Personalized Passenger Comfort Assessment Using CAN Bus Data and Explainable AI

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***Abstract*—This study explores the utilization of CAN Bus data from vehicles to analyze, assess, and predict driving styles concerning passengers' comfort thresholds, focusing on developing an explainable AI system. Passenger comfort is crucial for both traditional ride-hailing services and autonomous driving solutions. This research aims to elucidate the relationship between driving styles and passenger comfort. Data were collected from sensors integrated into the vehicle's CAN Bus via the OBD-II port. The AI system is trained using a baseline comfortability scale derived from existing research. The novel aspect of this research lies in integrating an AI model with self-labeled data to personalize and adapt to individual comfort levels. By determining passengers' comfort zones based on acceleration values and developing an AI capable of transforming linear comfort levels into nonlinear, personalized representations, this research promises significant contributions to the autonomous driving industry and ride-hailing services, enhancing passenger comfort and safety.**

***Index Terms*—Passenger Comfort, Predictive Models, Artificial Intelligence, Autonomous Driving, Ride-Sharing.**

I. Introduction

Since Carl Benz's invention of the first automobile in 1886, the automotive industry has witnessed substantial growth and remarkable technological advancements. Among these pivotal innovations is the On-Board Diagnostics (OBD) system, which facilitates seamless connectivity to the Controller Area Network (CAN) Bus. The OBD system has become indispensable for gathering comprehensive vehicle data, offering valuable insights into driving behavior and vehicle dynamics. This research paper explores the utilization of CAN Bus data from specific vehicles to analyze, assess, and predict drivers' driving styles concerning passengers' comfort thresholds, with a focus on developing an explainable AI system.

Passenger comfort is paramount for ride-hailing services such as Uber, Bolt, and traditional taxi operations. This study proposes solutions for effectively integrating this concept within these services, aiming to elucidate the relationship between driving styles and passenger comfort. The primary objective is to collect, analyze, and visualize data critical for enhancing passenger comfort through an AI system capable of understanding and adapting to individual comfort levels.

The initial phase of this research involves collecting data from various sensors integrated into the vehicle's CAN Bus via the OBD-II port. These sensors include longitudinal and lateral accelerometers, which are crucial for assessing driving comfort by capturing the body's forward-backward and left-right movements. These movements correlate directly with hard braking, sudden accelerations, and sharp turns. The AI system is initially trained using a baseline comfortability scale derived from existing research, which presents comfort levels linearly.

However, this study aims to advance beyond linear representations by incorporating nonlinearity through self-labeled data provided by each user. This approach allows the AI to learn and adapt to individual preferences, moving beyond the general comfort levels deduced by other research articles. The Neural Network model is designed to transform these general, linear comfort levels into personalized, nonlinear comfort zones, facilitating a more nuanced understanding of each passenger's comfort.

Implementing this research in ride-sharing applications can significantly enhance the understanding of individual driver behaviors, refine training programs, and boost client satisfaction. Additionally, the autonomous driving industry can leverage these insights to better comprehend passengers' comfort zones, thereby fostering increased trust and improving overall safety. This research paper also presents a solution that enables the easy visualization and comprehension of each user's distinct comfort zones during driving, based on a set of self-labeled data. This endeavor aims to enhance road safety, bolster trust in autonomous driving solutions, and advance transportation systems as a whole.

II. Related Works

The study of driving dynamics and comfort has long been a focal point in automotive research. Understanding these parameters is crucial for enhancing vehicle performance and ensuring both driver and passenger comfort. This section delves into various aspects of acceleration zones, driving styles, and comfort levels, drawing from established research and experimental data. The insights gained from these studies are pivotal for comprehending the factors that contribute to passenger comfort and for advancing the development of autonomous vehicles.

A. Driving Comfort Dynamics

Driving comfort is a significant concern in automotive performance. To address this, scientists have sought to understand the fundamental aspects of comfort. Through rigorous experimentation and data analysis, certain characteristics of the GG-Diagram have been identified and validated. These features of the GG-Diagram are described and rigorously explained in [11]. Understanding the data underlying these plots allows drivers to operate their cars in customized ways; for example, in professional racing, drivers can operate on the limit of grip levels of a car or on the limit of someone's comfort levels. These characteristics or zones, seen in Figure 1, include 'Pure Braking', 'Pure Left Cornering', and 'Trail Braking into Right Corner', all of which are critical for assessing the performance limits of a car.

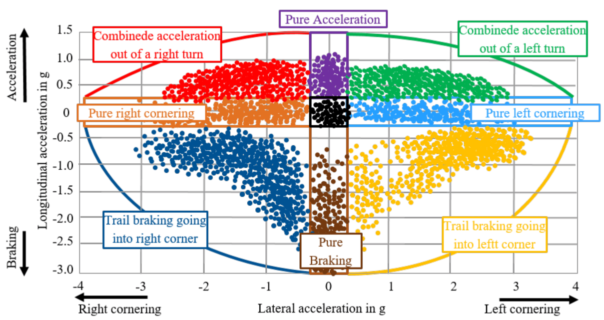

Fig. 1. The GG-Diagram explained in detail. [11]

The GG-Diagram has proven highly relevant for various studies, such as [1]–[3], as it enabled scientists to clearly delineate driving styles. As seen in Figure 2 presented in [1], each driving style exhibits a rhombus-like shape. Since our research did not involve race cars, drivers avoided certain areas to prevent crashes. The figure presented in this research paper includes comfort levels right up to the limit of grip for a regular car.

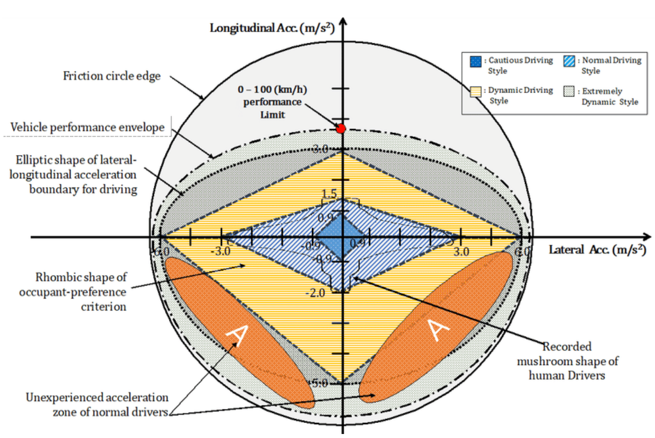

Fig. 2. Driving Styles on the GG-Diagram. Note that the units of the x- and y-axes are in m/s^2, instead of gravitational acceleration units. [1]

B. Current Approaches to Comfort Assessment

The scales mentioned earlier offer a direct means to describe comfort while driving. However, the study [1] provided a single measurement unit for each participant, indicating that comfort zones are general. As shown in Figure 3, specific criteria for accelerations and jerk, calculated in m/s^2, are presented. Each driving style can be precisely characterized using this metric, establishing clear thresholds between the driving styles. These thresholds are highly useful and easy to understand.

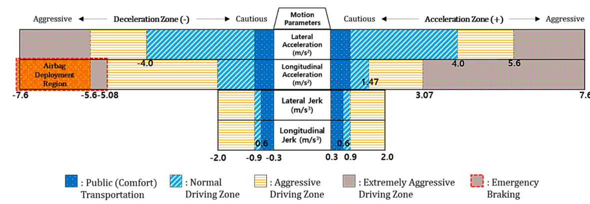

Fig. 3. Driving Styles presented in [1].

Importantly, the thresholds are linear if we split the axes into four quadrants. This means they follow a straight-line relationship, where changes in one variable result in proportional changes in another. This linearity simplifies the characterization of driving styles, ensuring a straightforward and easily interpretable model for assessing comfort levels.

The study [1] aimed to develop an autonomous shuttle bus for public transportation. This solution required a precise method to calculate comfort levels and determine specific criteria that would satisfy the majority of passengers. Given that comfort depends on numerous factors such as emotional state, health conditions, and other subjective criteria, the article's choice for comfort zones was highly conservative, allowing only minimal acceleration levels. This approach aimed to encompass as many cases of discomfort as possible and mitigate them effectively. As depicted in Figure 4, these comfort levels were carefully selected to ensure a pleasant and comfortable ride for all passengers.

By acknowledging that discomfort arises from high acceleration levels exerted on the human body, the article [5] proposed an innovative method to mitigate lateral acceleration values, recognizing the heightened sensitivity humans have towards lateral acceleration. The objective of this study was to design a tilting chair, a concept previously employed in prototype vehicles, which would tilt in the direction of the turn, akin to the dynamics observed in bicycles and motorcycles. This solution effectively reduced the typical lateral acceleration limits encountered during driving, as detailed in [4], by 1-2 m/s^2. Notably, this research adhered to the lateral acceleration boundaries of $[-2\ m/s^2, 2\ m/s^2]$ as established in [10].

Various research studies have developed applications that communicate with a vehicle's CAN Bus via the OBD-II Port to collect different sensor data and determine driver behavior in real-time. Examples of these studies include [6]–[9]. While some of the referenced articles utilized only acceleration

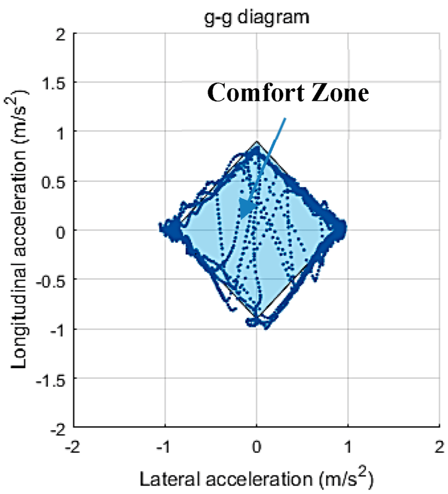

Fig. 4. Comfort Zone for Passengers proposed in [2]. Note that the units of the x- and y-axes are in m/s^2, instead of gravitational acceleration units.

values, as presented in this study, others employed data from different types of vehicle manufacturers and OBD sensors such as 'Engine RPM', 'Accelerator Pedal Position', 'Brake Pedal Position', among others. These sensors allowed researchers to compute and analyze driver behavior easily in dynamic driving situations.

III. Methodology

A. Data Collection

Data for this study were acquired using vehicle sensors integrated into the CAN Bus via the OBD-II port, facilitated by a CAN-Bus to USB-A interface linked to VCDS Software. Sensor availability varied by vehicle production year. Testing encompassed five distinct models from the VAG-COM Group to ensure data diversity. For instance, a 2009 Volkswagen Caddy provided basic acceleration data, while a 2018 Volkswagen Tiguan offered a wider range including brake pedal pressure and throttle input.

The primary goal was developing a universally compatible solution, necessitating the use of fundamental sensors common across models. GPS data were concurrently gathered to validate sensor accuracy and ensure synchronization, offering contextual driving information like road type and event timing. Each data point was meticulously timestamped to synchronize across diverse sources, bolstering accuracy and minimizing desynchronization errors.

Personalized comfort assessments were logged using a Python application presented in [12] where users inputted comfort levels, with timestamps and corresponding labels stored. This application operated on a laptop synchronized with VCDS Software, ensuring seamless integration and data correlation across platforms.

B. Human Reaction Time Error Mitigation

In this study, the option to calculate average reaction times and re-synchronize data accordingly was considered. However, given the availability of established comfort levels from previous research, the decision was made to mitigate human error using these known values. The solution involved utilizing baseline comfort values as proposed in [3]. For each participant, factors such as age, physical activity level, and other relevant elements were taken into account to compute an acceptable margin of human error in the data. For instance, in the 'Excellent' class represented as a rhombus, any data labeled outside the rhombus, plus an additional 30% margin, could be considered erroneous due to reaction time. It is important to note that the percentage of human error acceptance can be adjusted and should not be uniform for each participant. This approach leveraged validated standards from prior research to identify and minimize errors effectively.

C. Baseline Model Development

A Feedforward Neural Network (FNN) was developed to predict passenger comfort, referencing baseline comfort boundaries established in [3]. This model was trained on a comprehensive dataset containing sensor readings paired with comfort labels.

The Neural Network architecture for classifying driving styles based on vehicle acceleration sensor data begins with an input layer followed by three dense layers. The input layer processes lateral and longitudinal acceleration data. The first dense layer incorporates 16 neurons with ReLU activation, followed by a similar second layer to enhance feature extraction. The final layer employs softmax activation with 4 neurons to categorize driving styles into predefined comfort zones, aiming for straightforward interpretation.

Central to the model's design are lateral and longitudinal acceleration, pivotal for evaluating driving comfort by capturing dynamic vehicle movements. The classification task categorizes driving segments as "Excellent", "Acceptable", "So and So", and "Uncomfortable", refined from comfort levels outlined in prior studies. These categories enable precise classification based on acceleration data patterns.

The dataset includes acceleration values recorded during driving sessions, labeled according to defined comfort boundaries. This approach allows the model to discern relationships between acceleration metrics and passenger comfort. To validate accuracy and robustness, k-fold cross-validation was implemented with k=5, ensuring comprehensive training and validation across different data subsets. This iterative method enhances the model's performance and broad applicability.

D. Personal Preference Model Development

The Neural Network model is further refined using personalized comfort data collected from individual passengers during driving sessions. This approach is proposed to enable the model to learn and adapt to the specific preferences and comfort levels of each passenger. The effectiveness of the personalized model is validated through user feedback and additional driving sessions, ensuring its applicability in real-world scenarios.

E. Optimal Labeling Interval for Accurate Model Training

The experiment encompasses a substantial number of individuals and varying durations of labeling to address the question of the optimal self-labeling duration. For instance, a model is trained using a specified number of hours of driving data from an individual participant. This data is then segmented and analyzed over different durations to ascertain whether the individual's comfort levels remain consistent.

F. Explainable AI

Explainable AI (XAI) is a crucial aspect of this research, as it enhances the transparency and interpretability of the AI model used to predict passenger comfort levels. By making the AI system's decisions more understandable to users, XAI fosters trust and ensures effective integration into real-world applications such as autonomous driving and ride-sharing services.

The AI model developed in this study utilizes Neural Networks to predict passenger comfort based on vehicle sensor data. To ensure explainability, visualization techniques and model transparency were key factors. Visualization techniques, such as plotting comfort zones on the GG-Diagram, represent the model's predictions and the relationship between driving behaviors and comfort levels, making it easier for users to understand the AI's interpretations. Transparency ensures that the model architecture and training process are open and comprehensible, allowing users to understand how the model is developed and functions.

By incorporating these XAI principles, the study aims to enhance the reliability of comfort predictions and foster user confidence in AI-driven systems within the automotive industry.

IV. Results

A. Collected Data

In this research, 21 participants aged between 17 and 75 assisted in labeling data during driving scenarios. The total labeled driving times per participant ranged from 20 minutes to 5 hours, providing a comprehensive dataset for analysis. The dataset contained 350,000 rows, equivalent to 30 hours of continuous driving time, excluding stationary periods. Additionally, the comfort levels were not evenly distributed, with the 'Uncomfortable' class being underrepresented in each dataset quarter. As shown in Figure 5, the 'Acceptable' class was the most frequently used label during driving. In cases where 'Uncomfortable' labels were scarce, a mathematical formula was employed to create the smallest ellipse containing all entries labeled as 'So and So' and the baseline rhombus boundary for 'So and So'.

B. Human Reaction Time Error Mitigation

As illustrated in Figure 6, utilizing a higher acceptance percentage resulted in a dataset featuring more personalized and non-linear comfort zones. These individual traits were absent in datasets with 0% human error acceptance. Following

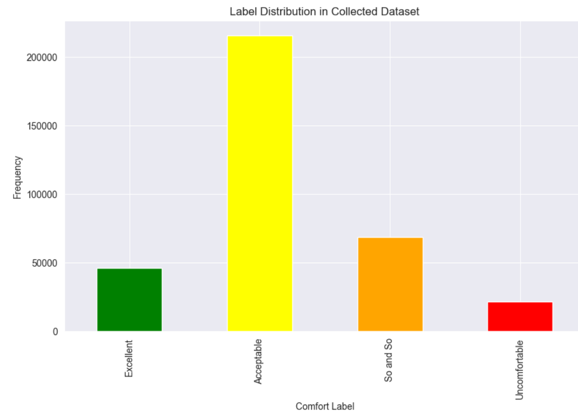

Fig. 5. Distribution of Self-Labeled Comfort Levels by all individuals.

the application of filtering to the collected data, the impact of human reaction time error became distinctly observable.

Fig. 6. Comparison of filtered datasets using different percentages of human error acceptance.

It was observed that participants who engaged in sports requiring quick changes in rhythm, such as football or basketball, generally exhibited faster reaction times, resulting in less erroneous data. For these individuals, approximately 20% of data was removed on average. Conversely, age was also a significant factor in determining the amount of human error acceptance. Older individuals often struggled to label data in time due to slower reaction times, necessitating a smaller human error acceptance margin, which resulted in the removal of almost 60% of their data.

These factors exemplify the various influences on the occurrence of erroneous data. While driving experience also showed some importance, it was not as critical as the aforementioned factors.

C. Baseline Trained Model Results

After training for 100 epochs, the model achieves an impressive accuracy of 0.998. Detailed metrics, including precision, recall, F1-score, and specificity for each comfort label, further corroborate this performance. The confusion matrix, shown in Figure 7, provides a comprehensive view of the model's performance.

Most data points align with the diagonal of the confusion matrix, indicating high accuracy. The 'Acceptable' category has the most correct predictions, reflecting the uneven data distribution; it's impractical to sustain discomfort over long periods. The 'Excellent', 'So and So', and 'Uncomfortable' categories also show strong performance with slight variability.

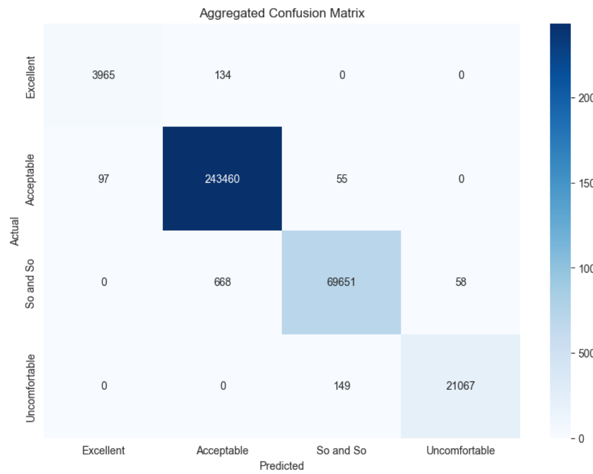

Fig. 7. Baseline-Trained Model Confusion Matrix generated by aggregating the results from a k-fold cross-validation technique with $k = 5$.

Overall, the model demonstrates robust classification with minimal misclassifications.

The classification report in Figure 12 complements the confusion matrix, showing high precision and recall across all comfort categories. The 'Acceptable' and 'Uncomfortable' labels highlight the model's robustness. However, there is a slight decrease in recall for the 'Excellent' category, indicating some misclassifications. Understanding these errors is crucial for future adjustments.

Classification Report

Label	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Excellent	97.68	96.71	97.14	99.97
Acceptable	99.67	99.94	99.8	99.16
So and So	99.71	98.96	99.33	99.92
Uncomfortable	99.73	99.3	99.51	99.98

Fig. 8. Baseline-Trained Model Classification Report showing high precision, recall, F1-score, and specificity across all categories of passenger comfort.

The Baseline-Trained Feedforward Neural Network (FNN) model excels in classifying passenger comfort levels, with high accuracy and robust metrics, indicating its potential for real-world applications to enhance passenger comfort during driving.

D. Personal Preference Trained Model Results

Initially, a naive approach involved training the model for 50 epochs on each person's self-labeled data, resulting in inaccurate comfort zone predictions (Figure 9). Human reaction time inconsistencies, like delayed responses during curves, led to misclassifications, affecting comfort level labels.

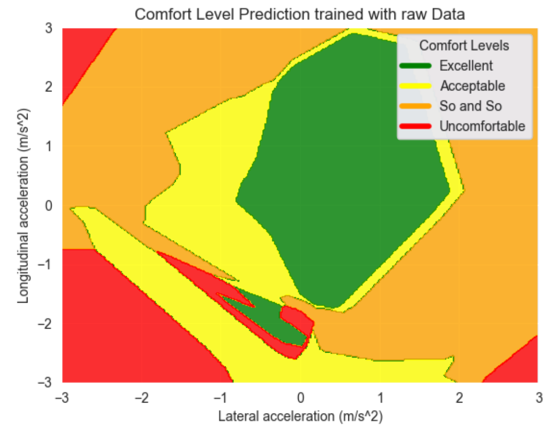

Fig. 9. Comfort Levels predicted by the trained model on raw data.

Refining the dataset with filters improved predictions (Figure 10). The model, trained on filtered data with human error acceptance rates, highlighted individual preferences, such as a preference for left turns over right turns.

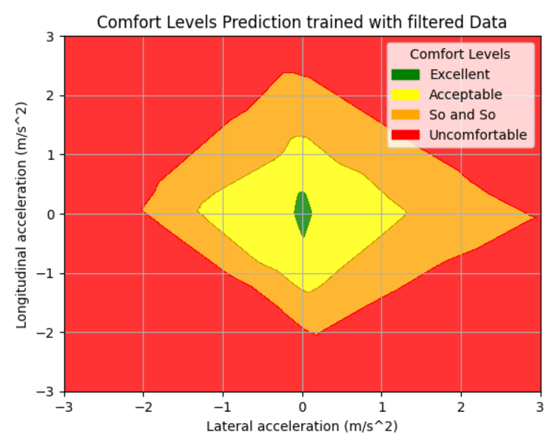

Fig. 10. Comfort Levels predicted by the trained model on filtered data.

The Personal Preference-Trained FNN achieved 0.97 accuracy after 50 epochs on self-labeled driving data. It effectively predicted comfort preferences, excelling in 'Excellent' comfort levels but needing improvement in distinguishing 'Acceptable' and 'So and So' categories.

The model's confusion matrix (Figure 11) shows reliable performance in critical categories like 'Excellent' and 'Uncomfortable'. Its classification report (Figure 12) demonstrates high precision, recall, F1-score, and specificity across all comfort categories, indicating robust performance in enhancing driving experiences.

E. Optimal Labeling Interval

The initial hypothesis proved to be incorrect. The models exhibited significant variation depending on the data segment

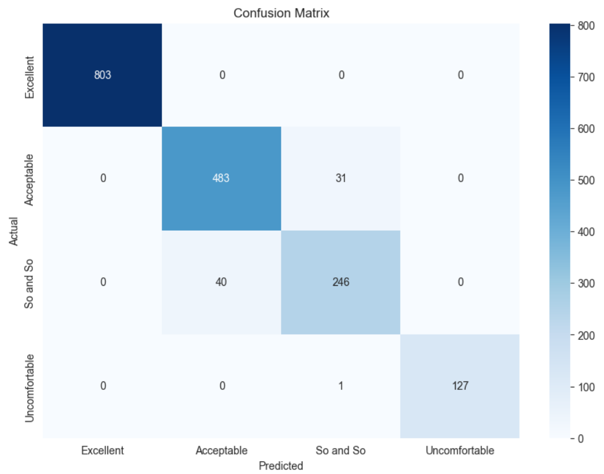

Fig. 11. Personal Preference Trained Model Confusion Matrix.

Classification Report

Label	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Excellent	97.68	96.71	97.14	99.97
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So and So	99.71	98.96	99.33	99.92
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Fig. 12. Personal Preference Trained Model Classification Report showing high precision, recall, F1-score, and specificity across all categories of passenger comfort.

they were trained on. This inconsistency indicated that self-labeling results were subjective and varied among individuals, suggesting that participants' perceptions and labeling criteria changed during the recording sessions.

An example of passenger inconsistency is illustrated in Figure 13, where the data labeled by the individual is shown on the left, and the comfort levels determined by the model are on the right. In this figure, the subject's inconsistency is evident in scenarios like braking and navigating a right corner. Due to the variability of driving scenarios in each session, there was insufficient data to validate the boundaries between comfort levels accurately. Consequently, the high-accuracy model extended the comfort level classifications, sometimes inaccurately labeling data as 'So and So' when it was clearly 'Uncomfortable'. This phenomenon, also seen in Figure 13, occurred because the model filled in the gaps based on limited data.

The solution to this problem was straightforward: ensuring at least one and a half hours of self-labeling covered all necessary comfort levels for model training. However, the

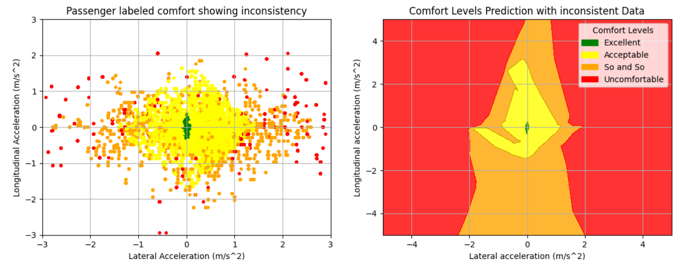

Fig. 13. Data labeled by an individual (left) and predicted comfort levels by the model trained on this data (right).

'Uncomfortable' class was underrepresented. Participants who labeled sufficient data saw the model yield excellent results, effectively correcting subjective errors. This is illustrated in Figure 15. Additionally, the model's versatility allowed it to be saved and further trained on extended driving sessions, enhancing its capability to handle longer recording periods.

In Figure 14, an instance is shown where 'Uncomfortable' entries were absent during a 30-minute drive. To mitigate this, data augmentation was implemented by creating an ellipse based on the maximum bounds of 'So-and-So' labeled data, with an additional 20% padding. This augmentation ensured a balanced representation of 'Uncomfortable' entries without overextending the 'So-and-So' comfort level, as depicted in Figure 13.

After training the model using these corrections on individual labeled data, the Neural Network successfully identified passenger comfort levels, achieving favorable scores across various metrics. Figure 15 demonstrates the data used for training on the left and the model's determined comfort levels on the right.

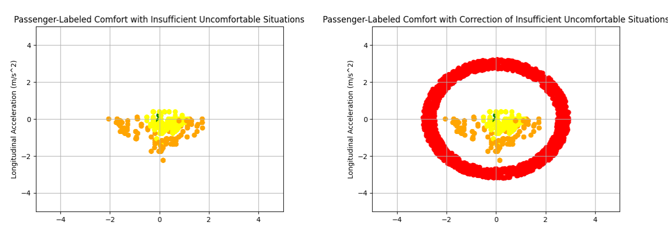

Fig. 14. A driving session labeled by an individual where no uncomfortable situations were recorded (left) and the correction of such data by incorporating the proposed ellipse to simulate uncomfortable scenarios (right).

V. Discussion

This section consists of an analysis of the implications of using these findings in real-time applications such as autonomous driving systems. It will present the importance of a correct dataset when working with solutions that could lead to very tragic situations in case of errors. By engaging in this comprehensive discussion, we aim to provide a deeper understanding of the research outcomes and their potential impact on enhancing passenger comfort, passenger experience, and promoting road safety when it comes to autonomous driving systems.

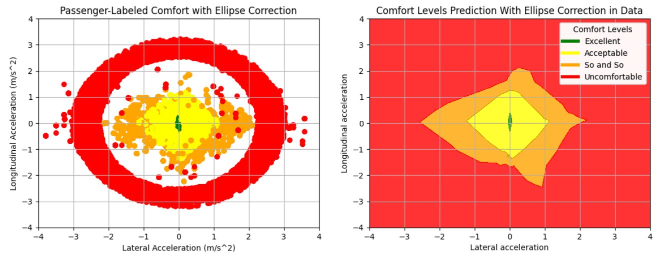

Fig. 15. Data labeled by an individual after correction (left) and predicted comfort levels by the model trained on this data (right).

A. Collected Data

Regarding the data collection results, the underrepresentation of the 'Uncomfortable' class is understandable, as prolonged discomfort would likely induce nausea. The data for this research was gathered during real-life driving scenarios without deliberately inducing specific comfort levels.

In the case of the collected data, several issues were revealed. For instance, in many cases involving elderly participants, instead of gradually progressing through all the comfort levels to reach a specific peak comfort level, some individuals, lacking a comprehensive understanding of the experiment, labeled all the data with a single comfort level that they pressed at the beginning of that moment. This resulted in a higher number of erroneous data points among older individuals (e.g. 60-75). These decisions and actions were not only due to a misunderstanding of the requirements but also due to some participants not possessing the best motor skills necessary to label each moment of driving accurately.

Despite the self-labeling application presented in [12] used for this experiment having a straightforward and intuitive graphical interface, some participants experienced difficulty labeling due to motion sickness when using a mobile device during driving. However, these challenges could be mitigated or further researched by using this solution to analyze different target groups across various demographics, allowing for comparative studies. Additionally, the data collection process could be enhanced by employing alternative software solutions or incorporating additional acceleration sensors.

B. Optimal Labeling Interval

This research paper and the hypotheses presented within it demonstrate that, in the context of this study, a self-labeling duration of at least one and a half hours allows the model to accurately capture all relevant comfort levels, except for prolonged discomfort. This conclusion is derived from an analysis of all the collected data on various roads in different counties of Romania. This approach corrects subjective labeling errors and enhances the model's ability to predict personalized comfort levels accurately.

C. Impact on Road Safety

Reducing passenger discomfort during extreme driving conditions is crucial as it directly enhances driver performance and vehicle control, thereby preventing accidents. The connection between safety and passenger comfort is integral yet often understated. By accurately predicting and effectively mitigating discomfort, predictive models empower drivers with real-time feedback. This helps them adjust their driving style promptly to not only enhance passenger comfort but also bolster overall vehicle safety, significantly reducing the risk of accidents.

D. Applications in Autonomous Driving Systems

Autonomous vehicles can benefit significantly from the proposed predictive models by ensuring passenger comfort and safety, thereby increasing trust in autonomous systems. Autonomous driving solutions plan and execute driving maneuvers based on predefined constraints on states such as velocity, acceleration, and steering. These constraints are bounded by the vehicle's physical limitations but can be further refined to ensure passenger comfort and safety. For this specific use case, the lateral and longitudinal acceleration bounds computed using the presented method are particularly relevant in velocity profile generation.

$$v_{\text{long}} = \sqrt{\frac{a_{\text{lateral, max}}}{\kappa_{\text{max}}}} \tag{1}$$

Here, v_{long} represents the longitudinal velocity and κ_{max} is the maximum curvature that the vehicle can take, which is calculated based on the physical vehicle parameters as follows:

$$\kappa_{\text{max}} = \frac{\tan(\delta_{\text{max}})}{L} \tag{2}$$

where δ_{max} is the maximum steering angle that the vehicle's steering mechanism can achieve, and L is the wheelbase of the vehicle.

As longitudinal acceleration presents the change in velocity over a timestep (Δt) will depend on the maximum acceleration value that is comfortable for a passenger.

Based on these formulas, an autonomous driving solution can seamlessly integrate a comfort profile to be adhered to during all driving conditions, except in emergency situations. This feature has been implemented in a related project on autonomous driving simulation, with both authors actively participating. For instance, as illustrated in Figure 16, the top-right section of the figure displays the tracking of a velocity profile (in black) using a PID longitudinal controller (in blue). The figure also depicts the calculated error between the reference velocity and the actual velocity.

E. Ride-Sharing Platforms

Integrating comfort prediction models into ride-sharing platforms can significantly enhance the user experience by ensuring smoother and more comfortable rides. These models enable ride-sharing companies to optimize their services by promoting driving styles that minimize passenger discomfort and elevate satisfaction. Additionally, the models can deliver real-time feedback to drivers, guiding them to refine their driving habits and further improve passenger comfort.

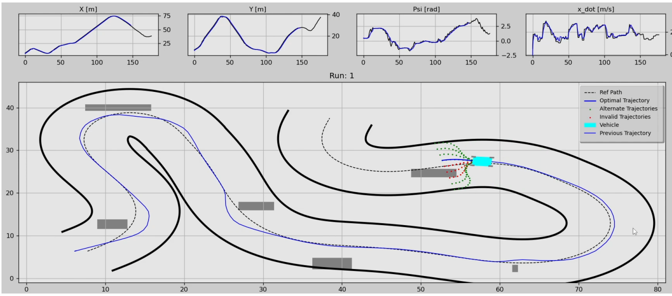

Fig. 16. Autonomous vehicle performing trajectory and velocity profile tracking in the simulation environment.

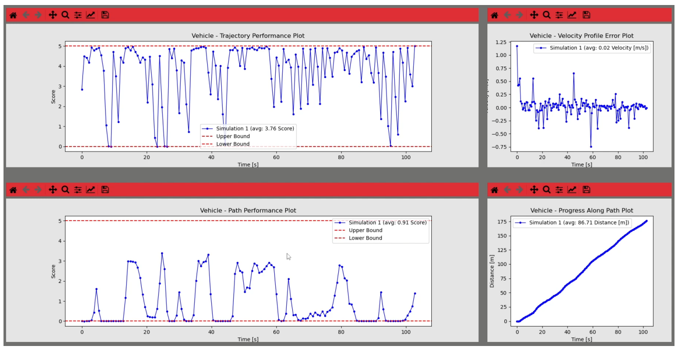

Fig. 17. Performance metrics and Velocity Tracking Errors of the simulated scenario.

F. Future Work and Limitations

As presented and discussed in this research paper, the proposed idea shows great value and potential for extension in future works, as well as some key limitations.

One limitation highlighted in this research was the amount of collected data and the crucial need for it to generate an accurate analysis of comfort levels. Although the gathered dataset contains a vast array of different entries, it proved to be insufficient to support various hypotheses found during the development of this paper.

With the data containing only basic sensors found in the majority of cars manufactured after 2010, extending the dataset to include multiple car types and brands should be a relatively straightforward step. This presents an opportunity to generate more data, enabling more precise predictions and a broader analysis of contributing factors.

Regarding the prediction models, this research aimed to develop a simple and efficient Neural Network model with key features such as speed, accuracy, and strong overall metrics. While this was proven to be possible, there remains significant room for improvement by employing different Artificial Intelligence methods to predict data more accurately. Utilizing alternative architectures, activation functions, or optimizer functions could result in a model that surpasses the performance of those presented in this paper.

VI. Conclusion

This research has successfully developed an AI model that integrates self-labeled data to personalize and adapt to individual comfort levels using CAN Bus data for comprehensive analysis. The study's findings indicate that implementing this model in ride-sharing applications can significantly enhance the understanding of individual driver behaviors, refine training programs, and boost client satisfaction. The data backs up these findings by demonstrating that the AI can transform linear comfort levels into more accurate, personalized nonlinear representations, as evidenced by the high accuracy achieved in model predictions. The autonomous driving industry can leverage these insights to better comprehend passengers' comfort zones, thereby fostering increased trust and improving overall safety.

Future work should focus on extending the dataset to include multiple car types and brands, enabling more precise predictions and a broader analysis of contributing factors. Additionally, employing alternative AI methods could further improve the accuracy of the predictive models. By enhancing transparency and interpretability through Explainable AI principles, this research fosters user confidence in AI-driven systems within the automotive industry.

The importance of a correct dataset when working with solutions that could lead to tragic situations in case of errors is emphasized. Ensuring comprehensive and accurate data collection, considering various demographics and vehicle types, is crucial for the continued development and application of these AI models.

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