnostic trouble codes (DTCs) [7] created by the Society of Automobile Engineers (SAE) International before the rise of Edge AI. AI-enabled smart sensors in vehicles can assert component conditions and cope with the federated management conditions (i.e. continuous connectivity, events processing, orchestrated functions, policy-based operation etc.) required in modern automotive diagnostics. This is particularly the case in remote diagnostics, where federated management has the potential to solve many of the problems of interoperability and integration [8]. Real-time audio processing and event detection are major challenges in current automotive systems. Audio event detection can be utilized to detect a fault with the engine or other components that was not detected by the vehicle's engine control module (ECM) or engine control unit (ECU). The high-fidelity audio captured during faulty conditions can be semantically labelled and used with data-driven training (semantic aggregation) to produce a more robust model for detecting faults. Initially, this process can be seen as a way to supplement existing systems with more intelligence. However, now that plug-and-play sensors are commercially available and more accessible neural processing unit (NPU) chipsets are starting to be used in the automotive industry, this intelligence is advancing very quickly. Chipsets designed for low-power audio event detection [9] offer a unique opportunity to intersect with the automotive industry's needs identified through the SAE standards to enhance energy efficiency and sustainability [10]. In this paper, Edge AI is distinguished from traditional advanced driver assistance systems (ADAS), which are primarily focusing on supporting driver decision-making using vision systems that require larger computing power. This paper will instead focus on the impact of AI-enabled systems at the edge to support vehicle health and performance troubleshooting while maintaining certain levels of energy efficiency and addressing the need for low-power systems. The integration of smart sensors into vehicle components with the ability to process aggregated data will enable significant improvements in the quality of automotive maintenance services.

This paper presents the technical requirements and the challenges when semantics are used on Edge AI systems for automotive engine troubleshooting. In Section 2, analysis of the different sensor semantics for integration with automotive systems are briefly described. Section 3 focuses on the design and methodology for supporting intelligent services and semantic applications with predictive models using DTCs and sensor capabilities. Section 4 introduces results from a prototype implementation using AudioSet with DTCs. Section 5 provides conclusions and relevant references.

II. Background and Related Technologies

Energy consumption is crucial in smart sensors; the energy demand due to the computing capacity needs to be managed, and it is growing dramatically based on increasing deployment of edge intelligence. Independent of the energy type that propels a vehicle (e.g., combustion or batteries), energy consumption is a critical metric as any continuously operating component has the potential to drain the battery or increase fuel consumption. Modelling SAE standards for electric vehicles shows that power electronics impact energy consumption significantly [11]. Modern Edge AI chipsets, designed for low power consumption, can operate continuously without substantially affecting the vehicle's energy resources.

Sensors are used to monitor the performance of the car including the components and circuits connected to the ECM), or ECU. Sensor semantics play an important role, particularly when DTC systems need to provide more than just a series of codes; rather, they maintain the DTC's entire life cycle and make it richer with full descriptions. The Internet of Things (IoT) community has developed a series of sensor semantics over the years, considering energy efficiency and performance.

A. *Semantic Background Technologies*

The following is a shortlist of the different semantics modelling initiatives for sensor network communications:

- SSN Ontology – W3C
  W3C Semantic Sensor Network (SSN) ontology V1 [12] describes sensors and their observations, procedures, features of interest, samples, observed properties, and actuators. It is a general-purpose sensor ontology for IoT applications.
- SOSA Ontology – W3C
  W3C SSN/SOSA V2 (Sensor, Observation, Sample, and Actuator) [13] has been a W3C Recommendation since October 2017. SOSA is a lightweight version of SSN, which focuses on elementary sensor classes and their properties.
- M3-Lite Ontology – Open Source Community
  The Machine-to-Machine Measurement (M3) ontology (and its extension M3_Lite) defines a taxonomy for various QuantityKinds (e.g., physical, and environmental phenomena), units of measurements, different types of sensors and domains of interest. M3-lite has been used in research projects such as FIESTA-IoT [14] [15] which extends standard ontologies such as W3C SSN.
- WoT Ontology – W3C
  W3C Thing Description (TD) ontology is still a draft (last updated December 2023) [16] that can be used to describe Web of Thing (WoT) things and their behavior, data schema, interaction affordances, security, and protocol binding. WoT TD provides a robust foundation to represent knowledge about Things in a machine-understandable way.
- LOV4IoT Ontology – IEC
  Linked Open Vocabularies for the Internet of Things (LOV4IoT) Ontology Catalog references more than 800 ontology-based projects using sensors in various domains such as sensor networks [17], automotive [18], etc. LOV4IoT is mentioned by standardization bodies such as the International Electrotechnical Commission (IEC). The objective of LOV4IOT Ontology is connecting different domains to share concepts/vocabularies and enable interoperability across domains for IoT applications.
- VSSo Vehicle Signal Ontology – W3C
  Vehicle Signal Specification Ontology (VSSo) defines vehicle signals and their attributes. The goal of this ontology is to provide a reusable model for describing and interacting with vehicle's data. W3C Automotive Working group [19] aims to describe all sensor signals in the automotive area.

There are other related standard ontologies that consider communications, such as ETSI Smart Applications REFerence (SAREF)[20], SmartM2M [21], and OneM2M ontologies [22].

B. *Scalability and Data Integration Analysis*

The use of Semantics in modern intelligent systems i.e. automotive, poses a challenge in the capacity to process and analyze information, while physical dimension and weight pose another challenge when sensors are manufactured. Edge AI chipsets' compact and efficient nature makes them ideal for integration into various vehicle system components. The importance of onboard processing due to bandwidth and latency constraints is highlighted in [23]-[26]. The processing capacity and time resolution is reduced with the computing capacity of modern chipsets and they bring intelligence to automotive components without latency constraints, such as those needed in traction control and anti-lock braking systems. The convergence of AI, wireless connectivity, edge computing, IoT, and other technologies contributes to vehicle automation.

C. *Condition Monitoring and Predictive Maintenance*

DTCs have been the linchpin of automotive diagnostics for decades. They are a universal language that technicians and automotive professionals use to identify and rectify vehicle malfunctions. However, with the advent of smart sensors and the integration of Edge AI technologies, the landscape of DTCs is poised for a transformative change. Traditionally, DTCs are generated when specific sensor readings cross predetermined thresholds, indicating potential malfunctions. DTCs have a logic associated with them. Setting one DTC sometimes helps to isolate the issue but sometimes makes it more difficult. The codes, often read via on-board diagnostics (OBD) tools, providing a generic description of the problem and necessitating further diagnostics to pinpoint the exact issue or related ones.

Previous generations of automotive SAE designs were criticized regarding sustainability for including an excessive number of circuits and systems and failing to address fundamental future needs, i.e. intelligent all time connected services [11]. The same paper proposed green engineering principles and future design guidance. Through audio event detection using smart sensors and Edge AI, components with built-in predictive maintenance can be designed and separated from the overall system design [22]. Condition monitoring using Tiny Machine Learning (TinyML)** and vibration sensors was described in [27]. TinyML is a machine learning technology that allows models to run on small, resource-constrained devices. It includes hardware, AI/ML algorithms, and software that can process and analyze sensor data on devices with low power consumption, making it ideal for always-on use-cases and battery-operated IoT smart sensors/devices.

Similarly, models such as YAMNet, an acoustic detection model that classifies more than 500 different sounds, can be employed to sample and predict given audio scenarios, drawing descriptions from the AudioSet ontology, a large-scale human-labeled dataset for sound events [28]. This classifier can detect and classify specific engine sounds, such as starting, knocking, and heavy engine use and can be utilized as a basis for transferring knowledge. Continuous monitoring audio events (semantically annotated sensor data) help predict and identify vehicle wear and tear or component malfunctions before they become critical. YAMNet is a deep net that predicts over 500 audio events semantically described with the objective of indicating what sensors, components, and/or car parts require maintenance, thereby reducing waste and the need for more extensive and resource-intensive repairs.

III. Design and Methodologies

This section describes how the integration of smart sensors, employing multimodal sensing capabilities such as audio event detection, vibration, and temperature, can directly detect faults at the source.

A. *Predictive Models*

The AI-enabled models described in this paper were developed to classify faults through audio event detection [29]. The use of predictive modeling in industrial applications is advancing quickly, and it is envisioned to improve the systems analysis, decision, and results when the actual systems become obsolete. In the Automotive Diagnostics sector, data models are developed using datasets of known inputs mapped to specific DTCs, like P2279, for air leaks [7]. An intake air leak can be identified through distinctive engine intake sounds. Sensors that have a microphone could be utilized to generate a DTC code for that fault after the classification of the matching sound. This could lead to the generation of a fault report from the sensor, such as the example shown in Table 1.

Table 1. An example of DTC codes and associated faults.

DTC Data Label	Fault	Input / Sensor	Associated Audio Description
P2279	Intake Air leak	Audio	Louder engine intake sound.

Those components and underlying sensors need to be able to log relevant DTC codes, which requires a map or ontology of the relationships between audio events and error codes. SAE J2012_201612 [7] defines the DTC format for vehicles, which is a five-digit alpha numeric format. The SAE J2012_201612 description can be constructed/defined as shown in Table 2.

Table 2. DTC code digit positions and their meaning.

Error Location	Manufacturer	System(s) Codes	Error 4th Digit	Error 5th Digit
(P) or (B) or (C) or (N)	(0) Generic SAE (1) Specific	Systems related error from list below	0-9 Fault Codes	0-9 Fault Codes

The first letter of the DTC code defines the location of the error as either Powertrain (P), Body (B), Chassis (C), or Network (N). The second character in the code is SAE generic or mmanufacturer-specific. The third character is selected from the list below, and the fourth and fifth digits are fault codes:

- 1 = Fuel and Air Metering
- 2 = Fuel and Air Metering
  (injector circuit malfunction specific)
- 3 = Ignition System or Misfire
- 4 = Auxiliary Emissions Controls
- 5 = Vehicle Speed Control and Idle Control System
- 6 = Computer Auxiliary Outputs
- 7, 8, 9 = Various transmission and Gearbox faults
- A, B, C = Hybrid Propulsion Faults.

B. *Challenges and Considerations*

Additional characteristics from the automotive audio sets used to train the models need to be considered to produce more accurate fault classification. Ontologies can help annotate and exchange data produced by sensors. One example is the M3 ontology, which unifies sensor data and measurement types such as temperature recorded with units in degrees Celsius. In this example, the M3 ontology and semantic interoperability approach can be used on the Cloud, Mobile (e.g., Android), and gateway applications (e.g., Raspberry Pi with Android) [30]. In the context of Automotive vocabulary, an intake air leak from above can be identified through distinctive engine intake sounds and may indicate multiple potential problems that usually cannot be identified without the use of semantics:

- intake air leak 1 = Fuel and Air Metering
- intake air leak 2 = Fuel and Air Metering
- (injector circuit malfunction specific)
- intake air leak 3 = Ignition System or Misfire
- intake air leak 4 = Auxiliary Emissions Controls
- intake air leak 5 = Vehicle Speed Control and Idle Control System

- intake air leak 6 = Computer Auxiliary Outputs
- intake air leak 7, 8, 9 = Various transmission and Gearbox faults
- A, B, C = Hybrid Propulsion Faults.

In the context of DTC code enhancement, as the range of detectable faults increases, ontologies must be extended to encompass a broader spectrum of problems detectable by audio or other advanced sensors. This vocabulary enrichment is part of the ongoing ontology engineering work necessary for these industrial applications. However, there is a need for better synergies among standardized ontologies from different organizations such as W3C, One Machine-to-Machine (OneM2M), and standards development organizations. For instance, they need to define common concepts such as devices, sensors, etc. The visionary approach is that various ontologies will emerge from the different standardization groups that share common vocabularies, and those vocabularies can be identified and mapped to each other. Thus, when data exchange is required, the standards can support data interoperability.

C. Proposed System Implications

Instead of just identifying a malfunction, smart sensors can provide a more nuanced diagnosis. For instance, audio event detection could differentiate between abnormal engine sounds, enabling the DTC to indicate an engine malfunction and the specific nature of the sound detected. Smart sensors, coupled with predictive maintenance models can foresee potential issues based on physical characteristics such as sound or vibration before component failure triggers conventional DTCs. This proactive approach could lead to a new category of warning of possible future failures. Unlike static thresholds of traditional systems, smart sensors, using machine learning models, can adapt to changing vehicle conditions and usage patterns. The results in dynamic thresholding for DTC generation ensure accurate and timely fault detection.

IV. Experiments and Results

The Automotive Sector extensively uses on-the-fly firmware updates for diagnostics, preventive maintenance, and call-backs for repairs. Federated systems can use this capacity to incorporate mechanisms that orchestrate and organise the multiple interconnected systems within a vehicle. Edge AI facilitates the processing of events and, combinated with data modeling from YAMNet, data insights can be identified, processed, and described using AudioSet ontology.

A. Edge-Intelligence Engine - Functionality

YAMNet is an audio event classifier used widely in audio-event processing engines, which samples a given audio waveform and makes predictions related to different scenarios. Fig. 1 shows the generic architecture that was implemented where the blue parts represent the sensors on the edge (CarSensing) that can utilize Data Modelling Techniques (YAMNet semantic events) and Data insights (TinyML) for federated automotive diagnostics and preventive maintenance applications (Car System). While sensors data and events at the end user side are disconnected and difficult to interpret, with Edge Intelligence Engine (central part in Fig. 1) these events acquire a more meaningful form using schemas and ontology.

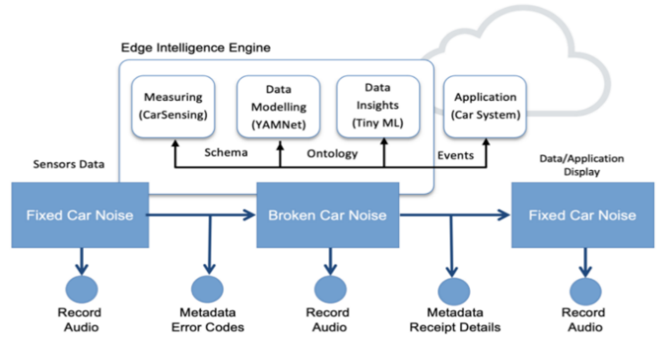

Fig. 1. Intelligence at the edge using semantics.

B. Benefits of using Semantics – Data Interoperability

The event modeling details are described in the AudioSet ontology which uses Ontology Web language (OWL) and the Resource Description Framework (RDF) as shown in Fig. 2. AudioSet is a large-scale ontology of audio events that categorizes sounds into classes and subclasses, providing a structured way to classify audio data. AudioSet only covers a limited number of specific automotive faults, but the original specification notes that AudioSet was designed to be expanded on. An extension of AudioSet to include DTC codes is shown in Fig. 2, an event "IgnitionSystemOrMisfire" using Unified Resource Identifier (URI) from "Engine Sounds" Library is linked to the Event Code "P0300" from the AudioSet. This link created between different data units (models) also opens the potential for interoperability among systems, allowing smart sensors to communicate and corroborate findings for more accurate fault identification.

```
<!-- Linking AudioSet Sounds -->
<owl:Class rdf:ID="EngineSounds"/>
<rdf:Description rdf:about="#EngineSounds">
    <rdfs:subClassOf
rdf:resource="http://example.org/audioset#EngineNoise"/
>
</rdf:Description>
<!-- Instances with AudioSet Links -->
<rdf:Description rdf:ID="P0300">
    <rdf:type rdf:resource="#IgnitionSystemOrMisfire"/>
    <hasDescription>Multiple Cylinder Misfire
Detected</hasDescription>
    <hasSoundFile
rdf:resource="http://example.org/audioset#EngineMisfire
Sound"/>
</rdf:Description>
```

Fig. 2. AudioSet ontology to include DTC codes extensions.

C. Prototype Implementation – Testing & Experiments

Tiny machine learning is broadly defined as a fast-growing field of machine learning technologies and applications including hardware, algorithms and software capable of performing on-device sensor data analytics at extremely low power, and hence enabling a variety of always-on use-cases and targets battery operated devices. TinyML, as both a concept and an organization, has acquired significant momentum over the last several years. To test and prototype edge-intelligence-enabled sensor for automotive diagnostics, at the time of this publication a selection of ML-enabled market ready devices were studied. The list of microcontrollers supported by the TensorFlow Lite is available online [31]. This list is built based on available market boards with the necessary TinyML capabilities but is not limited to new boards introduced in the market. The following development boards from different manufacturers were also considered as examples based on their capacity for supporting Tensorflow Lite as potential hardware to implement the edge-intelligent sensor required for automotive diagnostics. TensorFlow Lite for Microcontrollers is a part of Tensorflow Lite, designed to run machine learning models on DSPs, microcontrollers and other devices with limited memory.

- Wio Terminal: ATSAMD51
- Himax WE-I Plus EVB AI Development Board
- Synopsys DesignWare ARC
- EM Software Development Platform
- Sony Spresense

Fig. 3. Data flow & smart sensor prototype.

The hardware chosen for the prototype of this paper (Edge-Intelligence Sensor) was selected based on the hardware capability to run TinyML, however other hardware with the necessary specs that has similar features could also be used. Fig. 3 shows the prototype of smart sensors with edge intelligence implemented for demonstration in automotive diagnostics.

- Arduino Tiny ML Kit (Arduino Nano 33 BLE Sense) [32]
- The M5 Echo Atom (ESP32 with a Mic) has the bonus of being designed for scaling up (connect more) easily [33].

The major edge-intelligence smart sensor challenges addressed in the construction of this prototype were to adopt an open architecture with the capacity to integrate modeling and performance analysis that supports heterogenous wireless networking. It is essential to have resource allocation and energy efficiency to ensure quality of services (QoS) and quality of experience (QoE).

The prototype was used to perform experiments using real car engines on the road and in lab environments. The prototype was placed inside the car beside the gear box for cabin tests. The prototype was placed in the engine bay under the hood of the car for engine bay tests and used chiefly for idle conditions. The two tests consist of the same procedure of recording the sounds (noises) captured at the cabin and engine bay then detecting and annotating the condition as good or bad. Edge Impulses data collection app was used to collect the audio data.

D. *Event Detection Analysis – Edge-Intelligence*

Linking smart sensor data with information using semantics improves the identification of failures while using performance metrics induced in a confusion matrix. Fig. 4 summarizes the results of the experiments conducted. Four vehicle states were considered: intake air system leaks (with error code P2279), airflow at the throttle body (with error code P2282), the engine at idle, and the engine in other conditions that were not classified (background). Each row of the figure denotes the actual vehicle state, while each column represents the classification of the vehicle state from the hardware prototype. In the experiments, categorical cross-entropy was utilized as the loss function for classification. It is a standard function used for multiple classes involvement, such as our classification of the different engine conditions. The Database uses CBOR format for export and store data on the cloud according to the Edge Impulse Platform. There are 34 trainings and 5 testing datasets for these validation experiments, more extensive training would increase the probability of identifying the failure, as shown in Fig. 4. The correct classifications are those across the diagonal. In contrast, the misclassifications that occur in over 5% of cases are shown on both sides of the diagonal. The F1 score higher values show that sensors on components can be used to identify specific faults that are preconfigured and trained with different probabilities. The detected outcomes could be shared directly from the edge smart sensor and processed or used after adding the linked information. For these experiments, idle and background are the worst cases when specific vehicle states are not separated as different classifications with training data.

Confusion matrix (validation set)

	Background	IDLE	P2279	P2282
Background	76.20%	0.00%	23.8%	0.00%
IDLE	1.40%	36.10%	61.10%	1.40%
P2279	0.00%	1.20%	96.70%	2.00%
P2282	0.00%	0.00%	0.00%	100%
F1 Score	0.86%	0.51%	0.85%	0.81%

Fig. 4. Probability when using semantic models.

V. Conclusions and Future Work

This paper describes the advantages of semantics and ontology engineering in integrating edge AI-enabled smart sensors and related applications into automotive systems for troubleshooting faults. The automotive and aerospace sectors continue to evolve, and integrating such technologies will play a pivotal role in shaping the future of transportation.

This paper focuses on demonstrating the capabilities and benefits of using semantics rather than a specific contribution in automotive diagnostics. The motivation to use TinyML was for its listed capability for low consumption, a detailed study about this is required but it is out of the scope of this paper. The intersection of Edge AI designed for low-power audio event detection, with the automotive industry's need is highlighted by the SAE, and opens numerous possibilities for innovations in energy-efficiency and promoting sustainability

If ontologies are adopted to support a revised approach to generate DTCs, the automotive industry would need a consensus on new DTC categorizations and descriptions to ensure universal understandability and applicability. These descriptions should be reflected in the technical specification sheets. Technicians and automotive professionals will require training to understand and effectively use the new DTCs, ensuring the benefits of these advancements are fully realized. Regulatory bodies will need to revise and update standards, ensuring safety and efficacy in using smart sensor-derived DTCs. Future work delves into customizing the created models for specific vehicle types, creating new DTC standards for these sensors, and extending ontologies to encompass mechanical terminologies.

Acknowledgments

This work has been partially supported by the FAME project EU-Horizon Europe 101092639 and The Insight SFI Research Centre for Data Analytics supported by Science Foundation Ireland Grant Number SFI/12/RC/2289_P2 in collaboration with the National Institute of Standards and Technology (NIST).

** Certain commercial products or company names are identified here to describe our study adequately. Such identification is not intended to imply recommendation or endorsement by the U.S. National Institute of Standards and Technology, nor is it intended to imply that the products or names identified are necessarily the best available for such purpose.

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