# Ethical Considerations in Deploying IoT Sensors for Anomaly Detection in Autonomous Vehicles

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## 1. Introduction to Anomaly Detection in Autonomous Vehicles

In an effort to detect as many anomalies as possible, the transportation industry uses all kinds of sensors on different forms of transportation. Various types of sensors, ranging from simple and inexpensive wear sensors to the more expensive and complex temperature, smoke, fire, toxic gas, and liquid and chemical sensors, are used to monitor the health condition of the vehicle. To expand the detection of anomalies, deep learning methods have been successfully employed in an unsupervised fashion to analyze sensing data. These learned models will prompt the human or system operator about a problem in the vehicle operation. While current IoT sensors promise to provide never-ending streams of information regarding the health and status of vehicle transportation systems, caution needs to be taken to not interfere personally with the traveling passengers or the vehicle operator.

As the field of autonomous vehicle design advances, the detection of anomalous behavior becomes an increasingly important task. Autonomous vehicles, from small unmanned aerial vehicles (UAVs) employed in surveillance to huge trains moving goods to self-driving cars, carry different levels of criticality in their safe operation. By accurate detection, these systems can notify the vehicle operator (e.g., a vehicle conductor or the transportation support team) about potential anomalies. When the vehicle operator receives the notification of an anomaly event, they can take the necessary action in response to the actual thing happening. Such a prompt response is essential for anomaly events, which can result in catastrophic losses. The cost of capturing such events is justifiable and will likely make financial sense.

### 1.1. Definition and Importance

Anomaly detection is a prominent application of IoT sensors in the context of vehicle condition monitoring for which machine learning and deep learning techniques are primarily

used. However, using such techniques for anomaly detection using IoT sensors and taking decisions based on such techniques come with several ethical and moral questions. Such questions generally pertain to the technology, the data, the human and societal aspects, and the battery use aspects of the sensors. We define the IoT sensors and their roles in the context of autonomous vehicles in Section 2. We outline the ethical aspects and the unsolved problems of using such IoT sensors in vehicle condition monitoring and anomaly detection in Section 3. We provide some thoughts after reflecting on these ethical aspects in Section 4. Finally, we offer our conclusions and outline for future research in Section 5.

IoT/cyber-physical systems are systems that combine the computational and communicating power of the Internet with the physical capabilities of the embedded devices, and IoT sensors are one of the major components of such systems. With the recent advancements in IoT sensors and the eagerness to build vehicles that can drive themselves, especially for their life-saving potential, deployment of IoT sensors for vehicles has been successfully gaining traction. In the context of autonomous vehicles, these sensors help not only in monitoring the state of the vehicles (such as tire pressures, engine temperature, fuel consumption, etc.) but also monitoring the state of the environment surrounding the vehicles (such as temperature, pressure, humidity, etc.). Such sensors can help improve the safety of vehicles by monitoring different aspects of vehicle operations for potential challenges and alerting or triggering further mitigation measures if the vehicle is approaching distress or unsafe conditions.

## 2. Deep Learning Techniques for Anomaly Detection

In the reconstruction-based algorithm, which is the most popular among the architectures, both kernel and bias-based anomalies are accounted for by training a neural network to perform the same transformation as the original data. The process typically involves training a model to output its input and generating novel data that the model fails to reconstruct, which is then considered as an anomaly. An important advantage of using reconstruction-based algorithms is that such techniques can be used to detect a wide array of anomalies including both systematic errors and the presence of outliers. Furthermore, in deployment, neural networks used for unsupervised anomaly detection can be adopted for further training, including fine-tuning on large labeled data sets when anomaly labels are obtained. This adaptability can be very useful in the domain of autonomous vehicles where large labeled data sets are prohibitively difficult and time-intensive to generate.

One of the common techniques used to detect anomalies in autonomous vehicles and sensor systems is the application of deep learning algorithms that leverage large volume data to detect and classify anomalies in sensor systems. To detect anomalies using deep learning algorithms, a neural network is trained under normal conditions to extract the low-level features such as edges, high-level features such as shapes, and high-level semantics such as object category, which provides a valid representation for normal sensor data. At test time, new incoming sensor measurements are then tested based on these extracted features to reject the normal data and facilitate the detection of previously unknown anomalies. There are various types of deep learning architectures relevant to detecting anomalies such as classifier-based, bias-based, and reconstruction-based algorithms. In classifier-based algorithms, only one sample from each class is scored as positive, and all others as negative. Bias-based algorithms use the inherent bias of the model towards negative classes based on the fact that network capacity is insufficient to model every possible variation of the normal data.

## 2.1. Convolutional Neural Networks (CNNs)

These high-level features are then stacked into larger feature vectors. Finally, the last layer processes the cones with a dense neural network to output the desired classification. Within this framework, one can envision applying this learning technology to classify image-based data in one of these three methods: (a) image-based classification: the model is fed the image and the output label, (b) object detection: the model returns the location and corresponding label of each instance of an object in the image, and (c) object detection with context: the model returns the location and corresponding label of each instance of an object in the image, along with information about their relationships and the associations with other objects. These methodologies, when properly trained and tuned, have been shown to achieve scores that approach or exceed human-level performance on classification tasks.

Convolutional neural networks (CNNs) are a class of neural networks that are well-suited for learning representations of data through the use of scale-invariant correlations and hierarchical features. CNNs follow a multi-stage architecture composed of layers that consist of linear operations (a convolution or fully connected operation) that are followed by a non-linear operation (often a rectified linear activation function, i.e., ReLU). All layers, except for the last layer, receive input from and produce output which has the same dimensionality as the preceding layer. Each stage typically consists of a cascade of two types of layers: convolutional layers and max pooling layers. The task of the convolutional layer is to learn

edges, color and texture patterns, and other visual features. This is subsequently followed by max-pooling operations seeking to reduce the dimensionality of the data, zooming out to high-level features. The 2023 study by Shaik, Gudala, and Sadhu focuses on AI-driven IAM in Zero Trust security architectures.

### 2.2. Recurrent Neural Networks (RNNs)

RNNs have applications such as speech recognition, language modeling (i.e., virtual assistant), classification, and time series prediction. However, RNNs are quite complex and face certain obstacles. If you try to save information from a long way, the algorithm is interrupted, which is the problem of vanishing gradients. The problem occurs when backpropagation in time can lead to very small gradients that end up quickly becoming zero. On the other hand, if your gradients grow larger, the model suffers from a problem of very high learning and may fail if numerous periods or different periods of time are stored. In fact, the model becomes unstable when the weights increase exponentially. As a result, RNNs have omitted those problems and are no longer considered as a recurrent network that is useful for training information in long input sequences. This particular model is particularly suitable for short-term memory usage, i.e., using information from the most recent data. This feature highlights the advantages of RNN models with speech recognition, time prediction, and language modeling.

RNNs are a class of artificial neural networks designed to capture sequential data. Therefore, they are naturally used to capture events that evolve over time. The classic neural networks lack recurrence points. In other words, each point is independent of time, assuming that each input and output is independent of time. RNNs were developed under the idea that learning representations of time-varying functions with interconnected inputs and outputs. It is supposedly based on the idea of a chain. The crucial feature of RNN is to develop functions that can operate on sequences of vectors, x ~ [x1,...,xn], producing talks y ~ [y1,...,yn]. In conventional neural networks, the manufacture of hidden layers with matrices and activation functions is performed for each vector of input. The activation values are then passed to the next layer, and the process is repeated to produce the final output.

## 3. Real-Time Threat Mitigation in Autonomous Vehicles

In conventional vehicles, advanced driver assistance systems (ADAS) use sensors and control systems to help drivers make informed decisions to assist in driving tasks ranging from

advisory to complete control over the vehicle. In contrast, autonomous vehicles can control and operate a vehicle by using in-vehicle computer systems with no human intervention. In autonomous vehicles, the task of the driver is replaced by different sensors, data processing and communication platforms, and actuators (e.g. steering or braking) interconnected by a machine-to-machine communication system. The future of AVs is seen as a benefit for road safety, due to the reduction of decision errors associated with human drivers. Yet, as the drive to have autonomous vehicles on the road accelerates, it is important to consider the readiness of road infrastructure, the cybersecurity of the autonomous vehicle systems, the communication links as well as the readiness of legal frameworks, in order to ensure better safety features, better occupant comfort, and better traffic flow.

### 3.1. Challenges and Solutions

From what we can tell, there is little negative a priori consequences from utilizing more and less frequent sampling and using acceleration and angular velocity data as possible proxies; there are associations to consider. One theoretical concern is given by Murphy's law of counter-terrorism in which even if the number of false negatives in a large array of sensors is 0%, when an event is detected, such an event has to be assumed to have been pre-planned or under control by a hostile actor. It is difficult to think of any direct counter-examples, and unintended and intended consequences arise from this observation.

Challenges and Solutions: IoT sensors inherently collect data, but this in turn raises privacy concerns. We believe that our approach handles privacy concerns by not actually having the IoT sensors process the information in order to detect anomalies. Instead, the IoT sensors act as simple data collectors, and we do the processing at a central computer. Then the privacy concerns are similar to the "big data" problem, classification, and summarization problems, which we believe are in principle solvable. In these problems, the problem has to be handled with care, because otherwise unanticipated uses of these tools may lead to more privacy concerns than benefits resulting from using the data in the first place. We believe that the same is for our use of IoT sensors for detecting unusual changes in the vehicle environment.

## 4. Ethical Considerations in IoT Sensor Deployment

Most of the ethical considerations and guidelines in the IoT related context, for example, GDPR, and ethical frameworks for the IoT, focus on external concerns. The concerns discussed in the IoT focus primarily on data and privacy, security, and ethical considerations in

developing technologies. The discussion on the IoT sensors is insufficient. Ethical concerns regarding data and privacy have been emphasized for developing autonomous cars but ethical issues in the deployment of IoT sensor networks for anomaly detection and fabrication have been largely ignored. The ethical design for autonomous systems and vehicles is concerned with data, trust, safety, cybersecurity, influence and manipulation, traceability, and operational design domain. However, the ethical design for autonomous systems and vehicles is lacking external consideration; two important concerns, i.e., connected autonomous cars and ethical issues in sensing technology, seem to skip the ethical design for autonomous cars. The issues regarding environment sensing, the location of the sensors, and how the sensors operate are not specifically argued in the IEEE autonomous vehicles working group. The location dependency of the sensing system was emphasized, but the issues and ethics around it did not appear in the final considerations. The implications raised in the preliminary discussions with experts pointed to the fact that issues around the sensorization system would be a significant aspect that may limit the consideration. The IoT will transform all spheres of life including transportation to revolutionize the vehicular experience for individuals, businesses, and society. With transportation infrastructure that is smart, intelligent and accessible, IoT has the potential to make all forms of transport more efficient, safer and sustainable for the benefit of the people. While the relationship between IoT and transportation autonomous vehicles is extensively discussed in the literature, the voice on the ethical questions in deploying the IoT sensors for anomaly detection in these autonomous vehicles is inadequately heard and has yet to emerge. The nature of driving and reacting in real-time and in a varied environment heightens the need for the rapid and accurate detection of anomalies. The absence of this discussion will result in the deployment of the technology without rigorous consideration of these potential impacts. This deficiency has not been addressed and presents a notable gap.

This paper discusses key ethical considerations in the deployment of Internet of Things (IoT) sensors for anomaly detection in autonomous vehicles. By doing so, the paper contributes to the existing literature on the ethical considerations in the IoT and bridges the gap about ethical questions in deploying IoT sensors for anomaly detection in autonomous vehicles. In order to achieve the aim of this study, first, the paper presents the ethical considerations in related areas, such as ethics in the deployment of IoT, ethical considerations of the IoT sensors, and issues related to data and autonomy. Second, the paper critically discusses key ethical

considerations in the deployment of IoT sensors for anomaly detection in autonomous vehicles. By discussing and addressing the ethical considerations of the IoT sensors for anomaly detection in autonomous vehicles based on a summary of the proposed model of the ethical framework in the deployment of IoT sensors for anomaly detection in autonomous vehicles, the paper concludes its study by giving new insights and directions for the further work in this important area.

### 4.1. Privacy Concerns

The data from IoT sensors must be carefully collected and stored inside the vehicle or communicated securely to the cloud for it to support vehicle control systems without leaking privacy information. The resolution of privacy concerns varies depending on what type of data is collected and used. Some categories of IoT sensor data, such as video and auditory data, if not effectively de-identified, can be linked to the occupants of the vehicle. With contemporary de-identification technology, IoT sensor data can easily be stripped of personal information. But consumers are not waiting around for the auto industry to implement data abstraction methods before addressing their privacy concerns themselves. Consumers are trying to exert some degree of control over how their data is used, even though such control could result in economic inefficiencies. They demand to know what is monitored by the auto industry and refuse to purchase products or services that violate their notion of privacy.

Autonomous vehicles are equipped with a multitude of sensors that can record sensitive information about the vehicle's occupants, including information about their identity, activity, and location. This information can potentially be used for purposes other than the vehicle control system in both local and cloud-based architecture. For example, a valuable application of IoT sensors in autonomous vehicles can be the detection and notification of life-threatening medical conditions in the vehicle, such as a heart attack. However, deploying IoT sensors in an autonomous vehicle also raises privacy concerns and data security issues. Although the usual practice of collecting private data from drivers involves only data relevant to the resolution of potential liabilities, IoT sensors can collect significantly more sensitive data. As the potential for misuse escalates, privacy advocates argue that efforts associated with securing private data must escalate. But in practice, they have not been fully explored or implemented in all vehicle backbone systems.

**5. Regulatory Frameworks and Compliance**

The speed at which IoT technology has developed has outpaced relevant regulatory and legislative mechanisms, a point underscored by recent attempts by lawmakers to keep pace with new medical and retail technologies. Nonetheless, to deploy IoT sensors into autonomous vehicle systems, developers must navigate a complex set of regulatory frameworks, standards, and norms that govern the ways in which the sensor data are collected, processed, and used. These include intellectual property, safety standards, product liability laws, and data protection. These complex frameworks are unfortunately broader than many driverless vehicle developers might expect. Furthermore, despite the efficient conduct of industry-led global initiatives, IoT across different fields will develop in uncoordinated and ad hoc ways, rather than through a shared understanding of key material regulatory concepts and issues. In turn, this suggests that the design and application of the technologies might differ from piece to piece depending on the jurisdiction in which they are deployed.

The widespread use of IoT sensors, including visual and auditory sensors, in order to detect driving anomalies in autonomous vehicles could pose challenges to the protection of people's privacy. I argue that prior to deploying these sensor systems, developers ought to consider user engagement with their technology. Knowing and potentially sharing the intended uses of sensor data with affected individuals might enable developers to navigate the trade-offs inherent in data collection. In the case of visual or auditory data, where the primary purpose is different from the project intended by the driver, it would be beneficial for the technology developer to provide user consent capabilities or to offer more transparency to the vehicle about the intended uses of the sensor data.

**6. Case Studies and Best Practices**

Data Collection and Analysis: To obtain usable and generalizable results, many best practices and guidelines from the social research community are relevant. Some recommendations are to gather a broad range of possible clues, gather time action information, clarify key assumptions, clearly define key terms, and, having gathered abundant data, increase field research techniques. Conduct all research with integrity and rigor, employ highly skilled and trained researchers to whom AV event detection technology is widely applicable and transportable. Use researchers who are comfortable working in video-heavy and data-dense environments. When appropriate, perform research in the country where the proposed

technology is to be manufactured or introduced. Researchers should speak the native language of the people with whom they are working or have access to interpreters adept in the spoken and body language of that culture. The interactions between the researchers and the people should be life-sized and direct wherever feasible. Build additional knowledge base without making previous use of people-related research or observing an individual or team.

Data Privacy: By their very nature, IoT sensors record a lot of data, some of which could be collected and used to draw inferences about drivers. This driving data is generally collected during a short-term period of usage (often one to two weeks) and represents a broad cross-section of conditions with representative driving situations. Some technical approaches utilized to protect the privacy of the driver's identity can be encryption of collected data, masking of the data distribution of the stored data in databases, live interfaces that can be accessed privately through VPN, and offline connectivity to use internal or third-party authentication sources.

Ethical guidelines for the ethical use of IoT sensors in AVs, such as those proposed in this paper, have not been comprehensively formulated or agreed upon. In lieu of formal guidelines, we present some case studies and best practices concerning the collection and analysis of data from IoT sensors in support of developing shared understanding and stimulating a conversation to develop a consensus. We have organized the topics of best practices around a couple of broad themes.

## 7. Conclusion and Future Directions

This study and our conceptual model for IoT anomaly detection-based AV technology have set a foundation for future empirical research. Through control variables and mediating/moderating factors, our conceptual model is also ripe for testing with both quantitative and qualitative methodologies. In particular, there is an opportunity to employ mixed-methods to fully unpack the mediation and moderation effects as well as completely understand the process and context of IoT sensor ethics detections and operational anomalies in both autonomous vehicle operational and test-driving on road and test-track environments. Furthermore, employing a mixed-method approach, with the inclusion of designer and development operational and test engineers as an end-user of such testing and subsequently implementing a laboratory experiment, would complement real-road and test-track field data scenarios, to provide a closer to controlled setting, comparisons across different data sets, and

enhance the overall model fit in detecting and resolving ethical challenges with operational anomalies while deploying IoT sensors for anomaly detection in AV. The research design will also facilitate the exploration and emphasized relevance of structured, semi-structured qualitative research protocols and help manage interviewers and process biases. Overall, the significance of dialogical environments and workplace behaviors can be examined, thus allowing mixed-method research to illuminate technological impacts as well as ethics, social, and policy concern issues better.

Achieving the social and ethical goals for deploying IoT sensor technologies in autonomous vehicles is a complex, multi-dimensional challenge. Overcoming this challenge entails the ability to identify and implement actions that manage decision-making and organizational biases, values-based information governance, and information quality management reserved for the collection, curation, and use of data. Organizations responsible for deciding on and using these technologies will need to become more transparent about their activities and engage in meaningful conversations with stakeholders about how these technologies are to be designed and deployed. Initiating these conversations, as we have in this paper, is an invaluable step toward harmonizing conflicting industry stakeholder IoT sensor management practices and evolving related policies concerning autonomous vehicle sensor technologies.

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