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Explainable artificial intelligence for traffic signal detection using LIME algorithm

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ABSTRACT

As technology progresses, so does everything around us, such as televisions, mobile phones, and robots, which grow wiser. Of these technologies, artificial intelligence (AI) is used to aid the computer in making decisions comparable to humans, and this intelligence is supplied to the machine as a model. As AI deals with the concept of Black-Box, the model's decisions were poorly comprehended by the end users. Explainable AI (XAI) is where humans can understand the judgments and decisions made by the AI. Earlier, the predictions made by the AI were not as easy as we know the data now, and there was some confusion regarding the predictions made by the AI. The intention for the use of XAI is to improve the user interface of products and services by helping them trust the decisions made by AI. The machine learning (ML) model White-box shows us the result that can be understood by the people in that domain, wherein the end users cannot understand the decisions. To further enhance traffic signal detection using XAI, the concept called local interpretable model- agnostic explanation (LIME) algorithm has been taken into consideration and the performance is improved in this paper.

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1. INTRODUCTION

Artificial intelligence (AI) is developed into a big framework that contains a wide range of algorithms and solutions to solve human problems. AI in general was developed for machines to act as humans. Can a machine act as a human? The answer to that is yes, once we train the system according to our needs and if we use the best algorithm then the machine can act like a human. The organizational structure within AI is such that, machine learning (ML) is a subset of AI, while ML and deep learning (DL) are subsets of AI. AI technology has been used in many fields such as medicine, science, transportation, and industries. The use of AI is found to be increased as technology usage is also increased. AI was developed during a workshop held at Dartmouth College in the USA by Alan Turing [1]. AI Intelligence is composed of intellectual stimulation, problem-solving, vision, and linguistic intelligence. Later as years passed the growth of AI systems showed a significant increase in its usage, which led to the introduction of a new concept called explainable AI (XAI). This model is intended to benefit clients by comprehending the assumptions and recommendations made by AI. The main aim of explainable AI is to improve the user interface of products and services by helping them trust the decisions made by the AI. The ML model White-box shows us the result that can be understood by the people in that domain [2], the end users cannot understand the decisions. On the other hand, the decisions made in the Black-box ML model [3], the experts in the domain could not understand the decisions. XAI is the new rising concept in modern technology. While the previous research lacked the need for traffic-related information the XAI model smart transportation using the local interpretable model- agnostic explanation (LIME) algorithm will influence the necessity of traffic signal detection in Vehicles by providing enough data related to traffic signals. The collection of strategies and methods that are developed to enable ML algorithms to produce data information along with its humanly comprehensible findings is known as XAI. Variants such as ML and AI, and in particular neural networks (NN) are rapidly growing and broadening their capabilities, resulting in sophisticated models being utilized more often in decision-making processes. Explainable AI has evolved as an approach to developing “black box” issues related to AI, which occurs when the model has concluded that their efficiency is not human-comprehensible [4]. XAI encompasses tactics and methodology that seek to present information about the outcome of an ML framework and present it in quality comprehended syntax or illustrates to the consumers of the framework. After continuous research, we have reached the conclusion that the XAI algorithm LIME can also be implemented in some other similar methods such as real-time accident updating models based on IoT, traffic management, autonomous vehicles (AVs), and many more.

From Figure 1, we can interpret that a comparison is been made between AI and XAI. In normal AI even after the model has undergone the training, and testing and finally when the AI model predicts the user cannot understand the final output. But when it comes to XAI the user can easily understand the output given by the model as the XAI algorithm has an explainable model and explainable interface.

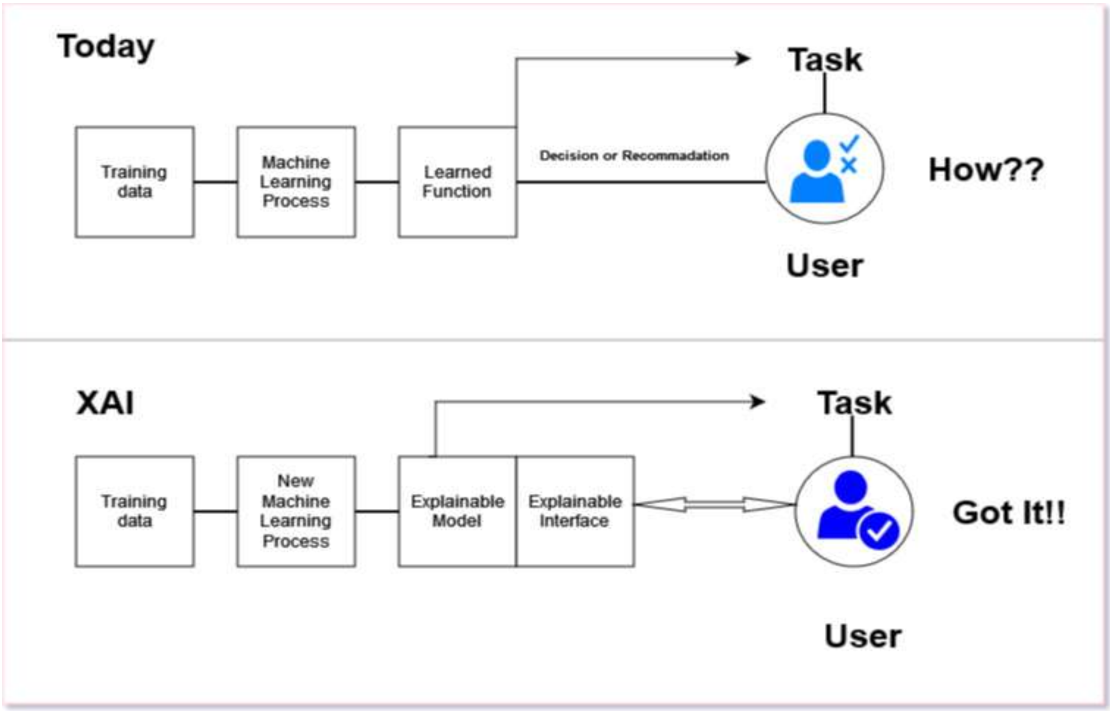

Figure 1. Architecture comparing XAI and AI

2. THE PROPOSED METHOD

2.1. XAI

As XAI is a new emerging technology in AI, we wanted to research XAI. While carrying out this research we came across many fields of applications in which XAI was used and how compactable it was to bring the desired output. Some judgments made by the DL models were compromised by the black box model, which helped researchers introduce XAI to their research [5]. The insufficiency of the DL framework’s interpretability and explainability was found in the decisions made, and the transparency, interpretability, and explainability were seen in an XAI mode [6], [7]. Some of the applications where an XAI can be used are in industries, the field of medicine, the gaming field, natural disasters, and transportation. XAI has various applications such as in health care, game design, industries, military, security, natural disaster management, and intelligent transportation. The establishment of conceptual segmentation of images for AVs employing FCNs that utilize the DL method is discussed. This study has used the SYNTHIA-San Francisco (SF) dataset for experimental studies. An approach that allows human drivers to supplement scene projection with an autonomous driving system with enhanced automated driving with human insight was proposed. A graphical user interface (GUI) is engineered and established to enhance the trust and explainability of the system. To evolve a driving system with no human foresight that can simulate the consciousness of an individual, autonomous driving using common sense reasoning (AUTO-DISCERN) was implemented which ensures the explainability, ethical decision-making, and correctness when the system modeling and inputs are correct. The XAI model in cybersecurity has faced Black-box Attacks, which focus on addressing the gap in understanding the security properties and threats faced in the domain of cybersecurity. The attack successfully misleads simultaneously the classification algorithm and the justification for the report, while not influencing the model's output [2]. From Figure 2, we can understand the working flow of XAI where the model can generate the explanation. AI plays a more important role in day-to-day life.

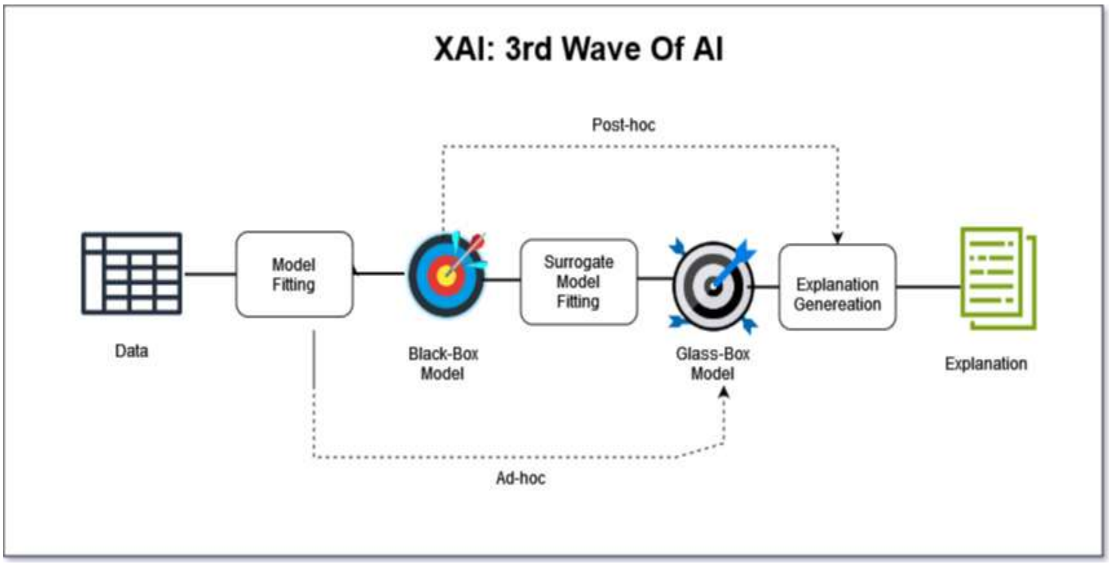

Figure 2. Working flow of XAI

AI so far has helped vehicles such as cars, ships, and airplanes to operate automatically without the need for humans. AI helps to reduce human error, which prompts road accidents to happen. AI has already been undergoing its drawbacks, but AI has made a lot of changes to its algorithm. But the decisions made by the AI model are made by the Black-box. XAI helps the users to understand the forecasting and judgment made by AI. The main aim of explainable AI is to improve the user interface of products and services by helping them trust the decisions made by the AI. These decisions made by Black-box AI were not able to be understood by the experts themselves. During this time the XAI model comes into effect. XAI is the fastest-growing method in the field of AI. XAI mainly focuses on using White-Box rather than Black-box. Trust and safety play the core part of AV, this explains why XAI is mainly needed in Transportation. The below diagram differentiates the current scenario and how the future will turn with the help of XAI. The training data is fed to the model and the explainable model fetches the input from the environment, then the explainable model classifies the inputs according to the training data. The predicted output is displayed in the screen display, which helps the user or the passenger to know why the model has taken this particular decision and prediction. AV are already famous in some parts of the world and in particular, AI is starting to rule the world. The society of automotive engineers (SAE) states that there are 6 levels for autonomous driving (level 0-level 5), no driving automation, driver assistance, partial driving automation, conditional driving automation, high driving automation, full driving automation, vehicular Ad-Hoc networks (VANET) enables communication between AVs. The data that is transmitted between Avs determines each vehicle's performance. Malicious information can cause havoc with the entire system. Hence, the monitoring of obnoxious vehicles is the most crucial [8]. Using XAI to these intricate AI models can guarantee the prudent application of AI for AVs. A visual representation of how an XAI model can be implemented in smart transportation is illustrated in Figure 3.

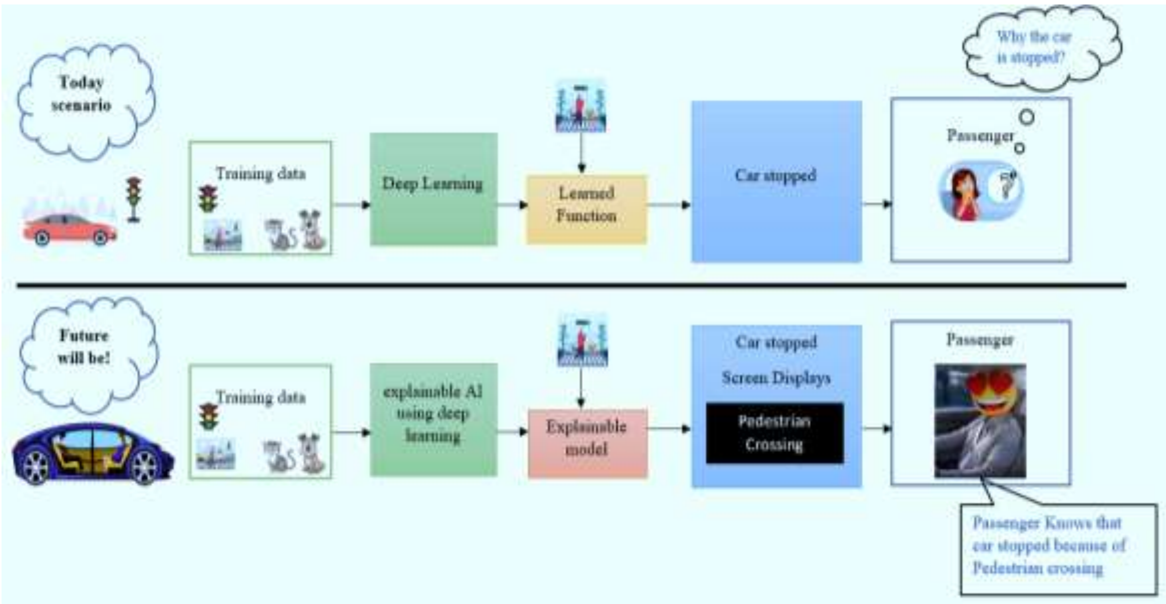

Figure 3. XAI in self-driving cars

3. RESEARCH METHOD

3.1. Lime

XAI techniques help to explain the method for making choices for AI models while making it easier for users to comprehend and have credibility towards the model's predictions. One popular XAI technique is LIME. LIME is a model-agnostic technique, which means it can explain the projections of any supervised learning methods, treating it as a "black box". LIME then uses this simpler model to generate explanations for individual predictions. As shown in Figure 4, a block diagram for the LIME framework is been illustrated step by step. LIME inquires what exactly takes place in the prediction whenever you are ready to give deviations of your values into ML models.

LIME provides a new collection of data that consists of modified samples and corresponds with the predictions in a black-box model. From the dataset that LIME has generated, training an understandable model parameterized by the proximity of the sampled occurrences instance of the expression for the local surrogate models with interoperability is shown. From Figure 5, the architecture of LIME is been illustrated. XAI can be used to be implemented in other fields such as in industries, gaming, medicine, and transportation.

Here are some applications that were implemented using XAI. The step-by-step process of how the LIME algorithm works is as:

A. Choose the feature to be explained
B. Random perturbation of the sample
C. Labelling the perturbation
D. Adding weights to the sample
E. Interpreting the model

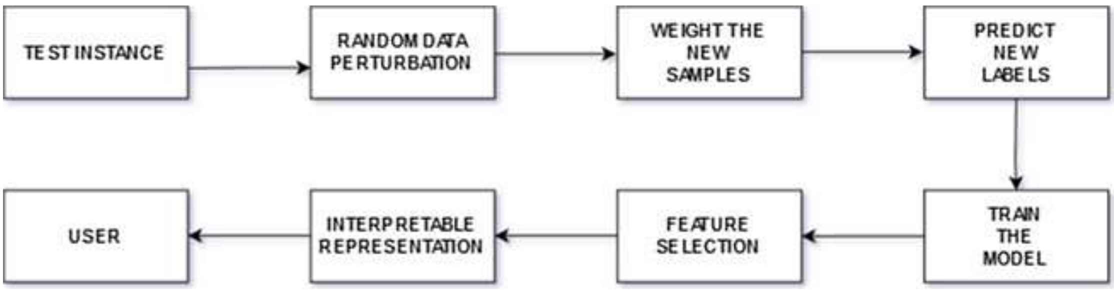

Figure 4. Block diagram of LIME framework

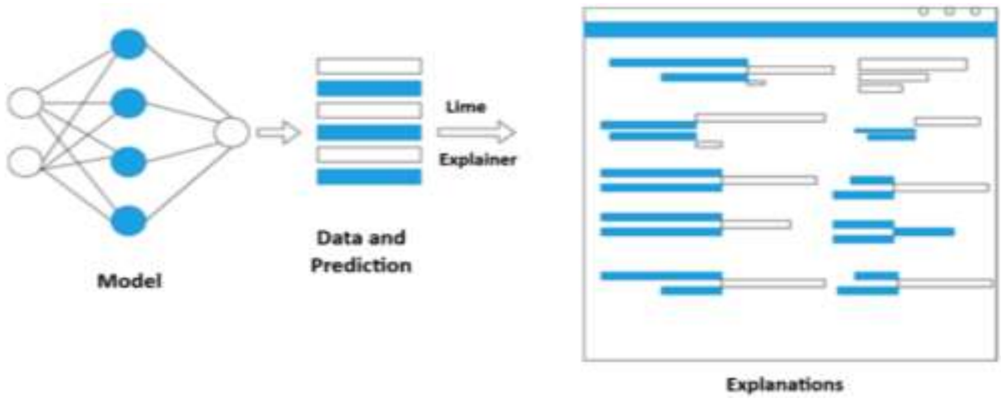

Figure 5. Local interpretable model-agnostic explanations

3.2. Industries

Industry 4.0 is a paradigm that incorporates AI, equipping machines with intelligence to perform functions like self-monitoring, interpretation, diagnosis, and analysis. Explainable AI investigates and implements methods, computational programs, and tools that deliver human-understandable explanations of data and recommendations that are based on AI systems. The leveraging community in the ML method is Cybersecurity, which slowly emerges to combat evolving threats, and the demand for transparency and explainability is increasing. Recent approaches focus on creating explainability methods for users to understand ML models, strikes on interpreters in white box settings, and defining the exact properties generated by the models [9].

The hazards of black-box AI and the necessity for XAI are discussed, along with the origin of XAI, objectives, and stakeholder groups. The paper also reviews different AI methods like ML, DL, and XAI to predict the end-user's opinions on food delivery services (FDs) during COVID. The outcome has shown that 77% of ML models are non-interpretable, highlighting the need for comprehensibility and credibility in the system [10].

3.3. Gaming

The paper introduces the XAI for designers also known as XAID research, focusing on developers of games who struggle to understand the complex decisions made by AI due to their algorithms. The approach aims to provide a gear towards humans XAID approach, empowering game developers to work along with AI/ML techniques, including ML, interface management, operational creation of content, and organization. This can enhance their potential to develop interactive player experiences with AI [11]. In the video game industry, one of the most difficult issues is coming up with believable characters. Even with the variety of authoring tools available, creating the behavior of characters who aren't players is still a difficult process requiring a high degree of technical expertise and complexity. We currently utilize a virtual case-based decision-making agent that learns how to mimic actual users of Ms. Pac-Man using a collaborative method where both the human participant and the computing agent take turns handling the character, given how effective learning from demonstrating is for creating intelligent agents that can mimic human player behaviors [12]. The paper also discusses the emerging issue of cheating in online gaming, where players often engage in illegal ways. The game industry has been working on introducing fraud leveraging multiview software data sources, achieving notably enhanced precision through the application of AI. The paper introduces the explainable multiview game cheating detection (EMGCD) mechanism directed by XAI, which integrated deceptive translators and analyzers from numerous perspectives to generate individualistic, localized, and global explanations [13].

3.4. Medicine

The presented article investigates the identification of insider threat detection using physiological signals like galvanic skin response, electrocardiogram, and electroencephalogram (EEG). It presents an insider evaluation of hazards system using explainable DL and ML techniques, the system classifies anomalous EEG signals that indicate potential insider threats. The paper also discusses XAI in healthcare, aiming to achieve transparency, responsibility achievement tracking, and enhancements to models in health data analysis [14].

The paper focuses on the explainability of AI-based remedies for domains like non-computer science, mainly healthcare professionals. The proposed approach promotes the explainability of ML models and workflows, making them easily integrated into standard ML workflows. The paper presents three approaches for demonstrating the relative ranking of features by ML models, based on the inclusion/exclusion of features, and the association of performance metrics [15].

The paper aims to deal with shortcomings in the explainability of AI programs and the outcomes presented to users by developing a conceptual model for explainable AI. The knowledge centers on XAI within the fields of health and medicine, given their unique requirements that render XAI distinctive and deserving of specific consideration [16].

3.5. Transportation

A summary of global AI related to transportation, which includes traffic management, safety, and public journeys. It analyses the state of AI in the air traffic management (ATM) domain, focusing on its usefulness, trends, features, and limitations [17]. The study challenges AV driving by using DL based techniques for semantic picture segmentation. Convolutional neural network (CNN) architectures were altered to construct fully convolutional networks (FCN), which were further used in experimental investigations. This author used the SYNTHIA-SF dataset to obtain the desired output [18]. Modern DL based autonomous driving techniques produce outstanding results and are now being implemented in some regulated circumstances. One popular method depends on inferring vehicle is handled directly from sensor-believed data. Both traditional supervised settings and reinforcement learning can be used with this end-to-end learning paradigm. However, explainability is a primary flaw in this strategy. This paper proposes training the attention model to help designers determine which aspect of the image has been highlighted [19].

Communication between AVs can be implemented by VANET. Counterfeit or illicit data may interfere with the entire system, with major repercussions. To address this issue, ML methods are used to forecast transmission errors. The accuracy of stacking ML through research has achieved a greater number, the researcher has used a decision tree-based random forest model using the dataset called VeRiMi [20].

4. RESULTS AND DISCUSSION

The implementation of XAI LIME in the research of traffic signal detection outstanding results, with a remarkable accuracy of 93.8%. XAI techniques such as LIME are essential for enhancing the interpretability and transparency of AI models in the domain of traffic signal detection. XAI LIME is particularly beneficial in safety-critical applications involving traffic signal detection since it focuses on offering justification regarding specific assumptions made by AI models. XAI LIME assists users in understanding the logic behind a particular signal's detection through the creation of contextual explanations that emphasize the essential elements impacting a choice. In addition to enhancing developer confidence in the AI system, this transparency enables it to detect and fix any potential biases or errors. Figure 6 shows the input image ie, the traffic sign that denotes the speed limit as 60 km/h. The XAI LIME model has been predicted accurately in Figure 7 as the traffic sign label has a speed limit of 60 km/h. From Figure 8, we can understand the accuracy of the XAI model using the LIME algorithm increases as the number of epochs increases.

During the comparison as shown in Table 1, we can understand that the XAI model using LIME algorithm has the best accuracy. As shown in the Table 1, After vigorous scrutiny and continuous surveys of ML algorithms related to traffic signal detection, we can conclude that the LIME algorithm can deliver more accuracy than any other algorithms. For example., the YOLOv5 algorithm has 82.8% accuracy in the detection of Traffic Signals, similarly in YOLOv7- WCN, YOLOv7- TINY, and YOLOv3 which has shown accuracy of 85.5-89.0%, 78.57% and 72.8% respectively.

Figure 6. Input

Figure 7. Predicted output

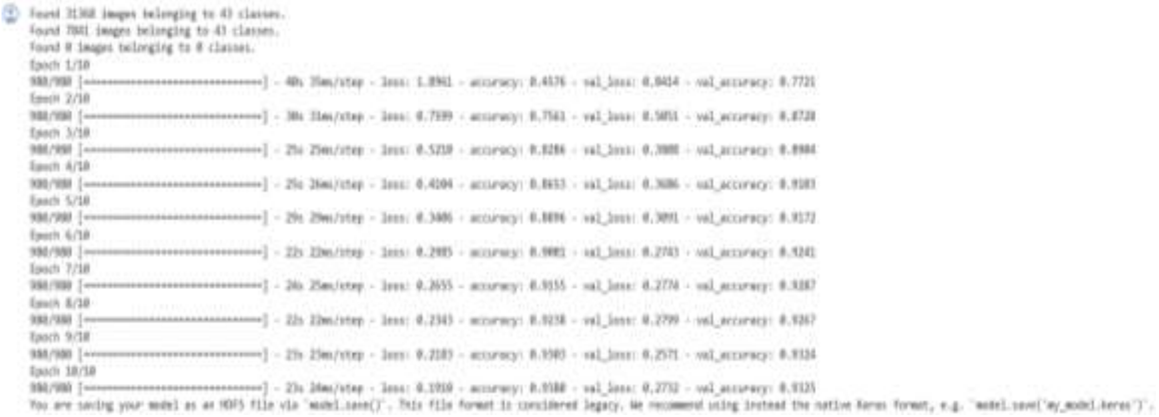

Figure 8. Shows the accuracy of the XAI model using LIME

Table 1. Shows the comparison between the XAI model and ML and DL models

S. No	Model	Algorithm	Accuracy
1.	XAI	LIME	93.80%
2.	YOLO [21]	YOLOv5	82.8%
3.	YOLO [22]	YOLOv7-WCN	85.5-89.0%
4.	YOLO [23]	YOLOv7 TINY	78.57%
5.	DL model [24]	YOLOv3	72.8%

From the Figure 9 we can understand that the SHAP value can encode the necessity that a model can give for the feature selected, by doing so we can understand the importance of the features we have selected [25], [26]. This paper discloses a wide range of approaches within the XAI domain, including interpretable machine-learning models, and rule-based systems. The wide range of techniques illustrates the complexity of interpretability in problems. This diversity provides the interpreter with a toolbox of diverse options to choose from based on the specific needs and constraints in their applications.

One of the limitations that we were able to interrupt was the computational resources, as XAI demands a timely response based on real-time explanation it is derived to be a computational resource. The frequently discussed subject is inheritance deals between accuracy and interpretability in models. To conclude, this discussion focuses on the nature of XAI, and the efforts made by various authors to make XAI the best human-centric technology. Which can give us the best outcome in the model accuracy, interpretability, and explanations.

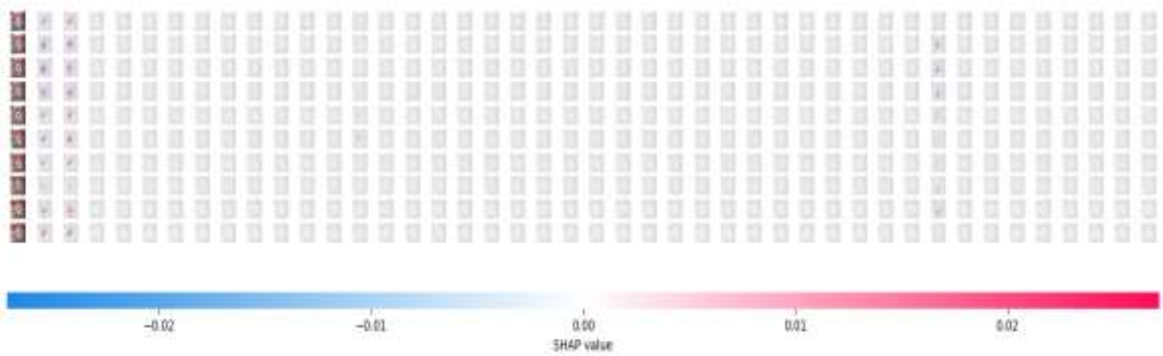

Figure 9. Illustrates the SHAP value

5. CONCLUSION

Through this research, we have identified the crucial need to incorporate XAI to solve the problems in the AI/ML field. This method has filled the gap between the opaque nature of complex ML and AI models and the need for transparency and interpretability in decision-making. By reading various research papers it has come to the conclusion that demand for XAI in various fields like transportation, medicine, industry, finance, gaming, designing, and many more. This survey paper focuses attention on various techniques that can be employed in XAI, ranging from interpretable ML algorithms to post-hoc explanation methods and rule-based methods. Our model deals with the implementation of traffic signal detection based on real-time explanation. To further develop the model our main goal is to implement traffic signal detection along with the lane detection method. Our research finding mainly contributes to the necessity of the XAI algorithm in today's technology.

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