Explainable Navigational Intelligence (XNI): Connecting Artificial Decision Making and Human Trust in Autonomous Vehicles

Shreyas Madhav A V[1], Amit Kumar Tyagi[2,3][0000-0003-2657-8700]

[1,2]School of Computing Science and Engineering, Vellore Institute of Technology, Chennai, 600127, Tamilnadu, India.

[3]Centre for Advanced Data Science, Vellore Institute of Technology, Chennai, 600127, Tamilnadu,

India

shreyas.madhav@gmail.com, amitkrtyagi025@gmail.com

Abstract: Automated Navigation Technology has established itself as an integral facet of Intelligent Transportation and Smart City Systems. Several international technological organizations have realized the immense potential of autonomous vehicular systems and are currently working towards its complete development for mainstream application. From deep learning algorithms for road object detection to intrusion detection systems for CAN Bus monitoring, functioning of a self-driving vehicle is powered by the simultaneous working of multiple inner vehicle module systems that perform proper vehicle navigation while ensuring the physical safety and digital privacy of the user. Transparency of the vehicle's thought processes can assure the user of its credibility and reliability. This paper introduces Explainable Navigational Intelligence, which aims to converge the decision-making processes of autonomous vehicle systems and the domain of Explainable AI (XAI) to provide clear insights into the role explainability plays in increasing human trust on AI solutions. This paper exhibits the trajectories of transportation advancements and the current scenario of the industry. A comparative quantitative and qualitative analysis is performed to compare the simulations of XAI and vehicular smart systems to showcase the significant developments achieved. Visual Explanatory Methods and an intrusion detection classifier were created as part of this research and achieved significant results over extant works.

Keywords: Intelligent Transportation Systems; Autonomous Navigation; Explainable Artificial Intelligence (XAI); Smart Vehicle Vision; Vehicle Security; Intrusion Detection

1. Introduction

Smart Urban mobility opportunities are currently on a rapid rise due to the recent advances of autonomous driving systems. Autonomy of vehicles and transportation systems is now becoming an integral part of every smart city's propaganda and is set to serve as a more efficient replacement to traditional transportation infrastructure. Urban administrators, policy makers, politicians and legislators are unnerved by the increase in machine autonomy due to the different disruptions that they may inflict upon existing policies and urban strategies. The evolution of artificial intelligence-based systems is now leading towards a point where humans are expected to accept the decisions of the system as it possesses higher insights and the computational power to produce accurate results in real time. The entry of AI systems into critical and essential domains such as finance, defense, education etc. has now instigated people to look towards a solution to the completely opaque decision-making process of the system. A typical AI system provides very little explanation or inferences, that is understandable by the layman, on how a particular decision was. Hence, the concepts of explainability and interpretability have now established themselves imperative for producing mainstream Ai powered applications. The extent to which the explanation provided by a system can be understood by a person is defined to be its interpretability. The biggest challenge is to produce a viable explainability solution to different neural networks to encourage transparency in the machine decision making to make humans understand and trust the conclusions provided by the learning networks. This generates the ability for the human to rationalize with the decision made by the system. Explainable AI (XAI) is an interdomain of AI [1] created for the aforementioned purpose. Self-driving vehicles perform several computations ranging from vision recognition to network intrusion detection and the ability to explain these computational decisions made by the vehicle will propagate human trust from ethical, moral and legal standpoint.

Hence, the organization of the work is follows as: Section 3 of the article focuses on the concepts behind autonomous and semiautonomous vehicles, followed by Section 4 which dives into the details of vehicle autonomy and related processes. Section 5 provides the principles behind Explainable AI and Section 6 describes how autonomous vehicles use their vision to make decisions. The focus is now shifted towards the ethics and morals surrounding self-driving cars followed by the exploration of methods to establish trust in connected vehicles and VANETS in Section 7. The simulation results of vision-based explanations and novel intrusion detection algorithm is provided in section 8. Section 9 discusses conclude this work in brief (with including some interesting future work).

2. Autonomous and Semi-Autonomous Vehicles

The intertwining research advances in embedded systems, wireless communication, vision networks, data analytics, sensors and ad hoc networks has led to the widespread emergence of autonomous vehicle and intelligent transportation systems [2]. Emerging in the 1920s, the origin of vehicle anonymity is rooted in the remote-controlled phantom autos which were showcased to prove the limitless potential of modern science and initiate the concept of driverless cars. Other significant developments in the path towards completely driverless vehicles were documented in the 1980s by the invention of the ALV (Autonomous Land Vehicle) by Carnegie Mellon University and introduction of Mercedes's Prometheus Project. These developments however required human intervention at certain levels of their operational process. The increase in high performance hardware and low-cost implementations in the 21st century has aggregated quite a lot of interest towards autonomous cars. Figure 1 showcases the different levels of automation in driving.

Several steps need to be executed in sync for the seamless functioning of self-driving vehicles. The vehicle must always be aware of its surroundings, constantly learn its environment, plan the route to achieve the lowest time for the travel and make well defined maneuvers in the street [3]. The aforementioned process can be split into three different operational segments such as environmental awareness, navigational planning and movement control. Apart from this, the QOs and safety of the passengers are also accentuated by accommodating assistive machine systems like stability control, assistive brakes, sensors of different modalities and GPS positioning [4]. Autonomous cars not only ease the burden of driving for existing drivers but also expands the market vastly to accommodate people with different disabilities. Mental health is also promoted in this process as this relieves the stress of driving and prevents most cases of road rage.

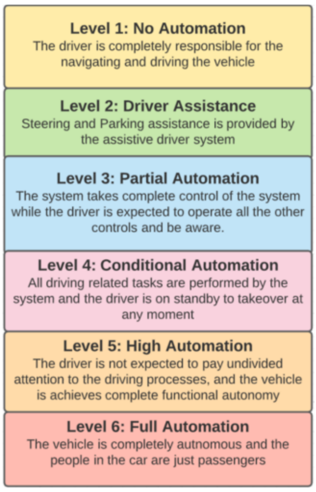

Figure 1: Levels of Driving Automation

With the decrease in health risks, passengers may experience improved quality and life and higher productivity. The implementation of connected autonomous cars in smart regions can intercommunicate in order to make sure minimal congestions and perform optimal route optimizations. It is essential that the passengers completely understand their self-driving cars in order to yield the aforementioned benefits to completely trust its functioning. This is where Explainable Navigational Intelligence comes into play. The fruition of autonomous cars will certainly transform the world and the human race and only the future can tell whether the outcome will be positive or negative.

3. Current Processes in Vehicle Autonomy

Several different components function in unison for the smart vehicles to understand their environment and make optimized decisions while ensuring the safety of the passengers. The most critical components for functioning of the vehicle are as mentioned below.

- *Sensors:* Sensors form the initial perception layer that interacts with the immediate surroundings. These hardware components observe and record data about the surroundings that is utilized by the learning systems of the vehicle to make decisions on the maneuvers and navigational changes that need to be made. The sensors may be of different modalities ranging from simple IR sensors to radars, LIDAR, stereo cameras etc.

- *Structuring inputs*: The data obtained through the sensors of the vehicle is processed to make it suitable for interpretation by the decision-making neural networks. This pre-processing stage involves accentuating the features of the obtained visual data employing image processing, segmentation, object detection, image classification etc. to provide a detailed analysis of the environment [6] that will be used by the network to take appropriate decisions. The combinational information obtained through both mediated perception (multiple visual understandings interpreted together to formulate the data) and direct perception systems (visual affordance extractions through scalar indicators) of the vehicle is utilized to understand the street environment.
- *Output representations:* The outputs of the main internal vehicle governing system is to produce and initiate vehicle controls to navigate the environment in a safe and efficient manner. Dual methodologies are employed for this purpose. End to end strategies obtain the final output directly by feeding deep learning networks with the sensory inferences obtained whereas End to Mid strategies tend to predict the future path of the vehicle, that is to be followed by a PID or similar controller.
- *Learning:* The learning algorithms [5] employed for propelling the vehicle to function autonomously fall into two major categories namely reinforcement learning and behavioral cloning [7]. Reinforcement learning depends upon the trial-and-error learning of the system where it is exposed to an unknown environment with no prior knowledge and is expected to iterate through multiple attempts until it achieves its goal, finding a unique balance between reinforcement and self-exploration[8]. Behavioral cloning on the other hand is similar supervised learning tasks where prior knowledge is fed into the networks in the form of well-defined datasets.

Many useful improvement details with respect to Vehicle's automation can be found in [26,28].

4. Explainable Artificial Intelligence (XAI) and its Principles

XAI (Explainable Artificial Intelligence) deals with eliminating the black box feeling associated with artificial decision making and improving the transparency of the process to make the final decisions understandable by non-expert humans [9]. It propagates the social right for explanation that can be exercised by humans to interpret why a particular critical decision was made so that they can accept it through reasoning and rationalization. XAI extends beyond any legal or ethical obligation and provides improved service in AI applications. The users feel more comfortable as they can now trust their AI system whole heartedly and understand its thinking methodologies. Hence XAI plays an integral part in human-AI trust building. The ability of XAI to document its proceedings by demonstrating its past performed, present executing and future predicted actions helps confirm extant information, generate new assumptions and challenge the available information. Figure 2 depicts the process of explainable passenger –AI process.

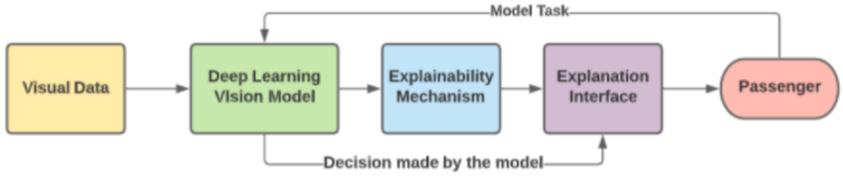

Figure 2: Visual Explanatory Process in a Vehicle

Explainability, transparency, interpretability are the three major principles that drive the development of XAI algorithms. The concept of explainability should provide an array of interpretable feature representations that can educate humans on the exact background processes that yield a particular decision. Interpretability of a model is often interchanged with comprehension of the model's underlying basis [10]. Transparency is about providing descriptions of the classification or regression processes carried out by the machine learning models. There are several different approaches towards solving the problem of AI explainability.

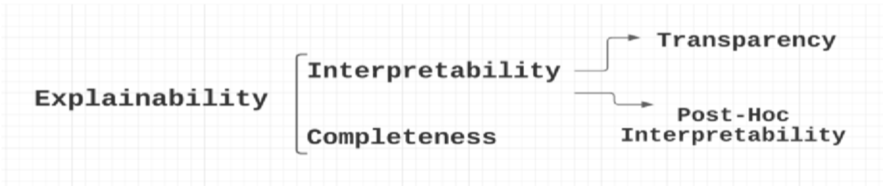

Figure 3: The interrelation of Explainability Concepts

In figure 3, interrelation of Explainability Concepts is depicted. LRP (Layer-wise relevance propagation) is a commonly employed methodology to which function primarily according to a defined set of propagation axioms and rules. This approach is highly appropriate for explaining deep and complex neural networks by propagating the prediction backwards. Counterfactual algorithms carry out impact evaluation to recognize the factors contributing to the impact of the intervention by analysing the different parts of the observed actual improvement. LIME (Local Interpretable Model agnostic Explanations) [11] as the name suggests focuses on the behaviour of the model towards the immediate prediction also known as local fidelity. Several other visual methods like Grad cam and its variations have been known to provide viable qualitative representations of the vehicle's vision [12-16]. GAM (Generalized Additive Modelling) works by combining the characteristics of additive models and generalized linear models. The linearized model relates a response univariate attribute to a selected number of predictor attributes. Let us consider Y to be the former and Xi be the latter. The equation (1) below showcases a link function g of a Y exponential distribution family relating the predictor variables and the Y expected value. The functions f1, f2 etc. are referred to as the smooth functions. GAM is quite flexible in assuming and establishing relationships between predictors and response variables

$$g(\mathrm{E}(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_m(x_m) \quad (1)$$

Rationalization in artificial intelligence is geared towards mimicking human explanatory behaviour for autonomous systems. These algorithms translate internal state-action representations of an autonomous agent into human natural language through the process of neural machine translations. The effectiveness of rationalization techniques is highly regarded as it provides more satisfaction to non-expert humans who can interpret the process much more easily through natural language [17].

5. Motivation

Human Trust is a major factor in determining the future of autonomous systems and XAI [18] has been positioned in the forefront of providing interpretable solutions to customers in order for them to gain understandings of the underlying processes [19]. Several experiments in the past have confirmed that providing information of the self-driving cars [20] and educating customers on its operational decision-making process made sure that the riders experienced higher trust and lower anxiety levels, according to the works of Koo et.al [21]. **Peterson et.al [22]** confirmed that the situational awareness among passengers propagated the impact of trust in driver assistance application and autonomous cars. Studies have also been conducted to explore the passengers' preferences among the four divisions of vehicle assistance: Zero assistance traditional vehicles, Semi-autonomous vehicles, autonomous vehicles without inferences/explanations and autonomous vehicles with interpretable results [23]. A diverse group of people ranging through different age groups were involved in the study. In autonomous cars, 88% of the people felt comfortable in the driver's seat [24] rather than the other seats even when the driving was autonomous. The stress and worry of the passengers motivated them to make sure that they were in a position of control so that they could take over if anything unexpected occurred. Close to 83% of the participating population felt much more comfortable in the autonomous vehicles with the interpretable systems. These works portray the importance of stress reduction and its interdependency towards development of human trust. The success of vehicle autonomy is tightly wound around the complete development of vehicle system explanations. This paper hopes to accentuate the scope of research in explainable autonomous vehicle development and inch closer towards a utopian future of complete human-AI trust.

6. Vision Learning for Autonomous Vehicles

Multiple streams of observational data are fed into the vehicle decision making systems of autonomous vehicles for analytical processing. A majority of these data streams are obtained from the vehicle's environment through sensory devices of different modalities such as radars, cameras, GPS, Ultrasonic sensors, LiDAR sensors etc. These play a vital role in the manoeuvrability and navigational functioning of the vehicle. The decisions taken by the vehicle's driving system are computed in an End 2 End learning fashion (direct mapping to output controls) or through perception planning-action pipeline, where the inferential system is built upon deep learning networks or non-learning based conventional planning algorithms [25]. Combinational execution of such algorithms is also facilitated in the real-world driving scenarios where an object detection network feeds its outputs to an A-star algorithm for path planning. Most common components are localization and perception, complex path planning, behaviour arbitration and manoeuvre control. The entire system can be demarcated as four different components that accommodate different strategies including classical methods and AI based algorithms [26]. The safety of each component is always monitored with appropriate safety monitors. Deep learning methodologies [27] always grab the spotlight when it comes to vehicle vision systems. These network architectures are utilized for learning to detect and identify different common objects during the vehicle's travel. The identification is done on the 2D images obtained through cameras or 3D point clouds obtained through LiDAR based sensors.

7. Self-Driving Ethics/ Morality and Trust in Connected and Autonomous Vehicles

The philosophical branch of ethics provides a collection of principles and morals that help define positive and justified outcomes for both the person and society in general. For the digital era and the concept of self-driving cars, the most appropriate ethical frameworks were selected based upon different premises. The frameworks include pluralism, absolutism, relativism, deontology and utilitarianism. Self-driving cars employ a unique combinational approach of ethical frameworks that have a standard set of ethical standards (absolutism) and a separate adaptable set of rules and policies based upon the consequences of the final situation (Utilitarianism). The primary goal of all ethical notions in vehicle autonomy focusses on minimizing human injury, preventing casualties and non-discrimination based on gender, age, race or other factors.

7.1. Trust in Connected and Autonomous Vehicles

The trust of vehicles in VANET networks/ inter transmissions is based upon the vehicle's reputation and trustworthiness that is developed based upon observing its previous activities as part of the network. The broadcasts and messages passed on by the vehicle system are evaluated to ensure a minimum trust score in order to prevent spoofing or imitation attacks. The establishment of such trust algorithms in vehicular networks help protect the functionality of the network and ensure that no customer data is accessed by unauthorized intruders. The prevention of cyberattacks are crucial to the success of intelligent transportation systems. This has motivated the development of trust based models for connected vehicles namely- data centric, entity centric and combinational trust approaches. Each transmitted message is linked with the vehicle's reputation score to determine its validity. The communications between the vehicles may be of three different typesBeacon. Alert and Disclosure. Beacon messages are transmitted periodically with simple driving status information. Alert messages are sent in the case of emergencies and disclosure messages are sent by witnessing vehicles and those with conflicting information. Figure 4 depicts an entity centric trust system that works primarily based upon vehicle reputation as its assessment criteria. The former actions of each vehicle are considered to build a weighted past behavioural analysis in terms of reliability. Another highly regarded approach to enhance the security of connected vehicles and gain consumer trust is a blockchain backbone as a means to decentralize the system. Figure 4 showcases a Reputation Based Communication System for Intervehicle Network Trust (RCSINT).

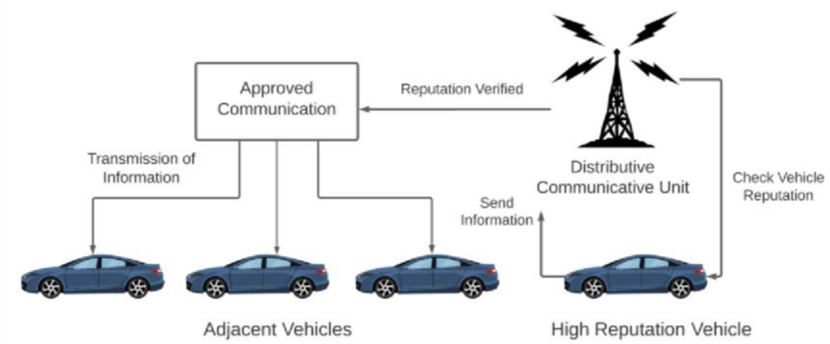

Figure 4: Reputation Based Communication System for Intervehicle Network Trust

7.2. Privacy in Connected and Autonomous Vehicles

Privacy is a fundamental right in India and other countries [29]. Privacy is taken care by user during accessing services by connected vehicles or autonomous vehicles (or both), but here this is our responsibility or service provider's responsibility (as ethics) not to use their passenger information with another no-authorized user. How, privacy in these autonomous vehicles, can be a serious issue, which detailed explanation can be found in [26].

7.3.Trust and Privacy issues in general Vehicle Adhoc Networks

Lightweight Self-Organized Trust models have achieved significant success in the past in extracting reliable trust evaluations from recommendations and trust certificates. These also provide the additional benefit of not needing any third-party vendors or supernodes in the process of reputation evaluation. The adoption of blockchain technology has been discussed extensively in multiple domains of technology, especially in the domain of autonomous transportation. While most application systems function under a client server network architecture, the principle behind blockchain propagates a peer-to-peer form of transmission establishing intercommunication between multiple entities on the network. The employment of this strategy in transportation as a service application system will eliminate the controlling entities and enable transport operators to moderate its use. This distributes the responsibilities/dependencies from a singular entity, eliminates the singular node of failure risk, thus improving public trust. These aforementioned methodologies can help promote the secureness and robustness of the CAV applications while improving consumer awareness and their technological literacy. The widely tested and reliable history of blockchain technology will certainly gain the approval of both the public and related officials as a viable means of opening up the system's operational process.

Moreover this, privacy is a serious issue in VANETs [25, 27] and its related applications like Location based services, navigation, carpooling, parking, etc., In the past decade, many solutions towards Privacy issue in VANETs have been recommended by various experts which can be found in [28] in detail. Further, the role of Software or software-based solutions for VANETs can be found in [30] to improve VANET's component efficiency.

8. Simulation Results

It has been determined that the key factors in enhancing human trust are explainable visual solutions of how the vehicle is interacting with the environment and the reassurance of complete security to the customer. Hence, we create an explainable simulation of GRAD CAM and LIME for autonomous vehicle RGB camera vision. We also explore a novel model for the results were obtained in a Windows 64bit x64-based processor Intel Core™ i7-8550U CPU@1.80GHz 1.99GHZ and 16GB RAM. The simulations were carried out in Python on the Google Colab platform. Figure 5 depicts the LIME explanations for predictions made by Imagenet pretrained Inception V3 weights for the rear end image of a moving vehicle. The image clearly depicts the image regions that have determined the label prediction process of the vehicle's classification system and helps passengers attain a qualitative understanding.

Another viable visual explanation methodology is Grad Cam, which analyses the last convolutional layer of the networks to utilize the flowing gradient information. An understanding of each neuron helps in deriving a decision of interest. The importance weights of the neurons are extracted by global average pooling for predicting the target label. Figure 6 showcases the Grad Cam visualization in a driving scenario for recognizing nearby passing vehicles. The heatmap ranging from red to blue depicts the hotspots in the image responsible for the classification outputs of the InceptionV3 model.

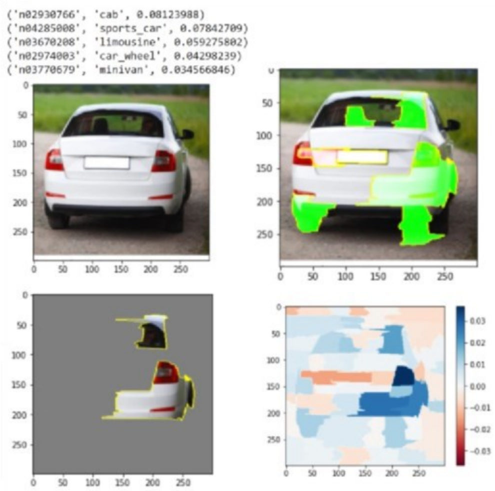

Figure 5: LIME Explanations for Vehicle Rear Image

A network intrusion detection system has also been proposed with a unique recursive feature selection algorithm that focuses on a score-based strategy to remove irrelevant features and keep the most imperative features. A decision tree model was employed as a classifier and the system was tested on the NSL-KDD dataset. The NSL KDD dataset provides extensive network traffic records with both normal authorized connections and intrusion connections for benchmarking cyberattack detection models. Table 1 showcases a comparative analysis of our model coupled with the feature selection algorithm with other extant works.

Figure 6: Grad-Cam Visualization for Vehicle Vision

Table 1: Comparison of Intrusion detection models

Methodology	DOS accuracy (%)	PROBE accuracy (%)	R2L accuracy (%)	U2R accuracy (%)
Naïve Bayes	99.3	97.5	95	60

Correlation based J48	99.1	99	97.8	98.7
SVM with Genetic Optimal Selection	99.1	99	96	97
Proposed Model	99.8	99.88	99.7	98.9

In the last, several privacy preserving techniques for Vehicle Adhoc Network (including future vehicles) has been included in detail. The researchers are recommended to refer these articles for enhancing their knowledge towards preserving of privacy of users in this smart era with emerging technologies/ modern tools.

9. Conclusion

Autonomous vehicles have positioned themselves as crucial contributors to the widespread adoption of smart city infrastructures. The ability to explain the decision-making processes and help passengers interpret why the vehicle performed an action plays an important role in determining the level of trust and reliability placed on it by humans. Visual explanations and the assurance of security to the passengers are the two most influential factors in reducing stress and anxiety levels of the passengers. This paper introduced Explainable Navigational Intelligence, which aims to converge the decision-making processes of autonomous vehicle systems and the domain of Explainable AI (XAI) to provide clear insights into the role explainability plays in increasing human trust on AI solutions. Visual explanatory methods were tested out along with a novel intrusion detection system for security and proved more accurate than other extant works.

References

[1] Arrieta, Alejandro Barredo, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI." *Information Fusion* 58 (2020): 82-115.

[2] Yoganandhan, A., S. D. Subhash, J. Hebinson Jothi, and V. Mohanavel. "Fundamentals and development of self-driving cars." *Materials Today: Proceedings* 33 (2020): 3303-3310.

[3] Cysneiros, Luiz Marcio, Majid Raffi, and Julio Cesar Sampaio do Prado Leite. "Software transparency as a key requirement for self-driving cars." In *2018 IEEE 26th international requirements engineering conference (RE)*, pp. 382-387. IEEE, 2018.

[4] Hilgarter, Kathrin, and Peter Granig. "Public perception of autonomous vehicles: a qualitative study based on interviews after riding an autonomous shuttle." *Transportation research part F: traffic psychology and behaviour* 72 (2020): 226-243.

[5] Ras, Gabriëlle, Marcel van Gerven, and Pim Haselager. "Explanation methods in deep learning: Users, values, concerns and challenges." In *Explainable and interpretable models in computer vision and machine learning*, pp. 19-36. Springer, Cham, 2018.

[6] Hussain, R. and Zeadally, S., 2018. Autonomous cars: Research results, issues, and future challenges. *IEEE Communications Surveys & Tutorials*, *21*(2), pp.1275-1313.

[7] Czubenko, Michał, Zdzisław Kowalczuk, and Andrew Ordys. "Autonomous driver based on an intelligent system of decision-making." *Cognitive computation* 7, no. 5 (2015): 569-581.

[8] Rödel, Christina, Susanne Stadler, Alexander Meschtscherjakov, and Manfred Tscheligi. "Towards autonomous cars: The effect of autonomy levels on acceptance and user experience." In *Proceedings of the 6th international conference on automotive user interfaces and interactive vehicular applications*, pp. 1-8. 2014.

[9] Adadi, Amina, and Mohammed Berrada. "Peeking inside the black-box: a survey on explainable artificial intelligence (XAI)." *IEEE access* 6 (2018): 52138-52160.

[10] Samek, Wojciech, and Klaus-Robert Müller. "Towards explainable artificial intelligence." In *Explainable AI: interpreting, explaining and visualizing deep learning*, pp. 5-22. Springer, Cham, 2019.

[11] Lee, Eunjin, David Braines, Mitchell Stiffler, Adam Hudler, and Daniel Harborne. "Developing the sensitivity of LIME for better machine learning explanation." In *Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications*, vol. 11006, p. 1100610. International Society for Optics and Photonics, 2019.

[12] Selvaraju, Ramprasaath R., Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. "Grad-cam: Visual explanations from deep networks via gradientbased localization." In *Proceedings of the IEEE international conference on computer vision*, pp. 618-626. 2017.

[13] Chattopadhay, Aditya, Anirban Sarkar, Prantik Howlader, and Vineeth N. Balasubramanian. "Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks." In *2018 IEEE winter conference on applications of computer vision (WACV)*, pp. 839-847. IEEE, 2018.

[14] Song, Wei, Shuyuan Dai, Dongmei Huang, Jinling Song, and Liotta Antonio. "Median-Pooling Grad-CAM: An Efficient Inference Level Visual Explanation for CNN Networks in Remote Sensing Image Classification." In *International Conference on Multimedia Modeling*, pp. 134146. Springer, Cham, 2021.

[15] Ramaswamy, Harish Guruprasad. "Ablation-cam: Visual explanations for deep convolutional network via gradient-free localization." In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 983-991. 2020. Shrikumar, Avanti, Peyton Greenside, and Anshul Kundaje. "Learning important features through propagating activation differences." In *International Conference on Machine Learning*, pp. 3145-3153. PMLR, 2017.

[16] Shrikumar, Avanti, Peyton Greenside, and Anshul Kundaje. "Learning important features through propagating activation differences." In *International Conference on Machine Learning*, pp. 3145-3153. PMLR, 2017.

[17] Arya, Vijay, Rachel KE Bellamy, Pin-Yu Chen, Amit Dhurandhar, Michael Hind, Samuel C. Hoffman, Stephanie Houde et al. "AI explainability 360: hands-on tutorial." In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, pp. 696-696. 2020.

[18] Wiegand, Gesa, Malin Eiband, Maximilian Haubelt, and Heinrich Hussmann. "“I’d like an

[19] Explanation for That!” Exploring Reactions to Unexpected Autonomous Driving." In *22nd International Conference on Human-Computer Interaction with Mobile Devices and Services*, pp. 1-11. 2020.

[20] Omeiza, Daniel, Helena Webb, Marina Jirotka, and Lars Kunze. "Explanations in autonomous driving: A survey." *arXiv preprint arXiv:2103.05154* (2021).

[21] Koo, Jeamin, Jungsuk Kwac, Wendy Ju, Martin Steinert, Larry Leifer, and Clifford Nass. "Why did my car just do that? Explaining semi-autonomous driving actions to improve

driver understanding, trust, and performance." *International Journal on Interactive Design and Manufacturing (IJIDeM)* 9, no. 4 (2015): 269-275.

[22] Luke Petersen, Lionel Robert, X. Jessie Yang, and Dawn M. Tilbury. 2019. Situational Awareness, Drivers Trust in Automated Driving Systems and Secondary Task Performance. (2019).

[23] Yuan Shen, Shanduojiao Jiang, Yanlin Chen, Eileen Yang, Xilun Jin, Yuliang Fan, & Katie Driggs Campbell. (2020). To Explain or Not to Explain: A Study on the Necessity of Explanations for Autonomous Vehicles.

[24] Wiegand, Gesa, Matthias Schmidmaier, Thomas Weber, Yuanting Liu, and Heinrich Hussmann. "I drive-you trust: Explaining driving behavior of autonomous cars." In *Extended abstracts of the 2019 chi conference on human factors in computing systems*, pp. 1-6. 2019.

[25] Amit Kumar Tyagi, N. Sreenath, "A Comparative Study on Privacy Preserving Techniques for Location Based Services", British Journal of Mathematics and Computer Science (ISSN: 2231-0851), Volume 10, No.4, pp. 1-25, July 2015.

[26] Amit Kumar Tyagi, S U Aswathy, Autonomous Intelligent Vehicles (AIV): Research statements, open issues, challenges and road for future, International Journal of Intelligent Networks, Volume 2, 2021, Pages 83-102, ISSN 2666-6030. https://doi.org/10.1016/j.ijin.2021.07.002.

[27] Amit Kumar Tyagi, N.Sreenath, "Location Privacy Preserving Techniques for Location Based Services over Road Networks", 2-4 April 2015, in proceeding of IEEE/ International Conference on Communication and Signal Processing (ICCSP), ISBN: 978-1-4799-8080-2, Tamilnadu, India, pp. 1319 – 1326.

[28] R, Varsha et al. 'Deep Learning Based Blockchain Solution for Preserving Privacy in Future Vehicles'. International Journal of Hybrid Intelligent System, Vol 16, Issue 4: 223 – 236, 1 Jan. 2020.

[29] Nair, Meghna Manoj; Tyagi, Amit Kumar "Privacy: History, Statistics, Policy, Laws, Preservation and Threat Analysis", Journal of Information Assurance & Security. 2021, Vol. 16 Issue 1, p24-34. 11p.

[30] Sugandhi Midha, Khushboo Tripathi and M.K.Sharma, "Software defined network horizons and Embracing its security challenges: From theory to practice", in Cloud and IOT Based Vehicular Ad hoc Networks, Chapter 9, Wiley, 22 April 20221, doi.org/10.1002/9781119761846.ch9.