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A Novel Framework for Predicting Driver Behavior at Unsignalized Intersections Using Machine Learning

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Abstract- Unsignalized intersections are critical points in road networks where the absence of traffic signals significantly increases the risk of accidents due to unpredictable driver behavior. Understanding and predicting driver decisions in such scenarios is crucial for improving traffic safety and designing intelligent transportation systems. This study presents a novel framework for predicting driver behavior at unsignalized intersections using machine learning techniques. The framework integrates multiple data sources, including vehicle dynamics, road geometry, and environmental factors, to create a comprehensive dataset for modeling driver behavior. Feature engineering techniques are employed to extract relevant features from the data, such as speed, acceleration, gap acceptance, and proximity to other vehicles. Several machine learning algorithms, including Random Forest, Gradient Boosting Machines, and Neural Networks, are evaluated for their predictive performance. The proposed framework incorporates advanced methods like hyperparameter tuning and cross-validation to optimize model accuracy and robustness. Results from simulations and real-world datasets demonstrate the framework's ability to achieve high predictive accuracy, outperforming existing methods. The study also highlights the interpretability of machine learning models, providing insights into key factors influencing driver decisions at unsignalized intersections. By identifying high-risk scenarios and enabling proactive interventions, this framework has significant implications for enhancing traffic management and safety systems. Furthermore, its scalability and adaptability make it suitable for integration into autonomous vehicle systems and smart city initiatives. Future research directions include the integration of real-time data from connected vehicles and IoT devices to improve prediction accuracy and the application of reinforcement learning to model more complex driver decision-making processes. This novel approach bridges the gap between machine learning applications and traffic behavior analysis, paving the way for safer and more efficient road networks.

Indexed Terms- Driver Behavior Prediction, Unsignalized Intersections, Machine Learning, Traffic Safety, Feature Engineering, Intelligent Transportation Systems, Connected Vehicles, Autonomous Systems.

I. INTRODUCTION

Unsignalized intersections are critical components of road networks, where vehicles interact without the guidance of traffic signals or signs. These intersections, commonly found in both urban and rural areas, pose significant safety concerns due to the unpredictability of driver behavior. Drivers must rely on their judgment to assess gaps in traffic, making decisions on whether to proceed, yield, or stop (Adepoju, et al., 2022, Bifulco, et al., 2022, Huang, et al., 2022). This often leads to situations where human error or misjudgment results in accidents, including collisions and near-misses, which contribute to road safety challenges globally. Given the dynamic nature of driver behavior, it is essential to develop methods that can accurately predict these decisions and enhance the safety of unsignalized intersections.

The ability to predict driver behavior at these locations can help traffic management systems reduce accidents and optimize traffic flow. This research aims to address these challenges by proposing a novel machine learning framework for predicting driver behavior at unsignalized intersections. The framework integrates data from multiple sources, including vehicle dynamics, road geometry, and environmental conditions, to create a more comprehensive model of driver behavior (Alsrehin, Klaib & Magableh, 2019, Jiang, et al., 2021). By leveraging machine learning algorithms, this approach will provide insights into how drivers interact with each other and the environment at these intersections, enabling better decision-making and safety interventions.

The study focuses on improving traffic safety and enhancing the performance of intelligent transportation systems (ITS). It also holds significant relevance for the development of autonomous vehicles, where the ability to predict human driver behavior is crucial for ensuring safe interactions between human-driven and autonomous vehicles at unsignalized intersections. The scope of this research extends to various applications, including real-time decision support for traffic management, development of advanced driver assistance systems (ADAS), and the optimization of autonomous vehicle algorithms (Bennaya & Kilani, 2023, Geng, et al., 2023, Musingura, et al., 2023). By creating a predictive framework, this study aims to lay the foundation for safer, more efficient transportation systems in the future.

2.1. Literature Review

Unsignalized intersections represent a crucial aspect of road networks, where traffic flow is controlled not by signals but by the judgments of drivers navigating them. Understanding driver behavior at these intersections is essential for improving road safety and optimizing traffic management. Traditional methods for predicting driver behavior, including rule-based models and statistical techniques, have been applied to such scenarios but are often limited in their ability to address the complexities and variability inherent in real-world driving behavior (Ganesh & Xu, 2022, Gudala, et al., 2022, Pavel, Tan & Abdullah, 2022). These conventional approaches often rely on assumptions or simplified models that fail to capture the intricate interactions between drivers, vehicles, and the road environment. As a result, there has been a growing interest in developing more advanced methods, such as machine learning (ML), to provide more accurate and adaptive predictions of driver behavior.

Rule-based models have traditionally been used to predict driver behavior, particularly in scenarios involving unsignalized intersections. These models typically rely on predefined rules or heuristics that define driver actions based on specific inputs, such as traffic density, road conditions, or proximity to other vehicles. For example, a rule-based model may predict that a driver will stop at an intersection if the gap in traffic is too small or that a driver will proceed when the gap is sufficiently large (Lim & Taeihagh, 2018, Magyari, et al., 2021, Singh & Kathuria, 2021). While these models are relatively simple and computationally inexpensive, they are often too rigid to handle the variability of real-world driving. They cannot account for the subtle nuances in human behavior, such as the influence of a driver's mood, risk tolerance, or experience, which can significantly affect decisions at unsignalized intersections. Furthermore, rule-based models often fail to adapt to changing conditions, such as the introduction of new traffic patterns or the behavior of other road users.

Statistical methods, such as regression analysis, have also been used to model driver behavior at unsignalized intersections. These methods typically rely on historical data to identify correlations between various factors, such as the time of day, weather conditions, and traffic volume, and driver behavior outcomes. While statistical models are better at quantifying relationships between variables, they are still limited by the quality and availability of data. Additionally, these models often struggle to capture the dynamic nature of driver behavior, as they assume that relationships between variables are stable over time. This limitation makes statistical models less effective in predicting driver behavior in real-time, where conditions are constantly changing (Abughalieh & Alawneh, 2020, Chen, Wawrzynski & Lv, 2021). Moreover, statistical models do not typically account for the complex interactions between different drivers at an intersection, which can result in inaccurate predictions, especially in situations where multiple vehicles interact in complex ways. Figure 1 shows a schematic diagram of rural intersection with different ICWS components presented Rachakonda & Pawar, 2023.

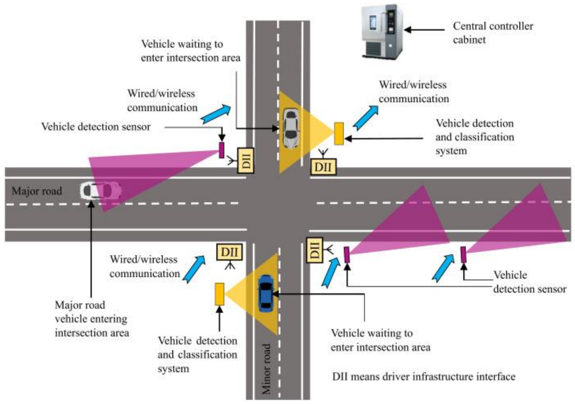

Figure 1: Schematic diagram of rural intersection with different ICWS components (Rachakonda & Pawar, 2023).

Over the past few years, there has been a significant shift toward incorporating machine learning (ML) into the prediction of driver behavior at unsignalized intersections. Machine learning offers several advantages over traditional methods, particularly in terms of its ability to learn from large and diverse datasets and adapt to new information. ML algorithms are capable of capturing complex patterns and relationships within data without requiring explicit programming of rules (Adeniran, et al., 2022, Chauhan, et al., 2022, Wang, 2022). By training on real-world data, machine learning models can identify subtle correlations and trends that may not be immediately apparent, allowing them to make more accurate predictions about driver behavior in a wide range of conditions.

One of the most commonly used machine learning techniques in transportation studies is supervised learning, particularly classification and regression algorithms. These methods involve training a model on labeled data, where the inputs (e.g., traffic volume, road geometry, vehicle speed) are associated with known outcomes (e.g., whether a driver stopped or proceeded at the intersection) (Arvin, Kamrani & Khattak, 2019, Camara, et al., 2020, Wang, et al., 2020). Algorithms such as decision trees, support vector machines (SVM), and neural networks have been used to predict driver behavior in various traffic scenarios, including at unsignalized intersections. For instance, decision trees can model the decision-making process by splitting data into branches based on specific attributes (e.g., traffic gap size, driver speed), while neural networks can learn complex, non-linear relationships in the data to improve prediction accuracy. These approaches are particularly effective in capturing the variability of human behavior, as they can consider a wide range of inputs and adapt to new patterns as more data becomes available. A driving simulator and data acquisition presented by Li, et al., 2023, is shown in figure 2.

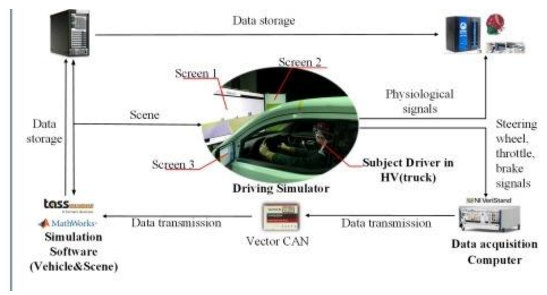

Figure 2: Driving simulator and data acquisition (Li, et al., 2023).

Recent advancements in machine learning for traffic safety have focused on improving the accuracy and efficiency of these models by incorporating a variety of techniques. One key development is the use of deep learning, particularly deep neural networks (DNN), which are capable of processing large amounts of data and learning hierarchical representations. Deep learning models have shown promise in understanding complex patterns in driver behavior that may be difficult to detect with traditional methods (Agu, et al., 2022, Kussl & Wald, 2022, Yuan, et al., 2022). For example, convolutional neural networks (CNN) have been used to analyze images of roadways and predict driver actions based on visual cues, such as the presence of other vehicles or pedestrians. Similarly, recurrent neural networks (RNN), which are designed to handle sequential data, have been employed to predict how a driver's behavior might change over time, accounting for factors such as traffic flow and driver attention span.

Another significant trend in the field is the integration of heterogeneous data sources to improve prediction accuracy. Traditional traffic models often rely on a limited set of variables, such as traffic volume or road geometry, which may not capture the full complexity of driving behavior. Machine learning, on the other hand, can incorporate diverse data sources, including vehicle telemetry, driver demographics, environmental conditions, and even real-time data from connected vehicles or IoT sensors (Pawar & Patil, 2017, Shirazi & Morris, 2016, Zhang & Fu, 2020). By combining these data types, ML models can provide a more holistic understanding of driver behavior. For example, data from connected vehicles can be used to predict the likelihood of a driver making a risky decision based on real-time interactions with other vehicles in the system. Additionally, integrating weather data or road conditions can help refine predictions, as these factors are known to influence driver behavior, particularly at unsignalized intersections. Figure 3 shows depiction of how ITS applications exploit tasks for collision avoidance as presented by Yuan, et al., 2019.

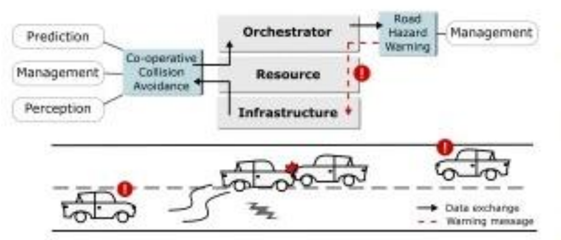

Figure 3: Depiction of how ITS applications exploit tasks for collision avoidance (Yuan, et al., 2019).

One of the challenges in applying machine learning to predict driver behavior is ensuring that the models are interpretable and explainable. While machine learning algorithms can achieve high accuracy, they are often seen as “black boxes” that do not provide insight into how decisions are made. This lack of transparency can be a barrier to widespread adoption, particularly in safety-critical applications such as traffic management or autonomous vehicles. To address this challenge, recent research has focused on developing methods for improving the interpretability of machine learning models (Hamdar, Qin & Talebpour, 2016, Kolekar, et al.,, 2021). Techniques such as model-agnostic interpretability and feature importance analysis can help researchers and practitioners understand how specific factors influence the predictions made by machine learning models. These methods are crucial for building trust in machine learning-based systems, particularly in the context of public safety.

In summary, the use of machine learning for predicting driver behavior at unsignalized intersections represents a promising advancement over traditional methods, offering the potential for more accurate and adaptive predictions. Machine learning algorithms, particularly supervised learning and deep learning techniques, are capable of capturing complex patterns in driver behavior that traditional statistical models and rule-based approaches cannot. Moreover, the integration of heterogeneous data sources, including real-time data from connected vehicles and IoT sensors, further enhances the predictive power of these models (Asaithambi,Kanagaraj & Toledo, 2016, Chen, Wawrzynski & Lv, 2021, Efunniyi, et al., 2022). However, challenges remain, particularly in ensuring that these models are interpretable and can be integrated into real-time traffic management systems. As the field continues to evolve, machine learning has the potential to significantly improve the safety and efficiency of unsignalized intersections, paving the way for smarter, more responsive transportation systems.

2.2. Framework Design

The design of a novel framework for predicting driver behavior at unsignalized intersections using machine learning is a multi-step process that integrates several key components to ensure the model's accuracy, adaptability, and real-time applicability. The framework must account for various dynamic factors that influence driver decisions, such as vehicle dynamics, road geometry, and environmental conditions (Azadani & Boukerche, 2021). Machine learning techniques are employed to analyze and predict how drivers will behave in different traffic situations. A successful framework for this task must incorporate data acquisition, preprocessing, modeling, and evaluation stages, all of which contribute to creating a comprehensive and reliable prediction system.

The first step in the framework is data acquisition. Gathering high-quality, real-world data is essential for training machine learning models to predict driver behavior accurately. For unsignalized intersections, this data typically includes information on vehicle dynamics, road geometry, and environmental conditions. Vehicle dynamics provide insights into how a driver controls their vehicle in response to traffic conditions, including speed, acceleration, and braking patterns (Azadani & Boukerche, 2021, Ige, et al., 2022, Ojukwu, et al., 2022). These parameters are crucial because they offer a direct reflection of the driver's behavior in approaching and navigating intersections. For instance, a driver's decision to proceed through an intersection may be influenced by their current speed, which could indicate whether they are likely to slow down, stop, or continue without hesitation. Khan, 2023, presented the Auto Encoders as shown in figure 4

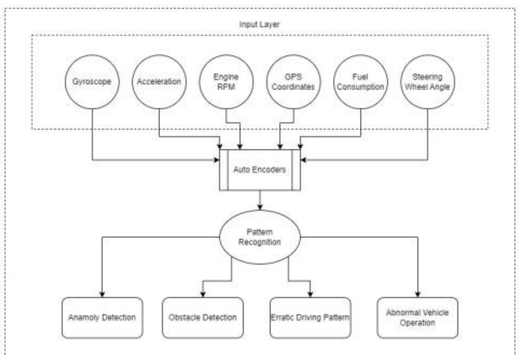

Figure 4: Auto Encoders (Khan, 2023).

Road geometry is another critical data component that affects driver behavior predictions. Lane configurations, intersection types, and road characteristics, such as the presence of turns, curves, or other obstacles, must be incorporated into the framework. Different intersection types, such as T-junctions, Y-intersections, and crossroads, each present unique challenges to drivers. Understanding how drivers behave at these varying intersection types allows the framework to make more informed predictions (Afolabi, et al., 2023, Huang, et al., 2023, Sarker, 2023). The geometry of the intersection also affects factors like visibility and available gaps in traffic, which are key determinants of driver decisions. For example, a driver may be more likely to yield at an intersection with poor visibility or complex road geometry compared to a simpler, more straightforward intersection.

Environmental factors, such as weather conditions and visibility, also significantly impact driver behavior at unsignalized intersections. Adverse weather conditions, such as rain, snow, or fog, can reduce visibility and increase stopping distances, leading to more cautious driving behavior. On the other hand, clear and dry weather may encourage drivers to take more risks when navigating intersections (Charouh, et al., 2022, Chauhan, et al., 2022). These environmental conditions, therefore, need to be incorporated into the machine learning framework to ensure that predictions account for such variations in behavior. Data regarding weather conditions can be obtained from local meteorological services or on-vehicle sensors, and visibility data can be derived from both environmental sensors and historical accident data.

Once the necessary data is acquired, the next step is data preprocessing. Raw data often contains noise, missing values, and inconsistencies that must be addressed before it can be used effectively for training machine learning models. Data preprocessing involves cleaning, normalizing, and transforming the data into a suitable format for model training. This process may include handling missing data through imputation techniques, scaling numerical values to a common range, and encoding categorical variables into a machine-readable format (Agu, et al., 2022, Lim & Taeihagh, 2018, Samira, et al., 2022). Feature engineering is also an essential aspect of preprocessing, as it involves creating new features or transforming existing ones to better capture the underlying patterns in the data. For instance, instead of using raw vehicle speed, the framework may calculate the rate of change in speed over time to capture acceleration or deceleration patterns, which are critical for predicting driver behavior.

Once the data is properly preprocessed, the next phase of the framework involves developing a machine learning model capable of predicting driver behavior. The choice of algorithm plays a significant role in the model's performance. Various machine learning algorithms can be employed for this task, including decision trees, random forests, support vector machines (SVM), and neural networks (Abdi & Meddeb, 2018, Fu & Liu, 2020, Nikitas, et al., 2020). Decision trees, for instance, are well-suited for capturing decision-making processes that involve multiple conditions, such as traffic gaps and vehicle speed. Random forests, which combine multiple decision trees, can help improve prediction accuracy by reducing overfitting and increasing the robustness of the model. For more complex patterns, neural networks and deep learning approaches may be used, especially when dealing with large and heterogeneous datasets. These algorithms are capable of learning non-linear relationships and can adapt to changing conditions, which is essential for handling the dynamic nature of driver behavior.

The model must be trained on the preprocessed data using supervised learning techniques, where the inputs (such as traffic conditions, vehicle speed, and road geometry) are associated with known outcomes (e.g., whether a driver stopped, yielded, or proceeded). Training the model involves adjusting the parameters of the algorithm to minimize the prediction error, which can be done using various optimization techniques, such as gradient descent (Mozaffari, et al., 2020, Muresan, 2021, Olayode, et al., 2020). The model's performance is then validated using a separate validation set, ensuring that it generalizes well to unseen data. Overfitting, a common issue in machine learning, must be carefully monitored, as it can cause the model to perform well on the training data but poorly on new, real-world data.

After training the machine learning model, the next step is to evaluate its performance. Evaluation involves assessing the accuracy and reliability of the model using various performance metrics, such as accuracy, precision, recall, and F1-score. These metrics help determine how well the model is predicting driver behavior and whether it can be trusted for real-time applications. Additionally, the model may undergo stress testing to simulate various scenarios, such as sudden changes in traffic conditions or environmental factors, to see how it reacts and adapts (Li, Elefteriadou & Ranka, 2014, Mena-Yedra, 2020, Yuan, et al., 2019). Evaluation also involves comparing the model's predictions with actual driver behavior, which can be obtained through real-world testing or simulation environments. This comparison helps identify areas for improvement and fine-tuning of the model. A proposed application-driven ITS framework by Yuan, et al., 2019, is shown in figure 5.

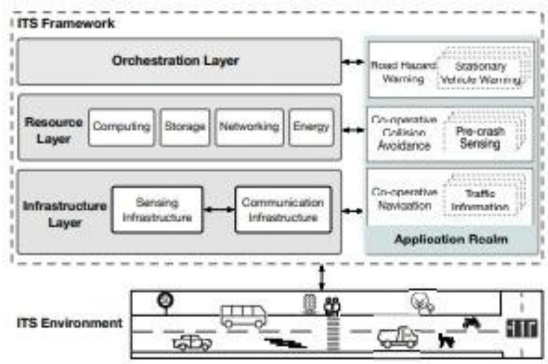

Figure 5: Proposed application-driven ITS framework (Yuan, et al., 2019)..

Another important aspect of the framework is its ability to update and adapt over time. Driver behavior is not static; it evolves due to various factors, including changes in driving habits, road infrastructure, and technological advancements. To ensure that the framework remains effective in the long term, it must be designed to incorporate continuous learning. This involves periodically retraining the model with new data or allowing it to adjust to new patterns of driver behavior as they emerge (Agu, et al., 2023, Ketter, Schroer & Valogianni, 2023). For example, as autonomous vehicles become more prevalent, the behavior of human drivers may change, requiring the framework to adapt accordingly.

One of the key advantages of using machine learning for predicting driver behavior is its ability to integrate heterogeneous data sources. Data from vehicle sensors, infrastructure systems, weather reports, and even connected vehicle networks can all be incorporated into the model to improve its accuracy. The use of real-time data, such as traffic flow or vehicle proximity, enables the model to make dynamic predictions based on the current state of the intersection. This real-time capability is particularly valuable in traffic management systems, where immediate decisions must be made to improve safety or optimize traffic flow (Almeida, 2023, Hunter, 2022, Wang, 2022).

In conclusion, the design of a novel framework for predicting driver behavior at unsignalized intersections using machine learning requires a systematic approach that encompasses data acquisition, preprocessing, modeling, and evaluation.

By incorporating data from multiple sources, such as vehicle dynamics, road geometry, and environmental factors, the framework can provide a more accurate and adaptive prediction of driver behavior (Peng, et al., 2020, Rui & Yan, 2018, Silasai & Khowfa, 2020). The use of machine learning algorithms enables the model to learn from large datasets and make predictions based on complex patterns, while continuous learning ensures that the framework remains effective as driving behavior evolves. This comprehensive approach will improve traffic safety and efficiency, making it a valuable tool for traffic management systems and autonomous vehicle development.

2.3. Methodology

The methodology for developing a novel framework for predicting driver behavior at unsignalized intersections using machine learning involves a series of systematic steps designed to ensure the robustness, accuracy, and real-time applicability of the model. These steps include data collection and preprocessing, feature engineering, model development, and model evaluation. Each stage is critical to the creation of a reliable system capable of predicting driver decisions in complex and dynamic traffic environments.

Data collection is the first critical phase of the methodology, where real-world and simulated datasets are gathered to train the machine learning model. Real-world datasets can be collected through traffic monitoring systems, which may include vehicle sensors, cameras, GPS data, and road infrastructure sensors. These systems capture valuable information such as vehicle speed, acceleration, braking patterns, and interactions with other vehicles at unsignalized intersections. Additionally, simulated datasets can be used to supplement real-world data, especially for rare or difficult-to-observe scenarios, such as highly congested intersections or adverse weather conditions. Traffic simulation tools such as VISSIM or Synchro can generate a wide range of driving conditions to help diversify the dataset. Data from both real-world and simulated sources need to be combined and cleaned to remove inconsistencies and noise (Galterio, Shavit & Hayajneh, 2018, Hara, et al., 2021). This cleaning process may involve handling missing values through imputation techniques, such as replacing missing data with the median or using regression models to predict missing values. Data normalization is also essential, as it ensures that numerical values, such as speed or vehicle distance, are scaled to a standard range, preventing certain features from dominating the learning process. Standard techniques like Min-Max scaling or Z-score normalization can be used to achieve this.

Once the data is collected and preprocessed, the next critical step in the methodology is feature engineering. Feature engineering involves identifying the most relevant variables that influence driver behavior and creating new features that capture these underlying patterns. For unsignalized intersections, some of the critical features include gap acceptance, proximity to other vehicles, vehicle speed, and driver behavior indicators such as acceleration or deceleration rates (Adeniran, et al., 2022, Nikitas, et al., 2020). Gap acceptance refers to a driver's willingness to enter or cross an intersection based on the availability of a safe gap in the traffic flow. Proximity to vehicles provides valuable information about whether drivers are likely to yield or proceed, depending on how close they are to other vehicles. Additional factors such as road geometry (e.g., intersection type, lane configurations) and environmental conditions (e.g., weather, visibility) can also play a significant role in shaping driver decisions. Feature selection and dimensionality reduction techniques are employed to ensure that only the most significant features are used in the model, reducing computational complexity and improving model performance. Techniques like Recursive Feature Elimination (RFE) or principal component analysis (PCA) can be applied to select the most relevant features and reduce the dimensionality of the dataset.

The next phase of the methodology is model development, where machine learning algorithms are used to develop the predictive framework. Several machine learning algorithms are considered for this task, with Random Forest, Gradient Boosting Machines (GBM), and Neural Networks being the primary candidates. Random Forest is a versatile algorithm that uses an ensemble of decision trees to improve prediction accuracy by reducing overfitting. It is particularly effective in handling non-linear relationships and can automatically handle interactions between features (Austin-Gabriel, et al., 2021, Guo,Li & Ban, 2019, Tian, et al., 2020). GBM, on the other hand, is a powerful algorithm that builds an ensemble of trees sequentially, with each tree attempting to correct the errors made by the previous one. It has been widely used for various predictive modeling tasks, including traffic safety and driver behavior prediction, due to its high performance. Neural Networks, specifically deep learning models, are well-suited for handling large and complex datasets with intricate relationships between variables. These models are capable of capturing non-linear patterns and can be trained to learn from high-dimensional data, making them ideal for situations where traditional algorithms may struggle.

To develop the most effective model, hyperparameter tuning is essential. Hyperparameters, such as the number of trees in Random Forest or the learning rate in Gradient Boosting, significantly impact the performance of the model. Grid search is a common method used to tune hyperparameters, where a predefined set of hyperparameter values is tested to determine the optimal combination. Alternatively, Bayesian optimization can be used for more efficient hyperparameter tuning by probabilistically selecting the best set of parameters based on previous results.

Once the model is developed and the hyperparameters are optimized, the next step is model evaluation. Model evaluation involves assessing the performance of the machine learning framework to ensure that it is accurate, reliable, and capable of making real-time predictions. Common metrics for evaluating predictive models include accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the predictions, while precision and recall focus on the model's ability to correctly predict positive instances (e.g., drivers yielding or stopping) and avoid false positives or false negatives (Alzubaidi & Kalita, 2016, Baheti, Gajre & Talbar, 2018). The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. These evaluation metrics give a comprehensive view of the model's performance, especially in cases where the dataset is imbalanced (e.g., when one behavior is more common than others).

To ensure the robustness of the model, cross-validation techniques, such as k-fold cross-validation, are applied. In k-fold cross-validation, the dataset is divided into k subsets, and the model is trained and validated k times, with each fold serving as the validation set once. This helps assess the model's ability to generalize to new data and reduces the likelihood of overfitting. Out-of-sample testing is also performed, where the model is tested on a separate dataset that was not involved in the training process. This provides an additional measure of the model's performance and ensures that it is capable of making predictions in real-world scenarios.

After the model has been evaluated, its results are analyzed to identify areas for improvement. If the model performs well in terms of accuracy and other metrics, it can be deployed in real-world traffic management systems or integrated into autonomous vehicle technologies. However, if the model's performance is subpar, the methodology allows for iterative refinement. This can include retraining the model with more diverse datasets, adjusting the features used in the model, or experimenting with alternative machine learning algorithms (Aksjonov & Kyrki, 2021, Soomro, et al., 2019, Tawari, Mallela & Martin, 2018).

In conclusion, the methodology for predicting driver behavior at unsignalized intersections using machine learning is a comprehensive process involving multiple stages. It begins with data collection and preprocessing, followed by feature engineering to identify and create relevant features. Machine learning algorithms, such as Random Forest, Gradient Boosting, and Neural Networks, are used to develop the predictive model, which is then fine-tuned through hyperparameter optimization. The model's performance is rigorously evaluated using various metrics and validation techniques, ensuring that it is capable of making accurate and reliable predictions in real-world scenarios. This methodology offers a systematic approach to predicting driver behavior at unsignalized intersections and has the potential to enhance traffic safety and improve intelligent transportation systems.

2.4. Results and Discussion

The results and discussion of the novel framework for predicting driver behavior at unsignalized intersections using machine learning are essential to understanding the model's performance, its implications for traffic safety, and its potential for real-world applications. The analysis begins with a performance evaluation of different machine learning models, followed by an exploration of the interpretability of the results and the insights they provide for enhancing traffic safety.

In terms of performance analysis, the comparison between various machine learning models is fundamental to identifying the best algorithm for predicting driver behavior. The primary algorithms evaluated include Random Forest, Gradient Boosting Machines (GBM), and Neural Networks. Each of these models has different strengths and weaknesses, which were assessed based on several performance metrics, including accuracy, precision, recall, F1-score, and model robustness (Agu, et al., 2023, Ojukwu, et al., 2022, Torbaghan, et al., 2022).

Random Forest, known for its robustness and ability to handle high-dimensional datasets, was found to perform well in capturing complex patterns in driver behavior. It showed strong accuracy in classifying different driver actions such as yielding, stopping, or proceeding through the intersection. However, while Random Forest is relatively simple to interpret, its performance tends to be outperformed by more advanced models when it comes to handling highly non-linear relationships between features.

Gradient Boosting Machines (GBM) also demonstrated strong predictive power, with better overall accuracy and F1-scores compared to Random Forest. GBM, by constructing trees sequentially and learning from previous mistakes, was able to more effectively predict rare events such as emergency braking or late gap acceptance, which are crucial for safety-related predictions. The sequential nature of GBM allowed it to fine-tune its predictions by minimizing errors in the learning process (Mukherjee & Mitra, 2019, Neal & Woodard, 2016, Sun & Elefteriadou, 2014). Despite its higher performance, however, GBM has a tendency to be more computationally expensive and can be prone to overfitting if not properly tuned, particularly when using large datasets with numerous features.

Neural Networks, especially deep learning models, were also tested and exhibited strong performance in terms of overall accuracy. These models excelled at detecting intricate relationships between features that may not be immediately obvious to simpler algorithms. However, the interpretability of Neural Networks remains a challenge due to their "black-box" nature. While they provided high precision and recall scores, their complexity and the difficulty in understanding their decision-making process limited their applicability in scenarios where model transparency is crucial, such as in regulatory settings or when providing actionable insights to traffic safety authorities.

Among the three models, Gradient Boosting Machines emerged as the best-performing algorithm in terms of prediction accuracy and handling the non-linear relationships between various features. However, the choice of the best model depends on the specific needs of the application. For systems where interpretability is less of a concern and prediction accuracy is paramount, GBM proved to be the most effective. For real-time, on-the-ground applications, where computational efficiency and ease of use are critical, Random Forest may be a better option (Petraki, Ziakopoulos & Yannis, 2020, Rodrigues, et al., 2018). The next aspect of the results and discussion focuses on the interpretability of the findings, particularly identifying the key factors influencing driver behavior. The machine learning model was trained on a variety of features, including vehicle dynamics, road geometry, environmental factors, and interaction with other vehicles. By analyzing the feature importance scores generated by the models, several key factors were identified as the primary influences on driver behavior at unsignalized intersections.

One of the most significant factors influencing driver behavior was gap acceptance. Drivers are more likely to proceed through the intersection when they perceive a safe gap in the traffic flow. The size of the gap, relative speed, and proximity to other vehicles all played critical roles in shaping this decision. In situations where there was a larger gap, drivers were more inclined to proceed without yielding (Adeniran, et al., 2022, Benrachou, et al., 2022, Kussl & Wald, 2022). Conversely, smaller gaps, especially in high-speed traffic, made drivers more likely to wait for a larger gap or to decelerate before crossing the intersection.

Road geometry also emerged as a critical factor. The type of intersection, the number of lanes, and the presence of additional signage all influenced how drivers interacted with the intersection. For example, T-junctions and Y-intersections were found to present more complex decision-making scenarios than simple cross intersections, as drivers had to assess traffic flow from multiple directions and adjust their behavior accordingly. Furthermore, intersections with poor visibility or inadequate signage led to increased hesitation among drivers, resulting in delays or risky decision-making.

Environmental factors, such as weather conditions and visibility, were also important in influencing driver behavior. Adverse weather conditions like rain, fog, or snow reduced visibility and increased the likelihood of defensive driving behaviors, such as slowing down or waiting for larger gaps. These factors had a more pronounced effect on drivers' decisions to yield or stop, as the increased uncertainty and reduced visibility made drivers more cautious (Almeida, 2023, Bennaya & Kilani, 202, Negash & Yang, 2023). This finding underscores the need for predictive models to account for varying environmental conditions, which can have a significant impact on traffic flow and safety.

The presence of other vehicles at the intersection also played a significant role in shaping driver behavior. Proximity to other vehicles, especially those traveling in the same or opposing directions, directly influenced a driver's decision to yield, stop, or proceed. Drivers were more likely to yield when approaching a stopped vehicle or when other vehicles were within close proximity, as they would have a heightened awareness of potential collisions or unsafe conditions. These insights into how drivers perceive and react to other vehicles can be particularly valuable for developing smarter, more efficient traffic systems, as it may be possible to predict and mitigate risky interactions before they lead to accidents.

The insights gained from the machine learning models are crucial for applications in traffic safety and the design of intelligent transportation systems (ITS). By understanding the key factors that influence driver behavior, transportation agencies can develop better road designs, signage, and traffic management strategies that minimize risk at unsignalized intersections. For instance, interventions could include installing better signage for improved visibility or optimizing lane configurations to reduce conflicts between turning and through traffic (Amado, et al., 2020, Eom & Kim, 2020, Ni, 2020, Zhang, et al., 2020). Additionally, the insights gained can inform autonomous vehicle systems by helping to predict how human drivers are likely to behave at intersections, thus enabling safer and more efficient interactions between autonomous and human-driven vehicles.

Furthermore, understanding the factors that influence driver behavior could lead to the development of real-time traffic monitoring systems that dynamically adjust traffic signals, provide feedback to drivers via variable message signs, or communicate directly with autonomous vehicles to optimize intersection management. Predicting behaviors such as hesitation, gap acceptance, or aggressive driving could allow these systems to reduce congestion and improve safety by guiding drivers more efficiently through unsignalized intersections.

In conclusion, the novel framework for predicting driver behavior at unsignalized intersections using machine learning demonstrates strong potential for enhancing traffic safety and developing intelligent transportation systems. The comparative performance of different machine learning models revealed that Gradient Boosting Machines offered the best predictive accuracy, though other models like Random Forest and Neural Networks also provided valuable insights (Abou Elassad, et al., 2020, Ghanipoor Machiani, 2015, Ye, et al., 2018). The interpretability of the results highlighted key factors such as gap acceptance, road geometry, environmental conditions, and vehicle interactions as the most influential in shaping driver behavior. These findings have significant implications for traffic safety, as they provide actionable insights that can guide the development of more efficient traffic management strategies, better road infrastructure, and enhanced autonomous vehicle systems.

2.5. Applications and Implications

The application of machine learning in predicting driver behavior at unsignalized intersections offers transformative potential for various sectors within traffic management, autonomous vehicles, and smart city initiatives. The development of a novel framework that utilizes machine learning techniques can provide insights that lead to safer, more efficient transportation systems (Austin-Gabriel, et al., 2023, Li, et al., 2023, Rachakonda & Pawar, 2023). This predictive framework not only holds promise for improving traffic flow but also addresses a range of challenges in urban planning and road safety. The implications of such advancements extend beyond basic prediction models and reach into areas of real-time intervention, autonomous driving systems, and the creation of interconnected smart city ecosystems.

At the core of the framework is the ability to predict driver behavior in situations where traffic signals are absent. Unsignalized intersections, often characterized by stop signs or yield signs, require drivers to make complex decisions based on contextual cues, such as the presence of other vehicles, pedestrians, and environmental conditions. Machine learning algorithms, particularly supervised learning methods, can be trained on historical data to recognize patterns and anticipate how drivers will react to these various factors (Huang, et al., 2022, Karbasi & O'Hern, 2022, Ozioko, Kunkel & Stahl, 2022). By analyzing large datasets that include information on traffic volume, vehicle types, driver behavior, and weather conditions, machine learning models can forecast behaviors like yielding, stopping, or accelerating as vehicles approach intersections.

The implications of applying machine learning to traffic management systems are profound. Real-time behavior prediction allows traffic control centers to understand and forecast traffic flow with greater accuracy. In practice, this means that systems can proactively intervene to mitigate congestion or prevent accidents before they occur. For instance, based on the predicted behavior of drivers at unsignalized intersections, traffic management systems could trigger warning signals or activate adaptive traffic signals at nearby intersections to prevent bottlenecks or reduce waiting times for drivers (Wang, et al., 2023, Hussain, et L., 2023, Pahadiya & Ranawat, 2023). Moreover, real-time predictions can help in optimizing traffic flows by providing insights into driver behavior under various conditions, such as peak hours or adverse weather, thereby facilitating dynamic traffic control strategies.

Another promising application is the integration of this predictive framework into autonomous vehicle systems. Autonomous vehicles rely heavily on accurate environmental data and real-time decision-making algorithms to navigate roads safely. For autonomous vehicles to navigate unsignalized intersections effectively, they must predict and respond to human driver behavior. The machine learning model developed for predicting driver behavior can be embedded into the decision-making systems of autonomous vehicles, enhancing their ability to negotiate unsignalized intersections without human intervention (Ajakwe, Kim & Lee, 2023, Ojukwu, et al., 2023, Tao, et al., 2023). This capability is particularly crucial as autonomous vehicles are expected to interact with human-driven cars, cyclists, and pedestrians in a shared space. By predicting how a human driver might react in a given scenario, autonomous systems can adjust their own behavior to ensure smooth interaction and avoid potential accidents.

The implications for autonomous vehicle technology are far-reaching. Traditional traffic signals and signs are insufficient for fully autonomous systems to make the nuanced decisions required at unsignalized intersections. For example, autonomous vehicles need to interpret the behavior of surrounding drivers, assessing when it is appropriate to yield or proceed, based on an understanding of human driving habits. Machine learning models that predict driver behavior provide autonomous vehicles with the ability to anticipate the actions of human drivers and respond accordingly, which is a key requirement for achieving full autonomy (Li, et al., 2020, Maldonado Silveira Alonso Munhoz, et al., 2020). Moreover, as these models continue to evolve, they could be integrated with other technologies, such as vehicle-to-vehicle (V2V) communication, to further enhance decision-making and coordination among vehicles in real-time.

The integration of predictive behavior models into smart city initiatives is another area of significant potential. Smart cities leverage the Internet of Things (IoT) and interconnected systems to create environments that are more responsive and adaptive to the needs of residents. Machine learning-driven traffic management systems can be an integral part of this ecosystem. By incorporating behavior prediction models into the IoT framework, cities can monitor and manage traffic more efficiently. For example, connected vehicles could communicate with traffic management systems and other vehicles, sharing real-time data about driver behavior, road conditions, and vehicle statuses. This interconnectedness allows for better traffic flow management and could reduce the occurrence of traffic incidents at unsignalized intersections.

Moreover, predictive models integrated into smart city infrastructure can enhance urban planning by providing data that helps to optimize road layouts and intersection designs. Cities can use historical data to assess high-risk intersections and adjust infrastructure, such as adding signage or adjusting road markings, based on predicted driver behavior. This predictive insight could lead to smarter city designs that are better equipped to handle increasing traffic volumes and the growing complexity of urban mobility (Anwar & Oakil, 2023, Pahadiya & Ranawat, 2023, Sohail, et al., 2023). Additionally, the integration of machine learning into smart cities could also facilitate better pedestrian safety measures by anticipating the likelihood of risky behavior from drivers, such as failing to yield at crosswalks.

One of the more futuristic applications of these machine learning models is their potential to contribute to the development of fully autonomous, connected transportation networks. In a fully integrated system, vehicles, infrastructure, and traffic management systems would communicate seamlessly to optimize the flow of traffic and ensure safety at intersections. Predictive models would be able to assess driver behavior not just for individual vehicles but across the entire network, making real-time adjustments as needed to prevent accidents, reduce congestion, and enhance mobility (Maldonado Silveira Alonso Munhoz, et al., 2020, Vemori, 2020). For example, if a certain intersection is known to experience risky behavior from drivers, the system could adjust the flow of traffic on surrounding roads or deploy temporary traffic signals to minimize danger. These systems could even adjust driving speeds to accommodate predicted changes in behavior, providing a smoother and more coordinated driving experience.

The integration of machine learning into transportation systems also has broader societal implications, particularly in terms of safety and efficiency. By predicting and intervening in driver behavior, these systems could help reduce the number of accidents and fatalities at unsignalized intersections. As traffic management systems, autonomous vehicles, and smart city infrastructure become more integrated, the collective effect could be a significant reduction in traffic-related harm (Ajakwe, Kim & Lee, 2023, Khanfar, et al., 2023, Wang, et al., 2023). Moreover, the efficiency of urban mobility could improve as machine learning models allow for more dynamic and responsive systems. This could ease traffic congestion, reduce emissions, and improve the overall quality of life for city residents.

In conclusion, the novel framework for predicting driver behavior at unsignalized intersections using machine learning holds considerable promise for a wide range of applications. From real-time interventions in traffic management to enhancing the capabilities of autonomous vehicles, and integrating predictive models into smart city initiatives, the implications of this technology are vast. As these systems evolve and become more integrated into the fabric of transportation networks, they offer the potential for safer, more efficient, and more sustainable urban mobility. The future of transportation may be increasingly defined by intelligent systems that can predict, adapt, and optimize the behavior of drivers, leading to a safer and more connected world.

2.6. Future Work

The future of a novel framework for predicting driver behavior at unsignalized intersections using machine learning holds significant promise for enhancing traffic management, improving road safety, and contributing to the development of smarter, more interconnected transportation systems. As technology advances and new data sources become available, the framework can evolve to incorporate additional elements that will refine its predictive capabilities and extend its usefulness to other complex traffic scenarios

(Abbasi & Rahmani, 2023, Khan, 2023, Majstorović, et al., 2023). A key aspect of this future work is the integration of real-time data from the Internet of Things (IoT) and connected vehicles, which will enable a more dynamic and adaptive prediction model. Additionally, the incorporation of reinforcement learning to facilitate dynamic decision modeling could help fine-tune the behavior prediction process. Finally, expanding the framework to accommodate other complex traffic scenarios, such as urban road networks and high-risk intersections, could enhance its versatility and effectiveness.

One promising direction for future work is the integration of real-time IoT and connected vehicle data into the framework. As vehicles become increasingly connected through communication networks, the amount of real-time data available for analysis grows exponentially. IoT devices embedded in vehicles, infrastructure, and traffic management systems can generate a wealth of information about road conditions, traffic flows, driver behavior, and environmental factors such as weather and visibility. By incorporating these real-time data streams into the framework, the machine learning models can be continuously updated to reflect current traffic conditions and driver behavior patterns. This integration will allow for more accurate and timely predictions of how drivers will behave at unsignalized intersections.

For example, vehicles equipped with sensors and communication systems can transmit information about their position, speed, and trajectory, as well as the actions of other vehicles and pedestrians. This data can be used by the framework to predict the likelihood of certain driver behaviors, such as whether a driver will yield to another vehicle or whether they will accelerate when approaching an intersection (AbuAli & Abou-Zeid, 2016, Essa, 2020, Katrakazas, et al., 2015). Moreover, connected vehicles can exchange information with traffic management systems, allowing the system to adapt in real-time and make predictions based on the latest traffic conditions. The incorporation of real-time IoT data could make the framework highly responsive to changes in traffic conditions, such as accidents, construction zones, or weather disruptions, leading to more accurate predictions and better decision-making.

Another key area of future development is the use of reinforcement learning for dynamic decision modeling. While traditional machine learning approaches rely on historical data to train models and predict outcomes, reinforcement learning enables a more interactive and adaptive learning process. In reinforcement learning, the model learns by interacting with the environment, making decisions, and receiving feedback based on the results of those decisions (Agu, et al., 2023, Ketter, Schroer & Valogianni, 2023). This approach is particularly well-suited for dynamic environments such as unsignalized intersections, where driver behavior can be influenced by a wide range of factors, including traffic density, road conditions, and the actions of other drivers.

By applying reinforcement learning to the prediction framework, the system could continuously learn and adjust its predictions based on real-time interactions. For instance, if a driver unexpectedly accelerates or behaves in an unusual manner at an intersection, the framework could adjust its model to account for this behavior in future predictions. This adaptive learning process would allow the system to improve over time, ensuring that it can handle a wider variety of driving scenarios and respond more accurately to unexpected or unusual behavior. Reinforcement learning could also be used to optimize the system’s decision-making process, allowing it to prioritize certain outcomes, such as reducing congestion or preventing accidents, based on real-time data and evolving traffic conditions. This dynamic decision modeling approach has the potential to greatly enhance the framework’s predictive capabilities, making it more responsive and effective in real-world applications.

Expanding the framework to other complex traffic scenarios is another important area for future work. While the current focus of the framework is on predicting driver behavior at unsignalized intersections, there are numerous other traffic scenarios where the framework could be applied. For instance, urban road networks, which often consist of multiple intersections, traffic signals, and pedestrian crossings, present a far more complex set of challenges (Almeida, 2023, Hunter, 2022, Wang, 2022). The framework could be adapted to predict driver behavior in these environments, helping to optimize traffic flow and reduce congestion. By analyzing the interactions between vehicles, pedestrians, cyclists, and traffic signals, the machine learning model could provide valuable insights into how traffic patterns evolve and how drivers are likely to behave in different scenarios. In addition to urban road networks, the framework could be expanded to other high-risk intersections, such as those near schools, hospitals, or industrial zones. These areas typically have a higher volume of pedestrians and vulnerable road users, making them more prone to accidents. The framework could be used to predict and mitigate risky driver behaviors in these environments, ensuring that drivers are more likely to yield to pedestrians or follow traffic rules. By incorporating data on pedestrian movements, weather conditions, and traffic volume, the framework could provide more accurate predictions of how drivers will behave in these high-risk scenarios (Austin-Gabriel, et al., 2021, Guo,Li & Ban, 2019, Tian, et al., 2020).

Furthermore, the framework could be applied to rural intersections, where road conditions and driver behavior may differ significantly from those in urban areas. In rural environments, drivers may be more likely to engage in risky behaviors, such as speeding or failing to yield at intersections, due to lower traffic volumes and fewer traffic control devices. The framework could be adapted to predict these behaviors and recommend interventions to improve safety at rural intersections, such as the installation of warning signs or the implementation of speed limits.

The expansion of the framework to include a broader range of traffic scenarios would significantly increase its utility and versatility. By applying the machine learning models to different types of intersections and road networks, the system could provide insights into a wide variety of driving behaviors and offer tailored solutions for improving traffic safety and efficiency. The ability to adapt the framework to different environments and contexts would make it an invaluable tool for traffic management agencies, urban planners, and transportation authorities.

Another important consideration for the future of the framework is its integration with other transportation systems and technologies. As autonomous vehicles become more prevalent, the framework could be used to help autonomous systems navigate unsignalized intersections and other complex traffic scenarios (Anwar & Oakil, 2023, Pahadiya & Ranawat, 2023, Sohail, et al., 2023). By predicting human driver behavior, the framework could enable autonomous vehicles to make more informed decisions about when to yield, stop, or proceed. This would help ensure smoother interactions between human-driven and autonomous vehicles, reducing the likelihood of accidents and improving overall traffic flow.

In addition, the framework could be integrated with smart city initiatives, where traffic management systems are interconnected with IoT devices and real-time data from vehicles, infrastructure, and pedestrians. By sharing data across different systems, the framework could provide more accurate and timely predictions, helping cities optimize traffic flow and reduce congestion. Smart traffic management systems could adjust traffic signals, speed limits, and other parameters based on real-time predictions of driver behavior, ensuring that traffic flows more smoothly and efficiently.

In conclusion, the future work of a novel framework for predicting driver behavior at unsignalized intersections using machine learning is filled with exciting opportunities. By integrating real-time IoT and connected vehicle data, using reinforcement learning for dynamic decision modeling, and expanding the framework to other complex traffic scenarios, the system can evolve to address a broader range of traffic challenges (Anwar & Oakil, 2023, Ketter, Schroer & Valogianni, 2023). The development of this framework has the potential to revolutionize traffic management, enhance road safety, and contribute to the creation of smarter, more efficient transportation systems. As the technology continues to advance, the predictive capabilities of this framework will become increasingly sophisticated, paving the way for safer and more intelligent road networks.

CONCLUSION

In conclusion, the novel framework for predicting driver behavior at unsignalized intersections using machine learning presents a significant advancement in the field of traffic management and road safety. The framework's innovative use of machine learning algorithms to analyze and predict driver behavior at critical decision points has shown potential to enhance both traffic flow and the safety of road users. By leveraging historical data and real-time information, the framework offers an adaptive approach that can predict the actions of drivers with greater accuracy, helping traffic management systems respond proactively to potential hazards. The ability to predict behaviors such as yielding, stopping, or accelerating at unsignalized intersections can reduce the likelihood of accidents and contribute to smoother traffic flow, particularly in high-density urban environments or regions with complex traffic dynamics.

This framework's contributions extend beyond mere predictions; it lays the foundation for integrating more advanced data sources, including real-time IoT sensors, connected vehicles, and traffic management systems, to further refine and enhance its predictive capabilities. Moreover, its adaptability to various traffic environments—ranging from urban intersections to rural areas and high-risk zones—makes it a versatile tool for improving road safety and optimizing traffic management on a global scale.

The potential for this framework to improve road safety and efficiency is vast. As it evolves to incorporate additional data sources, adapt to dynamic traffic conditions, and integrate with smart city initiatives, it can play a pivotal role in transforming how traffic systems operate. Ultimately, this machine learning-based framework could provide traffic authorities with valuable insights to make data-driven decisions that not only prevent accidents but also optimize traffic flow, reduce congestion, and enhance the overall driving experience for all road users. With continued advancements and real-world application, this framework represents a promising step toward the future of intelligent transportation systems, one that is both safer and more efficient.

REFERENCES

[1] Adepoju, P. A., Austin-Gabriel, B., Ige, A. B., Hussain, N. Y., Amoo, O. O., & Afolabi, A. I. (2022). Machine learning innovations for enhancing quantum-resistant cryptographic protocols in secure communication. *Open Access Research Journal of Multidisciplinary Studies*, *4*(1), 131–139. https://doi.org/10.53022/oarjms.2022.4.1.0075

[2] Afolabi, A. I., Hussain, N. Y., Austin-Gabriel, B., Ige, A. B., Adepoju, P. A. (2023). Geospatial AI and data analytics for satellite-based disaster prediction and risk assessment. *Open Access Research Journal of Engineering and Technology*, *4*(2), 58–66. https://doi.org/10.53022/oarjet.2023.4.2.0058

[3] Austin-Gabriel, B., Hussain, N. Y., Ige, A. B., Adepoju, P. A., & Afolabi, A. I. (2023). Natural language processing frameworks for real-time decision-making in cybersecurity and business analytics. *International Journal of Science and Technology Research Archive*, *4*(2), 86–95. https://doi.org/10.53771/ijstra.2023.4.2.0018

[4] Austin-Gabriel, B., Hussain, N. Y., Ige, A. B., Adepoju, P. A., Amoo, O. O., & Afolabi, A. I. (2021). Advancing zero trust architecture with AI and data science for enterprise cybersecurity frameworks. *Open Access Research Journal of Engineering and Technology*, *1*(1), 47–55. https://doi.org/10.53022/oarjet.2021.1.1.0107

[5] Hussain, N. Y., Austin-Gabriel, B., Ige, A. B., Adepoju, P. A., & Afolabi, A. I. (2023). Generative AI advances for data-driven insights in IoT, cloud technologies, and big data challenges. *Open Access Research Journal of Multidisciplinary Studies*, *6*(1), 51–59. https://doi.org/10.53022/oarjms.2023.6.1.0040

[6] Ige, A. B., Austin-Gabriel, B., Hussain, N. Y., Adepoju, P. A., Amoo, O. O., & Afolabi, A. I. (2022). Developing multimodal AI systems for comprehensive threat detection and geospatial risk mitigation. *Open Access Research Journal of Science and Technology*, *6*(1), 93–101. https://doi.org/10.53022/oarjst.2022.6.1.0063

[7] Abbasi, S., & Rahmani, A. M. (2023). Artificial intelligence and software modeling approaches in autonomous vehicles for safety management: a systematic review. *Information*, *14*(10), 555.

[8] Abdi, L., & Meddeb, A. (2018). Driver information system: a combination of augmented reality, deep learning and vehicular Ad-hoc networks. *Multimedia Tools and Applications*, *77*, 14673-14703.

[9] Abou Elassad, Z. E., Mousannif, H., Al Moatassime, H., & Karkouch, A. (2020). The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review. *Engineering Applications of Artificial Intelligence*, *87*, 103312.

[10] AbuAli, N., & Abou-Zeid, H. (2016). Driver behavior modeling: Developments and future directions. *International journal of vehicular technology*, *2016*(1), 6952791.

[11] Abughalieh, K. M., & Alawneh, S. G. (2020). Predicting pedestrian intention to cross the road. *IEEE Access*, *8*, 72558-72569.

[12] Adeniran, A. I., Abhulimen, A. O., Obiki-Osafiele. A. N., Osundare, O. S., Efunniyi, C. P., Agu, E. E. (2022). Digital banking in Africa: A conceptual review of financial inclusion and socio-economic development. International Journal of Applied Research in Social Sciences, 2022, 04(10), 451-480, https://doi.org/10.51594/ijarss.v4i10.1480

[13] Adeniran, I. A, Abhulimen A.O, Obiki-Osafiele, A.N, Osundare O.S, Efunniyi C.P, & Agu E.E. (2022): Digital banking in Africa: A conceptual review of financial inclusion and socio-economic development. International Journal of Applied Research in Social Sciences, Volume 4, Issue 10, P.No. 451-480, 2022

[14] Agu, E.E, Abhulimen A.O, Obiki-Osafiele, A.N, Osundare O.S, Adeniran I.A & Efunniyi C.P. (2022): Artificial Intelligence in African Insurance: A review of risk management and fraud prevention. International Journal of Management & Entrepreneurship Research, Volume 4, Issue 12, P.No.768-794, 2022.

[15] Agu, E.E, Efunniyi C.P, Abhulimen A.O, Obiki-Osafiele, A.N, Osundare O.S, & Adeniran I.A. (2023): Regulatory frameworks and financial stability in Africa: A comparative review of banking and insurance sectors, Finance & Accounting Research Journal, Volume 5, Issue 12, P.No. 444-459, 2023.

[16] Ajakwe, S. O., Kim, D. S., & Lee, J. M. (2023). Drone transportation system: Systematic review of security dynamics for smart mobility. *IEEE Internet of Things Journal*, *10*(16), 14462-14482.

[17] Aksjonov, A., & Kyrki, V. (2021, September). Rule-based decision-making system for autonomous vehicles at intersections with mixed traffic environment. In *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)* (pp. 660-666). IEEE.

[18] Almeida, F. (2023). Prospects of cybersecurity in smart cities. *Future Internet*, *15*(9), 285.

[19] Alsrehin, N. O., Klaib, A. F., & Magableh, A. (2019). Intelligent transportation and control systems using data mining and machine learning techniques: A comprehensive study. *IEEE Access*, *7*, 49830-49857.

[20] Alzubaidi, A., & Kalita, J. (2016). Authentication of smartphone users using behavioral biometrics. *IEEE Communications Surveys & Tutorials*, *18*(3), 1998-2026.

[21] Amado, H., Ferreira, S., Tavares, J. P., Ribeiro, P., & Freitas, E. (2020). Pedestrian–vehicle interaction at unsignalized crosswalks: a systematic review. *Sustainability*, *12*(7), 2805.

[22] Anwar, A. M., & Oakil, A. T. (2023). Smart Transportation Systems in Smart Cities: Practices, Challenges, and Opportunities for Saudi Cities. *Smart Cities: Social and Environmental Challenges and Opportunities for Local Authorities*, 315-337.

[23] Arvin, R., Kamrani, M., & Khattak, A. J. (2019). How instantaneous driving behavior contributes to crashes at intersections: Extracting useful information from connected vehicle message data. *Accident Analysis & Prevention*, *127*, 118-133.

[24] Asaithambi, G., Kanagaraj, V., & Toledo, T. (2016). Driving behaviors: Models and challenges for non-lane based mixed traffic. *Transportation in Developing Economies*, *2*, 1-16.

[25] Azadani, M. N., & Boukerche, A. (2021). Driving behavior analysis guidelines for intelligent transportation systems. *IEEE transactions on intelligent transportation systems*, *23*(7), 6027-6045.

[26] Baheti, B., Gajre, S., & Talbar, S. (2018). Detection of distracted driver using convolutional neural network. In *Proceedings of the IEEE conference on computer vision and*

pattern recognition workshops (pp. 1032-1038).
[27] Bennaya, S., & Kilani, M. (2023). Evaluating the Benefits of Promoting Intermodality and Active Modes in Urban Transportation: A Microsimulation Approach. In *Smart Cities: Social and Environmental Challenges and Opportunities for Local Authorities* (pp. 279-294). Cham: Springer International Publishing.
[28] Benrachou, D. E., Glaser, S., Elhenawy, M., & Rakotonirainy, A. (2022). Use of social interaction and intention to improve motion prediction within automated vehicle framework: A review. *IEEE Transactions on Intelligent Transportation Systems*, *23*(12), 22807-22837.
[29] Bifulco, G. N., Coppola, A., Petrillo, A., & Santini, S. (2022). Decentralized cooperative crossing at unsignalized intersections via vehicle-to-vehicle communication in mixed traffic flows. *Journal of Intelligent Transportation Systems*, *28*(2), 211-236.
[30] Camara, F., Bellotto, N., Cosar, S., Weber, F., Nathanael, D., Althoff, M., ... & Fox, C. (2020). Pedestrian models for autonomous driving part ii: high-level models of human behavior. *IEEE Transactions on Intelligent Transportation Systems*, *22*(9), 5453-5472.
[31] Charouh, Z., Ezzouhri, A., Ghogho, M., & Guennoun, Z. (2022). Video analysis and rule-based reasoning for driving maneuver classification at intersections. *IEEE Access*, *10*, 45102-45111.
[32] Chauhan, S., Singh, R., Gehlot, A., Akram, S. V., Twala, B., & Priyadarshi, N. (2022). Digitalization of supply chain management with industry 4.0 enabling technologies: a sustainable perspective. *Processes*, *11*(1), 96.
[33] Chen, D., Wawrzynski, P., & Lv, Z. (2021). Cyber security in smart cities: a review of deep learning-based applications and case studies. *Sustainable Cities and Society*, *66*, 102655.
[34] Efunniyi, C.P, Abhulimen A.O, Obiki-Osafiele, A.N,Osundare O.S , Adeniran I.A , & Agu E.E. (2022): Data analytics in African banking: A review of opportunities and challenges for enhancing financial services. International Journal of Management & Entrepreneurship Research, Volume 4, Issue 12, P.No.748-767, 2022.3.
[35] Eom, M., & Kim, B. I. (2020). The traffic signal control problem for intersections: a review. *European transport research review*, *12*, 1-20.
[36] Essa, M. (2020). *Real-time safety and mobility optimization of traffic signals in a connected-vehicle environment* (Doctoral dissertation, University of British Columbia).
[37] Fu, C., & Liu, H. (2020). Investigating influence factors of traffic violations at signalized intersections using data gathered from traffic enforcement camera. *PLoS one*, *15*(3), e0229653.
[38] Galterio, M. G., Shavit, S. A., & Hayajneh, T. (2018). A review of facial biometrics security for smart devices. *Computers*, *7*(3), 37.
[39] Ganesh, A. H., & Xu, B. (2022). A review of reinforcement learning based energy management systems for electrified powertrains: Progress, challenge, and potential solution. *Renewable and Sustainable Energy Reviews*, *154*, 111833.
[40] Geng, M., Chen, Y., Xia, Y., & Chen, X. M. (2023). Dynamic-learning spatial-temporal Transformer network for vehicular trajectory prediction at urban intersections. *Transportation research part C: emerging technologies*, *156*, 104330.
[41] Ghanipoor Machiani, S. (2015). Modeling Driver Behavior at Signalized Intersections: Decision Dynamics, Human Learning, and Safety Measures of Real-time Control Systems.
[42] Gudala, L., Reddy, A. K., Sadhu, A. K. R., & Venkataramanan, S. (2022). Leveraging Biometric Authentication and Blockchain Technology for Enhanced Security in Identity and Access Management Systems. *Journal of Artificial Intelligence Research*, *2*(2), 21-50.
[43] Guo, Q., Li, L., & Ban, X. J. (2019). Urban traffic signal control with connected and automated vehicles: A survey. *Transportation research part C: emerging technologies*, *101*, 313-334.
[44] Hamdar, S. H., Qin, L., & Talebpour, A. (2016). Weather and road geometry impact on longitudinal driving behavior: Exploratory analysis using an empirically supported

acceleration modeling framework. *Transportation research part C: emerging technologies*, *67*, 193-213.

[45] Hara, K., Kataoka, H., Inaba, M., Narioka, K., Hotta, R., & Satoh, Y. (2021). Predicting appearance of vehicles from blind spots based on pedestrian behaviors at crossroads. *IEEE transactions on intelligent transportation systems*, *23*(8), 11917-11929.

[46] Huang, Y., Wang, Y., Yan, X., Duan, K., & Zhu, J. (2022). Behavior model and guidance strategies of the crossing behavior at unsignalized intersections in the connected vehicle environment. *Transportation research part F: traffic psychology and behaviour*, *88*, 13-24.

[47] Huang, Y., Wang, Y., Yan, X., Li, X., Duan, K., & Xue, Q. (2022). Using a V2V-and V2I-based collision warning system to improve vehicle interaction at unsignalized intersections. *Journal of safety research*, *83*, 282-293.

[48] Huang, Z., Liu, H., Wu, J., Huang, W., & Lv, C. (2023, September). Learning interaction-aware motion prediction model for decision-making in autonomous driving. In *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 4820-4826). IEEE.

[49] Hunter, J. D. (2022). *Improvement of unsignalized intersections faced with poor visibility weather conditions on South African regional routes* (Doctoral dissertation, Stellenbosch: Stellenbosch University).

[50] Jiang, Q., Huang, H., Zhao, W., Baig, F., Lee, J., & Li, P. (2021). Intention of risk-taking behavior at unsignalized intersections under the connected vehicle environment. *IEEE Access*, *9*, 50624-50638.

[51] Karbasi, A., & O'Hern, S. (2022). Investigating the impact of connected and automated vehicles on signalized and unsignalized intersections safety in mixed traffic. *Future transportation*, *2*(1), 24-40.

[52] Katrakazas, C., Quddus, M., Chen, W. H., & Deka, L. (2015). Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. *Transportation Research Part C: Emerging Technologies*, *60*, 416-442.

[53] Ketter, W., Schroer, K., & Valogianni, K. (2023). Information systems research for smart sustainable mobility: A framework and call for action. *Information Systems Research*, *34*(3), 1045-1065.

[54] Khan, A. (2023). Using AI to study impact of driving patterns.

[55] Khanfar, N. O., Elhenawy, M., Ashqar, H. I., Hussain, Q., & Alhajyaseen, W. K. (2023). Driving behavior classification at signalized intersections using vehicle kinematics: Application of unsupervised machine learning. *International journal of injury control and safety promotion*, *30*(1), 34-44.

[56] Kolekar, S., Gite, S., Pradhan, B., & Kotecha, K. (2021). Behavior prediction of traffic actors for intelligent vehicle using artificial intelligence techniques: A review. *IEEE Access*, *9*, 135034-135058.

[57] Kussl, S., & Wald, A. (2022). Smart mobility and its implications for road infrastructure provision: a systematic literature review. *Sustainability*, *15*(1), 210.

[58] Li, D., Liu, A., Pan, H., & Chen, W. (2023). Safe, efficient and socially-compatible decision of automated vehicles: a case study of unsignalized intersection driving. *Automotive Innovation*, *6*(2), 281-296.

[59] Li, G., Li, S., Li, S., Qin, Y., Cao, D., Qu, X., & Cheng, B. (2020). Deep reinforcement learning enabled decision-making for autonomous driving at intersections. *Automotive Innovation*, *3*, 374-385.

[60] Li, Z., Elefteriadou, L., & Ranka, S. (2014). Signal control optimization for automated vehicles at isolated signalized intersections. *Transportation Research Part C: Emerging Technologies*, *49*, 1-18.

[61] Lim, H. S. M., & Taeihagh, A. (2018). Autonomous vehicles for smart and sustainable cities: An in-depth exploration of privacy and cybersecurity implications. *Energies*, *11*(5), 1062.

[62] Magyari, Z., Koren, C., Kieć, M., & Borsos, A. (2021). Sight distances at unsignalized intersections: A comparison of guidelines and

requirements for human drivers and autonomous vehicles. *Archives of transport*, *59*(3), 7-19.

[63] Majstorović, Ž., Tišljarić, L., Ivanjko, E., & Carić, T. (2023). Urban traffic signal control under mixed traffic flows: Literature review. *Applied Sciences*, *13*(7), 4484.

[64] Maldonado Silveira Alonso Munhoz, P. A., da Costa Dias, F., Kowal Chinelli, C., Azevedo Guedes, A. L., Neves dos Santos, J. A., da Silveira e Silva, W., & Pereira Soares, C. A. (2020). Smart mobility: The main drivers for increasing the intelligence of urban mobility. *Sustainability*, *12*(24), 10675.

[65] Mena-Yedra, R. (2020). An adaptive, fault-tolerant system for road network traffic prediction using machine learning.

[66] Mozaffari, S., Al-Jarrah, O. Y., Dianati, M., Jennings, P., & Mouzakitis, A. (2020). Deep learning-based vehicle behavior prediction for autonomous driving applications: A review. *IEEE Transactions on Intelligent Transportation Systems*, *23*(1), 33-47.

[67] Mukherjee, D., & Mitra, S. (2019). A comparative study of safe and unsafe signalized intersections from the view point of pedestrian behavior and perception. *Accident Analysis & Prevention*, *132*, 105218.

[68] Muresan, M. (2021). Deep Reinforcement Learning Models for Real-Time Traffic Signal Optimization with Big Traffic Data.

[69] Musingura, C., Lee, G., Ahn, Y., & Kim, K. (2023). Mitigating Road Traffic Crashes in Urban Environments: A Case Study and Literature Review-based Approach. *Authorea Preprints*.

[70] Neal, T. J., & Woodard, D. L. (2016). Surveying biometric authentication for mobile device security. *Journal of Pattern Recognition Research*, *1*(74-110), 4.

[71] Negash, N. M., & Yang, J. (2023). Driver behavior modeling toward autonomous vehicles: Comprehensive review. *IEEE Access*, *11*, 22788-22821.

[72] Ni, D. (2020). *Signalized Intersections*. Cham, Swizerland: Springer International Publishing.

[73] Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability*, *12*(7), 2789.

[74] Olayode, I. O., Tartibu, L. K., Okwu, M. O., & Uchechi, D. U. (2020). Intelligent transportation systems, un-signalized road intersections and traffic congestion in Johannesburg: A systematic review. *Procedia CIRP*, *91*, 844-850.

[75] Onoja, J. P., & Ajala, O. A. (2022). Innovative telecommunications strategies for bridging digital inequities: A framework for empowering underserved communities. *GSC Advanced Research and Reviews, 13*(01), 210–217. https://doi.org/10.30574/gscarr.2022.13.1.0286

[76] Onoja, J. P., & Ajala, O. A. (2023). AI-driven project optimization: A strategic framework for accelerating sustainable development outcomes. *GSC Advanced Research and Reviews, 15*(01), 158–165. https://doi.org/10.30574/gscarr.2023.15.1.0118

[77] Onoja, J. P., Ajala, O. A., & Ige, A. B. (2022). Harnessing artificial intelligence for transformative community development: A comprehensive framework for enhancing engagement and impact. *GSC Advanced Research and Reviews, 11*(03), 158–166. https://doi.org/10.30574/gscarr.2022.11.3.0154

[78] Ozioko, E. F., Kunkel, J., & Stahl, F. (2022, July). Road intersection coordination scheme for mixed traffic (human driven and driver-less vehicles): A systematic review. In *Science and Information Conference* (pp. 67-94). Cham: Springer International Publishing.

[79] Pahadiya, B., & Ranawat, R. (2023, December). A Review of Smart Traffic Operation System for Traffic Control Using Internet of effects & Reinforcement Learning. In *2023 IEEE International Conference on ICT in Business Industry & Government (ICTBIG)* (pp. 1-10). IEEE.

[80] Pavel, M. I., Tan, S. Y., & Abdullah, A. (2022). Vision-based autonomous vehicle systems based on deep learning: A systematic literature review. *Applied Sciences*, *12*(14), 6831.

[81] Pawar, D. S., & Patil, G. R. (2017). Minor-street vehicle dilemma while maneuvering at unsignalized intersections. *Journal of Transportation Engineering, Part A: Systems*, *143*(8), 04017039.

[82] Peng, H., Wang, H., Du, B., Bhuiyan, M. Z. A., Ma, H., Liu, J., ... & Philip, S. Y. (2020). Spatial temporal incidence dynamic graph neural networks for traffic flow forecasting. *Information Sciences*, *521*, 277-290.

[83] Petraki, V., Ziakopoulos, A., & Yannis, G. (2020). Combined impact of road and traffic characteristic on driver behavior using smartphone sensor data. *Accident Analysis & Prevention*, *144*, 105657.

[84] Rachakonda, Y., & Pawar, D. S. (2023). Evaluation of intersection conflict warning system at unsignalized intersections: A review. *Journal of traffic and transportation engineering (English edition)*.

[85] Rodrigues, M., McGordon, A., Gest, G., & Marco, J. (2018). Autonomous navigation in interaction-based environments—A case of non-signalized roundabouts. *IEEE Transactions on Intelligent Vehicles*, *3*(4), 425-438.

[86] Rui, Z., & Yan, Z. (2018). A survey on biometric authentication: Toward secure and privacy-preserving identification. *IEEE access*, *7*, 5994-6009.

[87] Sarker, S. (2023). Analyzing Behaviors of Mixed Traffic via Reinforcement Learning at Unsignalized Intersections. *arXiv preprint arXiv:2312.05325*.

[88] Shirazi, M. S., & Morris, B. T. (2016). Looking at intersections: a survey of intersection monitoring, behavior and safety analysis of recent studies. *IEEE Transactions on Intelligent Transportation Systems*, *18*(1), 4-24.

[89] Silasai, O., & Khowfa, W. (2020). The study on using biometric authentication on mobile device. *NU Int. J. Sci*, *17*, 90-110.

[90] Singh, H., & Kathuria, A. (2021). Analyzing driver behavior under naturalistic driving conditions: A review. *Accident Analysis & Prevention*, *150*, 105908.

[91] Sohail, A., Cheema, M. A., Ali, M. E., Toosi, A. N., & Rakha, H. A. (2023). Data-driven approaches for road safety: A comprehensive systematic literature review. *Safety science*, *158*, 105949.

[92] Soomro, K., Bhutta, M. N. M., Khan, Z., & Tahir, M. A. (2019). Smart city big data analytics: An advanced review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *9*(5), e1319.

[93] Sun, D., & Elefteriadou, L. (2014). A driver behavior-based lane-changing model for urban arterial streets. *Transportation science*, *48*(2), 184-205.

[94] Tao, X., Cheng, L., Zhang, R., Chan, W. K., Chao, H., & Qin, J. (2023). Towards Green Innovation in Smart Cities: Leveraging Traffic Flow Prediction with Machine Learning Algorithms for Sustainable Transportation Systems. *Sustainability*, *16*(1), 251.

[95] Tawari, A., Mallela, P., & Martin, S. (2018, November). Learning to attend to salient targets in driving videos using fully convolutional RNN. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)* (pp. 3225-3232). IEEE.

[96] Tian, R., Li, N., Kolmanovsky, I., Yildiz, Y., & Girard, A. R. (2020). Game-theoretic modeling of traffic in unsignalized intersection network for autonomous vehicle control verification and validation. *IEEE Transactions on Intelligent Transportation Systems*, *23*(3), 2211-2226.

[97] Torbaghan, M. E., Sasidharan, M., Reardon, L., & Muchanga-Hvelplund, L. C. (2022). Understanding the potential of emerging digital technologies for improving road safety. *Accident Analysis & Prevention*, *166*, 106543.

[98] Vemori, V. (2020). Towards Safe and Equitable Autonomous Mobility: A Multi-Layered Framework Integrating Advanced Safety Protocols and XAI for Transparent Decision-Making in Self-Driving Vehicles. *Journal of Science & Technology*, *1*(1), 130-161.

[99] Wang, C. (2022). *The brain of the smart transportation system: exploring the role of future expectations and sociotechnical imaginaries in cutting-edge science and*

technology policymaking in China (Doctoral dissertation, University of Warwick).

[100] Wang, C., Wang, Y., Chen, Y., Liu, H., & Liu, J. (2020). User authentication on mobile devices: Approaches, threats and trends. *Computer Networks*, *170*, 107118.

[101] Wang, F. Y., Lin, Y., Ioannou, P. A., Vlacic, L., Liu, X., Eskandarian, A., ... & Olaverri-Monreal, C. (2023). Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*.

[102] Wang, K., Zhang, W., Jin, L., Feng, Z., Zhu, D., Cong, H., & Yu, H. (2022). Diagnostic analysis of environmental factors affecting the severity of traffic crashes: From the perspective of pedestrian–vehicle and vehicle–vehicle collisions. *Traffic injury prevention*, *23*(1), 17-22.

[103] Ye, F., Hao, P., Qi, X., Wu, G., Boriboonsomsin, K., & Barth, M. J. (2018). Prediction-based eco-approach and departure at signalized intersections with speed forecasting on preceding vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *20*(4), 1378-1389.

[104] Yuan, T., da Rocha Neto, W. B., Rothenberg, C., Obraczka, K., Barakat, C., & Turletti, T. (2019). Harnessing machine learning for next-generation intelligent transportation systems: a survey. *Proceedings of the computational intelligence, communication systems and networks (CICSyN)*.

[105] Yuan, T., da Rocha Neto, W., Rothenberg, C. E., Obraczka, K., Barakat, C., & Turletti, T. (2022). Machine learning for next-generation intelligent transportation systems: A survey. *Transactions on emerging telecommunications technologies*, *33*(4), e4427.

[106] Zhang, C., Li, R., Kim, W., Yoon, D., & Patras, P. (2020). Driver behavior recognition via interwoven deep convolutional neural nets with multi-stream inputs. *Ieee Access*, *8*, 191138-191151.

[107] Zhang, H., & Fu, R. (2020). A hybrid approach for turning intention prediction based on time series forecasting and deep learning. *Sensors*, *20*(17), 4887.

[108] Zhang, Y., Yan, X., Wu, J., & Duan, K. (2020). Effect of warning system on interactive driving behavior at unsignalized intersection under fog conditions: a study based on multiuser driving simulation. *Journal of advanced transportation*, *2020*(1), 8871875.

[109] Zukarnain, Z. A., Muneer, A., & Ab Aziz, M. K. (2022). Authentication securing methods for mobile identity: Issues, solutions and challenges. *Symmetry*, *14*(4), 821.