Haptic Perception of Force Profiles: A Data-Driven Approach to Quantifying Human Interaction with Car Doors

Waseem Hassan*, Mudassir Ibrahim Awan*, Ahsan Raza, and Seokhee Jeon

***Abstract*—Haptic perception plays a crucial role in user experience, particularly in the automotive industry where the tactile quality of components can influence customer satisfaction. This study aims to accurately predict the haptic perception of opening a car door by analyzing its force profile using a deep learning model. The model is designed to capture the underlying relationships between force profiles and user-defined adjective ratings, providing insights into the door-opening experience. The dataset employed in this research consists of force profiles and user adjective ratings collected for six car models, reflecting a diverse set of door-opening experiences. The model's performance is assessed using Leave-One-Out Cross-Validation (LOOCV), a robust evaluation technique that effectively measures the model's generalization capability on unseen data. The results demonstrate that the proposed model achieves a high level of prediction accuracy, indicating its potential in various applications related to haptic perception and automotive design.**

I. Introduction

The automotive industry has increasingly recognized the importance of user experience, with particular emphasis on the physical sensations and emotions experienced by drivers and passengers when interacting with various aspects of a vehicle [1], [2]. One critical aspect of this interaction is the car door, as it constitutes the first point of contact between the user and the vehicle [3]. Interaction with a car door imprints a lasting impression on the perception of the overall car. Therefore, there is a growing need for a virtual evaluation system capable of predicting the haptic perceptions and emotions users feel for interacting with various car doors without the need to manufacture physical prototypes.

However, several challenges and bottlenecks exist within the current research landscape. Firstly, the relationship between the physical properties of a car door and user experience remains elusive, requiring a more in-depth analysis to establish correlations [4]. Moreover, the tactile sensation of the vehicle interface can significantly vary depending on factors such as assembly parts, tolerances between components, and wear conditions [5]. This is due, in part, to the complex and multidimensional nature of human perception and the fact that individual users may have different preferences and expectations. Consequently, these challenges necessitate further investigation to develop accurate perception prediction models for car door design.

In automotive design, the physical attributes of a car door are known to have a significant effect on user experience [6], [7]. The development of a system that links these physical attributes to the user experience can be a beneficial exercise. This relationship can be conceptualized as a sequential pipeline that starts with the car door attributes and culminates with user experience, as shown in Fig. 1. Various aspects of a car door assembly (weight, friction, hinge profile, etc.) contribute to delivering a specific physical signal throughout the opening or closing motion of a car door. This signal is often in the form of a torque profile that can be estimated using a physics simulation of the door assembly [7], [8]. The relationship between the components of the car door and its physical signal is well-studied and remains common knowledge in the automotive industry [9], [10]. The torque profile is experienced by a user as a force during the act of opening or closing the door. This conversion of the torque profile to the user-experienced force profile can also be simulated or recorded using sensors [11]. The force profile experienced by a user informs their cognitive process and develops the cognitive attributes of the door in their mind. These cognitive attributes ultimately manifest in user experience and can be evaluated using psychophysical experiments with human participants. It is also possible to derive these cognitive attributes directly from the assembly space, or the torque profile of the door. However, on one hand, such an endeavor could complicate the design as a higher number of permutations would be required (due to the individual influence of parts). On the other hand, the conversion between the assembly space and torque profile to the user-experienced force profile can already be accurately estimated.

Existing studies primarily focus on reproducing the physics of the current system and evaluating its performance [12]. Such research tends to be profile-oriented and lacks a systematic approach that encompasses all emotional design processes, including prototyping, physical sense modeling, and authoring and application. The relationship between car door components (or force profile) and the user's haptic perception remains elusive and difficult to quantify. Although some studies have analyzed cognitive characteristics [13], there is a dearth of research exploring the creation and recommendation of novel physical sensations based on this knowledge.

To address the challenges and bottlenecks in the field, researchers have turned to machine learning as a potential

* These authors contributed equally to this paper. Seokhee Jeon is the corresponding author.

W. Hassan, M.I. Awan, A. Raza, and S. Jeon are with the department of Computer Science and Engineering, Kyung Hee University, Yongin-si, Gyeonggi-do, South Korea (e-mail: [waseem.h, miawan, ahsanraza, jeon]@khu.ac.kr)

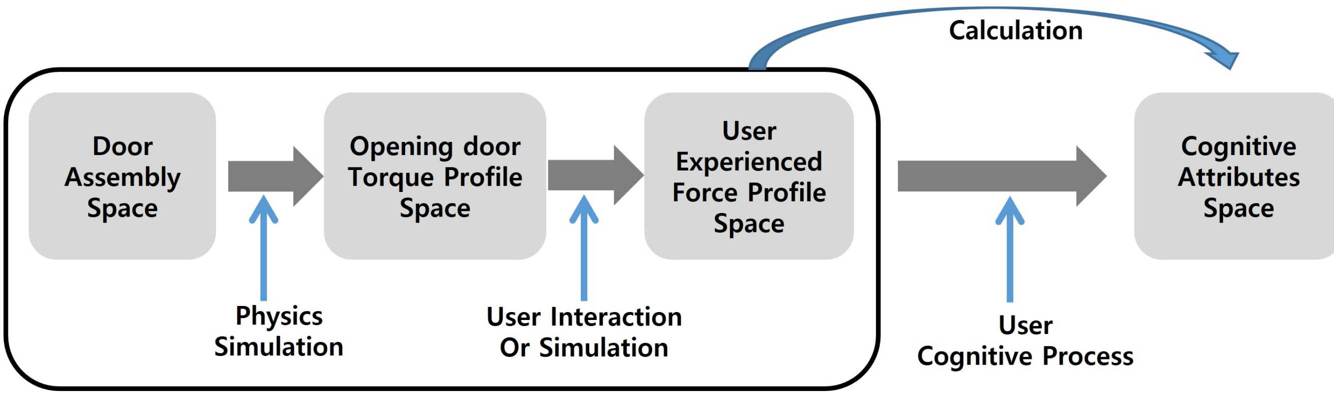


Fig. 1: Schematic representation of the sequential pipeline linking physical attributes of a car door to user perceptual experience.

solution. By leveraging advanced algorithms, machine learning models can identify patterns and relationships that may be difficult for humans to discern [14], [15], [16]. This approach has the potential to overcome some of the limitations of traditional research methods and identify nuances in force profiles that may lead to significantly different haptic perceptions.

In recent years, machine learning and deep learning techniques have gained popularity in various fields due to their capacity to learn complex patterns and make predictions based on those data. These techniques have been applied to numerous applications in the automotive industry, such as predictive maintenance, autonomous driving, and driver behavior analysis. For example, machine learning models can be trained on datasets containing information about a wide range of car door designs and user feedback, enabling them to predict users' haptic perception and emotions with greater accuracy [17]. This approach has the potential to save time and resources by reducing the need for physical prototyping and user testing. However, there has been limited research on leveraging these techniques to predict the human perception of different car door attributes based on vehicle data.

The perceptual characteristics of car door operation are highly dependent on the force profile required to open it. This study aims to mitigate the need for prototyping new changes in car door dynamics by enabling designers to make informed design decisions while prioritizing perceptual characteristics. The proposed system will allow designers to gauge the perceptual characteristics of a car door based on a force profile without the need for prototyping and user-studying the design. To achieve this, we propose a novel machine learning-based approach to predict users' haptic perception when interacting with car doors. Our approach not only allows for more accurate prediction of user experience but also has the potential to save time and resources spent on prototyping and testing.

This paper aims to address this research gap by proposing a novel deep-learning model that predicts human perception of car-door attributes using a CNN-LSTM network. The CNN-LSTM network is trained using force profiles of opening a car door, and the subjective ratings from users that describe the act of opening a car door. The force profile data were recorded, using force and optical trackers, from human participants opening the doors of different cars. Similarly, the perception of opening a car door was recorded by human participants, who rated this experience against a set of antonymously paired haptic adjectives. The trained network was then used to predict the perceptual attributes of opening a car door by using its force profile, in a cross-validation study. By developing a virtual evaluation system capable of predicting haptic perception and emotions experienced by users when interacting with car doors, we aim to contribute to the advancement of automotive design and ultimately enhance the overall user experience.

II. Related Works

This section provides an overview of the existing literature related to the perception of car doors and the use of machine learning in the automotive industry. We have divided the literature review into four subsections: machine learning and perception of cars/car parts, the role of emotions in product design, haptic perception in automotive design, and data-driven approaches in automotive design.

A. Machine Learning and Perception of Cars/Car Parts

In the contemporary research paradigm, machine learning techniques have touched various aspects of automotive design, such as comfort, aesthetics, and usability [14], [16]. By training models on large datasets containing information about car designs and user feedback, these studies have been able to identify patterns and relationships that can inform the design process.

One area where machine learning has shown particular promise is in the prediction of users' emotional responses to car designs. Researchers have developed models that can accurately predict users' emotional reactions to different car designs based on features such as color and shape [16]. This research has provided valuable insights into the emotional aspects of automotive design and has the potential to inform the creation of more emotionally engaging vehicles.

In addition to predicting users' emotional responses, machine learning has also been used to predict the performance of car designs. For instance, researchers have developed deep learning-based autoencoders that can carry out performance predictions of compressed 3D automotive design data [18]. This research has the potential to revolutionize car design by enabling designers to create designs that can perform well in terms of functionality.

Machine learning has been used to analyze the relationship between the physical properties of cars and their perceived quality, such as the perceived quality of sound produced by the engine [19], [20]. However, the application of machine learning in the context of predicting haptic perception and emotions related to car doors remains a relatively unexplored area.

B. The Role of Emotions in Product Design

Emotions play a crucial role in shaping users' perception of products and their overall satisfaction [21], [22]. Affective engineering has emerged as an interdisciplinary field that aims to incorporate users' emotions and preferences into the design process, thereby enhancing the overall user experience [23]. Some studies have explored the role of emotions in the context of automotive design, focusing on various aspects such as the interior environment, the driving experience, and the vehicle's appearance [24]. However, there is still limited research on the role of emotions in the design of car doors and their impact on users' haptic perception and satisfaction.

Car door design plays a critical role in the overall user experience of a vehicle. Early research in this area focused on the optimization of car door dynamics, with an emphasis on improving the opening and closing characteristics [25]. This body of work has led to the development of various techniques and approaches for optimizing car door design, such as the use of advanced materials and manufacturing processes.

Recently, there has been a shift in focus toward understanding the relationship between car door design and perception. Studies have explored the impact of car door design on users' perception of quality and luxury [17]. These investigations have revealed that users associate certain design elements, such as the smoothness of the door opening and closing motion, with higher-quality vehicles.

This growing body of research has underscored the need for a more systematic approach to car door design, which takes into account the emotional and cognitive aspects of user experience. By adopting such an approach, designers can create car doors that not only perform well in terms of functionality but also evoke positive emotions and contribute to an overall satisfying user experience.

C. Haptic Perception in Automotive Design

Haptic perception, the sense of touch, plays a critical role in how users experience and interact with products [26], [27]. In the context of automotive design, haptic perception encompasses not only the tactile sensations experienced when touching surfaces and materials [28] but also the kinesthetic feedback associated with operating mechanisms [29], [30]. A better understanding of haptic perception can help designers create more satisfying and user-friendly experiences [31]. Despite its importance, research on haptic perception in automotive design has been limited, with few studies exploring the factors that contribute to the perception of car door quality and the emotions they evoke.

The use of machine learning techniques to predict users' haptic perception of car doors and other automotive interfaces has the potential to revolutionize the way automotive interfaces are designed and evaluated. By leveraging machine learning techniques, designers can create more intuitive and engaging interfaces that cater to the diverse preferences and needs of users

D. Data-driven Approaches in Automotive Design

Data-driven approaches have gained traction in various fields, including automotive design, where they enable designers to make informed decisions based on empirical data [32], [33], [34]. Researchers have used data-driven models for various aspects of automobiles, such as improving the braking control systems [35], or evaluating the health of electronic systems on board [36].

Data-driven methods, combined with machine learning techniques, can facilitate the development of predictive models that account for the complex relationships between product properties [37]. Despite the potential benefits, there is still a need for more research on data-driven approaches in the context of automotive design, especially regarding car door perception and the emotions they trigger.

Overall, the literature review highlights the need for a more systematic approach to understanding the relationship between car door physical properties and user emotions, as well as the potential benefits of incorporating machine learning techniques in the design and evaluation process.

III. Overview

Figure 2 provides a summary of the different sections detailed in this paper. The overview section presents a concise version of the paper's content, outlining the main topics in each of the sections. Details are provided in the subsequent sections.

The main aim of the current study is to provide a robust and expeditious method to designers and engineers for anticipating the perceptual aspects of car doors without the need for prototyping. To this end, Sec. IV details the dataset, experiments, and their procedures for quantifying the perception of opening a car door. The experiments start with collecting a diverse corpus of adjectives to describe the perception of opening a car door, proceed with selecting a limited and more relevant set, and conclude with user ratings across a set of antonymously paired adjectives.

The force and optical data collection setup for generating the force profiles of opening car doors is explored in Sec. V. The force profiles portray the amount of force required at various stages of opening a door and are therefore represented as a function of force and angle of opening.

The data generated from user ratings and force profiles are used as input to train a CNN-LSTM network, presented in Sec. VI. The trained CNN-LSTM model can predict the haptic perception of car doors based on their force profiles. The predicting ability of the network is tested using LOOCV (leave one out cross-validation) in Sec. VII.

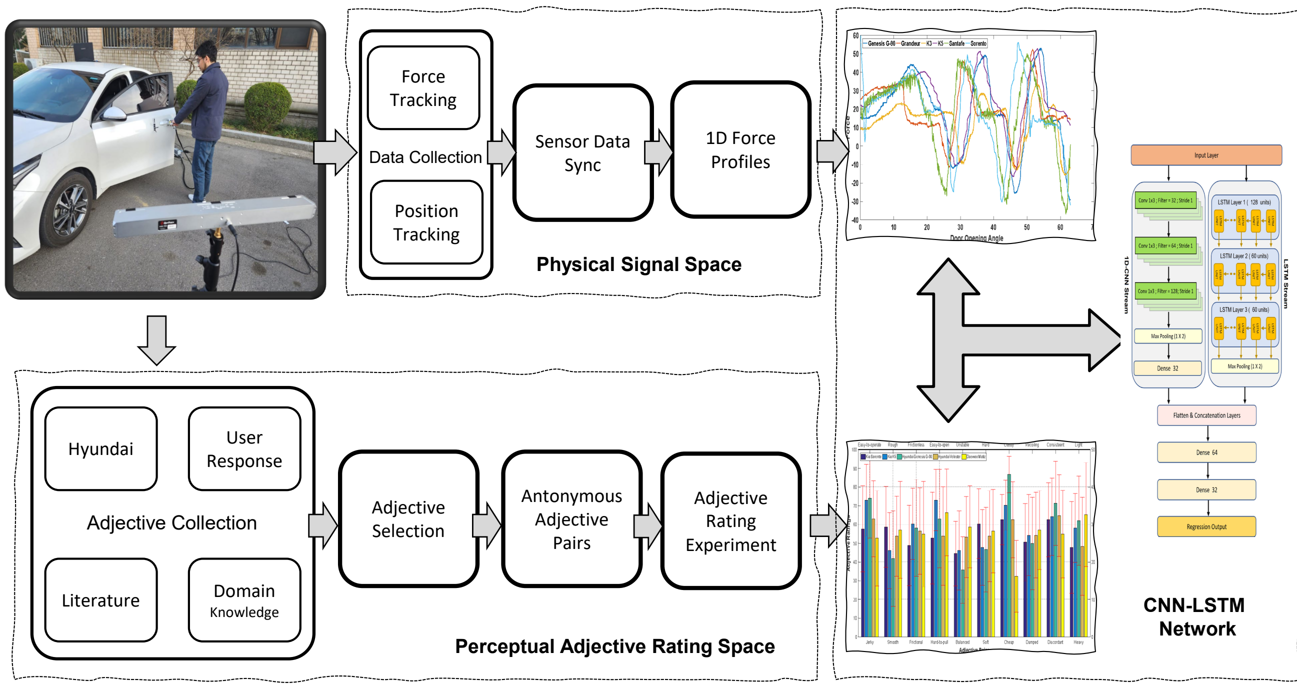


Fig. 2: An overview of the overall study. Experiments with a car door provide the force and position tracking values as well as user ratings for the perception of opening a car door. These data are used to train a CNN-LSTM model that predicts perceived ratings based on force profiles of opening a car door.

IV. Perceptual Adjective Rating Experiment

The aim of this experiment was to describe the act of opening a car door from a perceptual experience point of view. Users provided ratings against a set of attributes that describe the perception of opening a car door. The overall experiment can be divided into three smaller experiments which were conducted sequentially. First, users were asked to open a car door and provide adjectives that can describe the perception of opening a car door. These adjectives, along with adjectives gathered from literature and other sources were pooled together to form a lexicon of adjectives. In the second experiment, users selected the most appropriate adjectives from the lexicon of adjectives. In the third experiment, users rated the act of opening a car door against the selected adjectives in experiment two. Details of the dataset and all experiments are provided in the following subsections.

A. Participants and Dataset

A total of 20 participants took part in the first and second experiments, and 26 in the third. Around 75% of the participants in all experiments were common, the remaining were replaced due to non-availability. The majority of the participants identified as males, while 10 out of the combined 66 across all experiments identified as females. Their average age was 27.5 years (range: 21 - 34). None of the participants reported any disabilities or any other factors that could prevent them from successfully participating in the experiments. All participants were compensated with $15 USD per experiment.

TABLE I: The lexicon of adjectives built from four sources, i.e., Hyundai research, Experiment, literature, and domain expert. The overall list was formed as a result of experiments 1 and 2.

1 Agitating	18 Easy to operate	35 Harmonic	52 Cheerful, rhythmical
2 Archaic	19 Effortless	36 Heavy	53 Rigid
3 Balanced	20 Empty	37 High	54 Rough
4 Calm	21 Erratic	38 Jarring	55 Shaking
5 Calming	22 Exciting	39 Jerky	56 Shallow
6 Cheap	23 Expensive	40 Joyful	57 Smooth
7 Classy	24 Stepwise	41 Light	58 Soft
8 Clinging	25 Fluctuating	42 Like new	59 Sophisticated
9 Comfortable	26 Fluid	43 Loud	60 Stiff
10 Consistent	27 Forceful	44 Luxurious	61 Stressing
11 Constant	28 Free	45 Natural	62 Stuck
12 Cool	29 Frictional	46 Not fit	63 Tightly fit
13 Damped	30 Frictionless	47 Old	64 Uncomfortable
14 Discordant	31 Futuristic	48 Pleasant	65 Unpleasant
15 Disturbing	32 Gloomy	49 Quiet	66 Unstable
16 Easy	33 Hard	50 Recoiling	67 Vibrating
17 Easy to open	34 Hard to pull	51 Relaxing	68 Vintage

A total of six cars were used in this experiment. A wide variation of cars was included in the dataset to cover the range from luxury to utility cars. The six cars used in the experiment were the new k3 (Kia), K5 DL3 (Kia), the new Grandeur (Hyundai), Genesis G90 (Hyundai), Santafe 7 seater (Hyundai), and Sorento 5 seater (Kia).

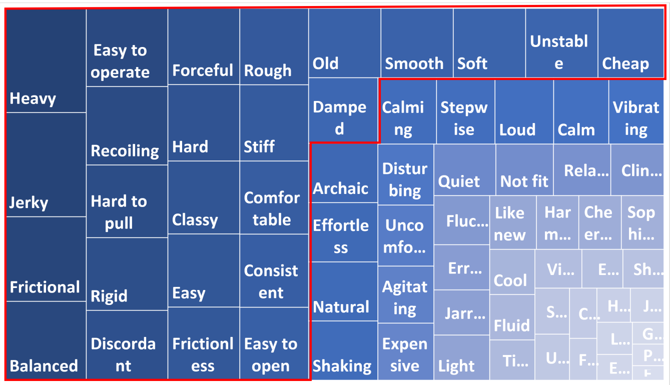


Fig. 3: Relevance of all adjectives shown in percentage. The sizes of the boxes are sorted according to relevance percentage and the red border outlines the top 20% adjectives considered as most relevant by users.

B. Experiment 1: Lexicon of Adjectives

The aim of this experiment was to gather all possible adjectives that can be used to describe the perception of opening a car door. A total of four different sources were used to establish the lexicon of adjectives. These sources were literature, the research provided by Hyundai, the authors' intuition/domain knowledge, and a user experiment.

In the experiment, users were asked to open the driver-side front door with their left hand and open it all the way. They were allowed to repeat the procedure if needed and there were no time restraints. The users were handed a paper to write down all the adjectives that could describe the perception of opening a door. They were informed that they could comment on the motion of the door, its perceptual aesthetics, overall feel, or any other aspect they deemed important. Every user repeated this process for all the cars.

C. Experiment 2: Selection of Adjectives

The main aim of this experiment was to select the most relevant adjectives that describe the perception of opening a car door. The lexicon of adjectives contained 68 adjectives, and it was not feasible or productive to continue with all 68. This experiment was conducted to filter out the adjectives that users considered relevant.

The users were asked to engage with the door of a car and open it at will. They were provided with a list of all the adjectives collected after the first two experiments. The users had to decide whether a particular adjective was relevant to opening the door of a specific car. The decision was either a 1 for yes or a 0 for no. All the users provided their own list of relevant adjectives for each car.

Results of Experiment 1 and 2:

In the lexicon of adjectives, four different sources contributed adjectives. Among these sources, The user experiment provided a total of 33 unique adjectives. Hyundai uses adjectives for measuring the physical performance of a car door, eight of these were usable for our purpose. Thirteen adjectives were collected from previous literature [6], [38]. After analyzing the above three sources, the authors included 14 more adjectives based on their experience and knowledge of working in this domain. They felt these could be useful additions to the lexicon of adjectives. Combining all these sources, the lexicon of adjectives contained a total of 68 adjectives, which are provided in Table I.

The second experiment was conducted to filter out the most relevant adjectives for describing the perception of opening a door. Every adjective was scored by the users, and these scores were averaged and combined for all cars and users. Figure 3 provides the relevance of each adjective. It was empirically decided to choose the adjectives that were selected by at least 20% of the users. A total of 25 out of the 68 adjectives were selected based on this criterion. These were further used in experiment 3.

TABLE II: The ten adjective pairs used for the adjective rating experiment. Six of the adjectives were combined with adjectives with similar perceptual connotations.

Antonymous Adjective Pairs		
1	Jerky	Easy to operate/Easy
2	Smooth	Rough
3	Frictional/Forceful	Frictionless/Comfortable
4	Hard-to-pull	Easy-to-open
5	Balanced	Unstable
6	Soft	Hard/Rigid
7	Cheap/old	Classy
8	Damped	Recoiling
9	Discordant	Consistent
10	Heavy/Stiff	Light

D. Experiment 3: Adjective Rating

The 25 adjectives selected after the second experiment were divided into pairs of antonymous attributes to represent the opposite ends of the same scale. Six adjectives were similar in meaning and paired at the same end of the scale. Heavy received the highest score from users in experiment 2, however, there was no straightforward antonymous pairing available from within the top 25 adjectives. Light was selected from outside the top 25 to pair with heavy. A total of ten pairs were formed at the end of this exercise, as shown in Table II.

In this experiment, users were provided with a list of the selected ten adjective pairs located at the opposite ends of a seven-point Likert scale. The task was to rate the perception of opening a car door against the ten adjective pairs. The same procedure of opening the car door was followed as in the earlier experiments. Each user rated all six cars in random order.

Results of Experiment 3: The data from experiment 3 were in the form of adjective ratings for six cars rated against ten adjective pairs. The data were averaged for all users and normalized onto a scale of zero to 100. Adjective rating data for all cars and adjective pairs are shown in Fig. 4.

V. Force Profile of Opening a Car Door

In the psychophysical experiments users opened a car door and provided perceptual ratings. The perceptual characteristics exhibited by an opening car door are highly dependent on the physical aspects of the door. Therefore, a physical signal that

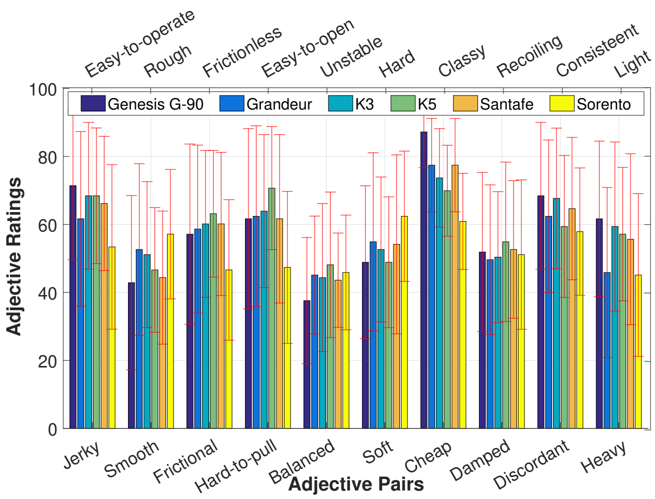


Fig. 4: Averaged adjective rating for ten adjective pairs from experiment 3. The error bars show the standard deviation for each bar.

can describe the act of opening a door should be considered significant. The force profile can be considered an important physical aspect of opening a door. It refers to the amount of force required to open (and close) the door at different points in its range of motion. It takes into account several factors that contribute to the perceptual characteristics of a car door. It can be considered as the combined effect of the weight of the door, its aerodynamics, and the shape of the hinge that keeps it attached to the main frame. Therefore, it was decided to use the force profile for predicting the perceptual characteristics of opening a door. In the current study, force profiles of the cars provided in IV-A were recorded.

A. Data Collection Setup

To record the force profile of the car door, we used an ATI force sensor and an Optitrack Trio120 optical sensor. The ATI force sensor was attached to the door handle, and Optitrack markers were placed just beside the handle so that they were visible to the cameras at all times. A one-time position tracking of the door hinge was carried out for every car. This was done to establish a reference point for measuring the opening angle. A user opened the door with their left hand. The users were instructed to make a conscious effort to maintain a constant velocity and avoid jerks. The force sensor recorded the force required to open the door at different points in its range of motion. The Optitrack Trio 120 was used to track the movement of the door and the markers to provide a visual representation of the door's range of motion. The setup is presented in Fig. 2. The data from both sensors were synchronized based on timestamps. The force sensor recorded data at 1 kHz while Optitrack provided position data at an update rate of 80 Hz. The position data were upsampled to match the force sensor update rate. A total of ten force profiles were recorded for each car.

B. 1D Force Profiles

The data collected from different cars was inconsistent because it was collected by human users. The maximum opening angles of the cars were also variable. To make the data more comparable and accurate, it was important to normalize it and make it uniform across all cars.

The maximum opening angle for all the cars was capped at 63°, as most of the cars had a maximum opening angle of less than that. For cars where the maximum opening angle was smaller, the data were zero-padded at the end. Since data were collected by human users, the opening velocity was variable. This was normalized by combining the position tracking data and force data. The force data were divided into subsets corresponding to a range of 1° of the angle. The subset of force data for each degree was then downsampled and truncated to 10 data points. This was done to make the data uniform across all cars and smooth out outliers. A total of ten force data points were selected for each degree of opening the car angle, resulting in a total of 630 data points for each car profile. A total of 10 recordings were carried out per car, to provide multiple training instances of the same data for the deep learning model. Force profiles of all six car doors and position tracking of three car doors are provided in Fig. 5.

VI. CNN-LSTM Network

Statistical approaches, such as AR(Auto-regressive), MA(Moving Average), ARMA (Auto-regressive Integrated moving average), and their other variants are widely been used to process time series data but these methods do not always give the best results. The reason is that these approaches do not take into account long-term temporal dependencies. While deep learning approaches, such as recurrent neural networks (RNN), can effectively process time-series data. However, even RNNs have their own set of challenges, especially when it comes to dealing with long input sequences. In such a case, RNN can face a vanishing gradient problem during back-propagation. This problem is well addressed by Long-short-term-memory (LSTM) network and exhibited notable performance in detecting long-short-term temporal dependencies [39],[40]. Likewise, Convolutional Neutral Network (CNN) showed good prediction accuracy in numerous applications related to image and speech processing such as image segmentation [41] and speech-emotion recognition [42] respectively by extracting spatial information.

Recently, deep learning approaches also attracted researchers in processing haptic data in various tasks such as surface texture classification [43], synthesis of high-frequency vibration signals [44], and perceptual similarity learning based on haptic data [45]. Given this, the main aim of this study is to develop a hybrid CNN-LSTM model to predict perceptual attributes of car doors based on the dynamics offered by the door hinge which we recorded as force signals (see Section V). Below we discuss the details of the proposed 1D-CNN and LSTM.

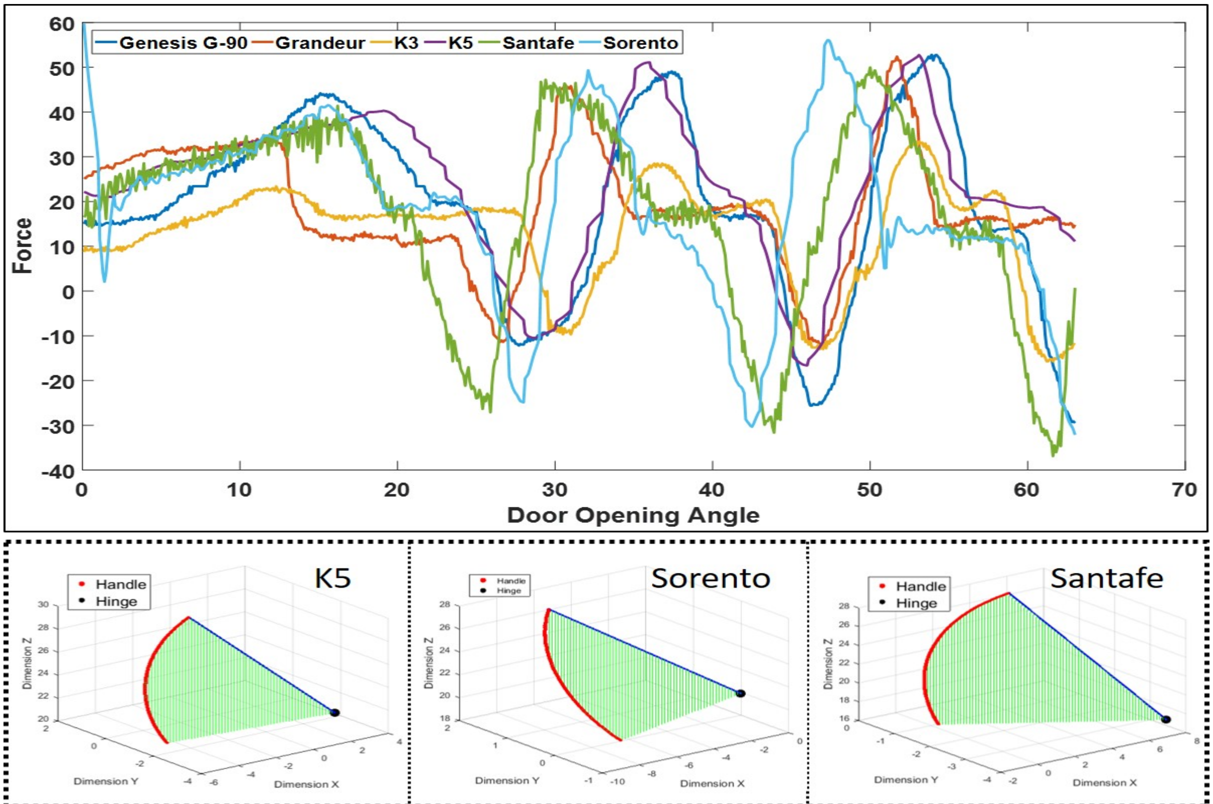


Fig. 5: Angle-normalized force profiles of the six cars used in this study (Top). The position tracking of the door opening is provided for K5, Sorento, and Santafe for reference (Bottom).

A. Long Short–Term Memory (LSTM):

Long short-term memory (LSTM) models are a special type of RNN and are proposed to solve the vanishing gradient or exploding issue faced by RNNs during back-propagation [39]. Unlike RNNs, the LSTM model contains one memory cell and three interactive gates. The first gate is known as Forget gate, the second gate is the input gate and the third gate is called the output gate. The memory cell is in charge of memorizing the previous state while forget gate enables the network to decide whether the previous information should be passed to the input gate or need to be thrown away. The input gate is used to update the memory cell while the output gate controls the activation for the subsequent layer [46] [40]. Mathematically the structure of LSTM at time t can be represented as:

$$i_t = \sigma(W_i(x_t + h_{t-1}) + b_i) \tag{1}$$

$$f_t = \sigma(W_f(x_t + h_{t-1}) + b_f) \tag{2}$$

$$O_t = \sigma(W_O(x_t + h_{t-1}) + b_O) \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot tanh(W_c(x_t + h_{t-1})) \tag{4}$$

$$h_t = O_t \odot tanh(C_t) \tag{5}$$

where i, f, and o are the inputs, forget, and output gates respectively, whereas c is the memory cell and h represents the hidden layer state. σ is the sigmoid function while b_i, b_f, b_O and W_i, W_f, W_O denote the bias terms and weight matrices.

The proposed LSTM structure can be seen in the upper part of Fig. 6 which consists of three subsequent LSTM layers and one Max pooling layer. The first LSTM layer employing 120 units reads force profile from the input layer followed by two identical LSTM layers containing 20 units. Afterward, a max pooling layer is utilized to compress the feature size and as a regularization technique and reduce the feature size. These extracted features from the LSTM stream, representing temporal dynamics of force profile are then passed to the flattened layer followed by a concatenation layer, to fuse them with the features extracted from CNN. The details of the 1D-CNN network and the feature fusion are described in the following sections.

B. 1D Convolution Neural Network

Convolution Neural Network(CNN) is one of the most famous approaches researchers adopted in a wide variety of vision-based applications and achieved state-of-the-art performance. These applications include image classification, emotion recognition, image segmentation, and so on. Moreover, CNNs also achieved good performance in numerous speech and haptic-related tasks, while employing it as a 1D-signal feature extraction technique. Motivated by these above works, we designed a 1D-CNN network to extract spatial features to predict the haptic attributes of car doors based on the dynamics offered by the door hinge. The illustration of the proposed 1D-CNN network can be seen in the lower section of Fig. 6

The proposed infrastructure of the 1D-CNN consists of three convolution layers, one max pooling layer, and a Dense layer. Similar to the LSTM module, the first layer of the CNN network takes force profile as input. This layer then applies 32

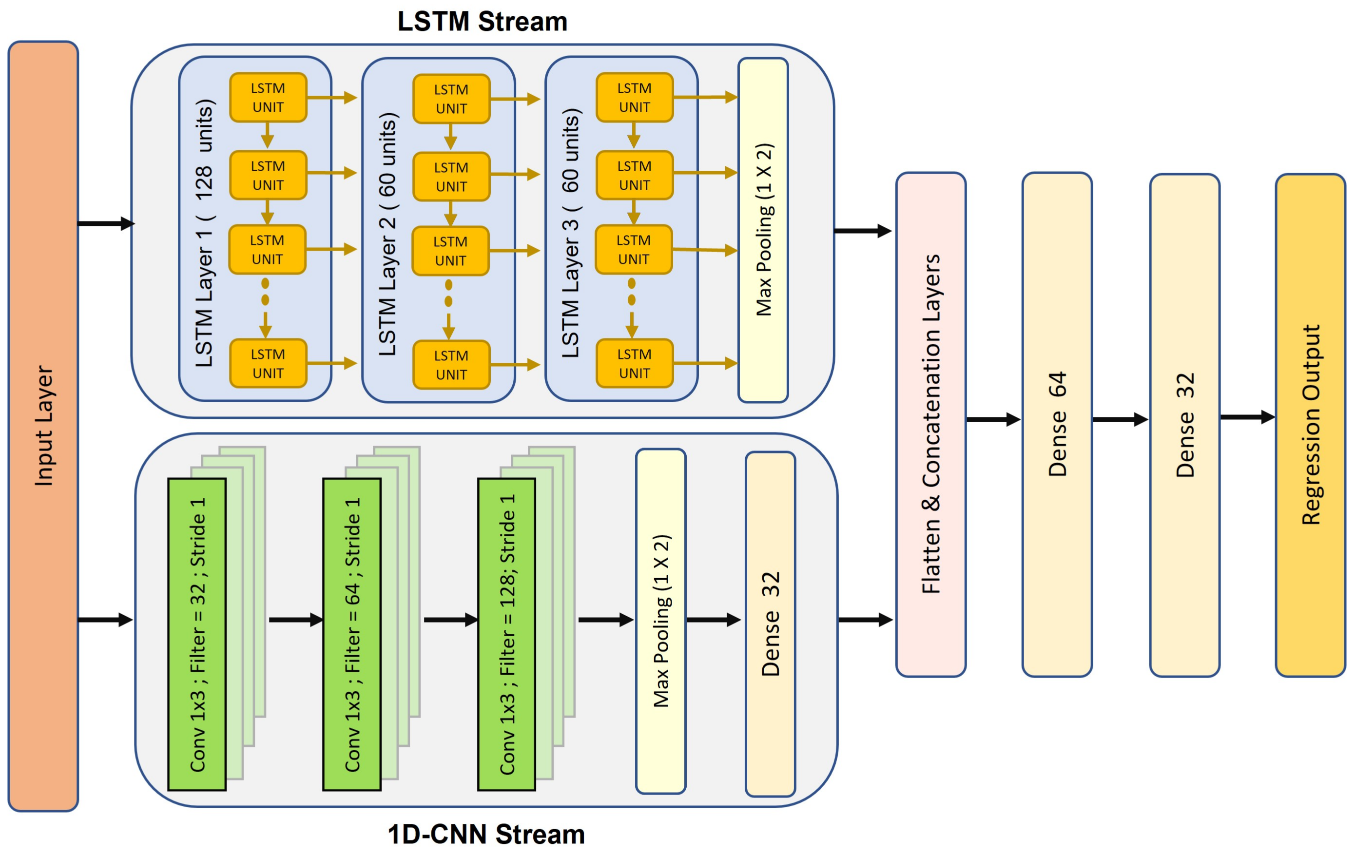


Fig. 6: A block diagram of the overall framework. The top row details the steps required to establish the HAS which is the first main contribution of this work. The next two rows show the training and testing methodology of the 1D-CNN.

filters with kernel size 3 followed by convolution containing 64 filters of size 3. For the third, convolution layer 128 filters are employed. Finally to reduce the dimension of extracted spatial features max poling operation is applied with a window size of 2 followed by the dense layer containing 32 nodes.

C. Model Training Method

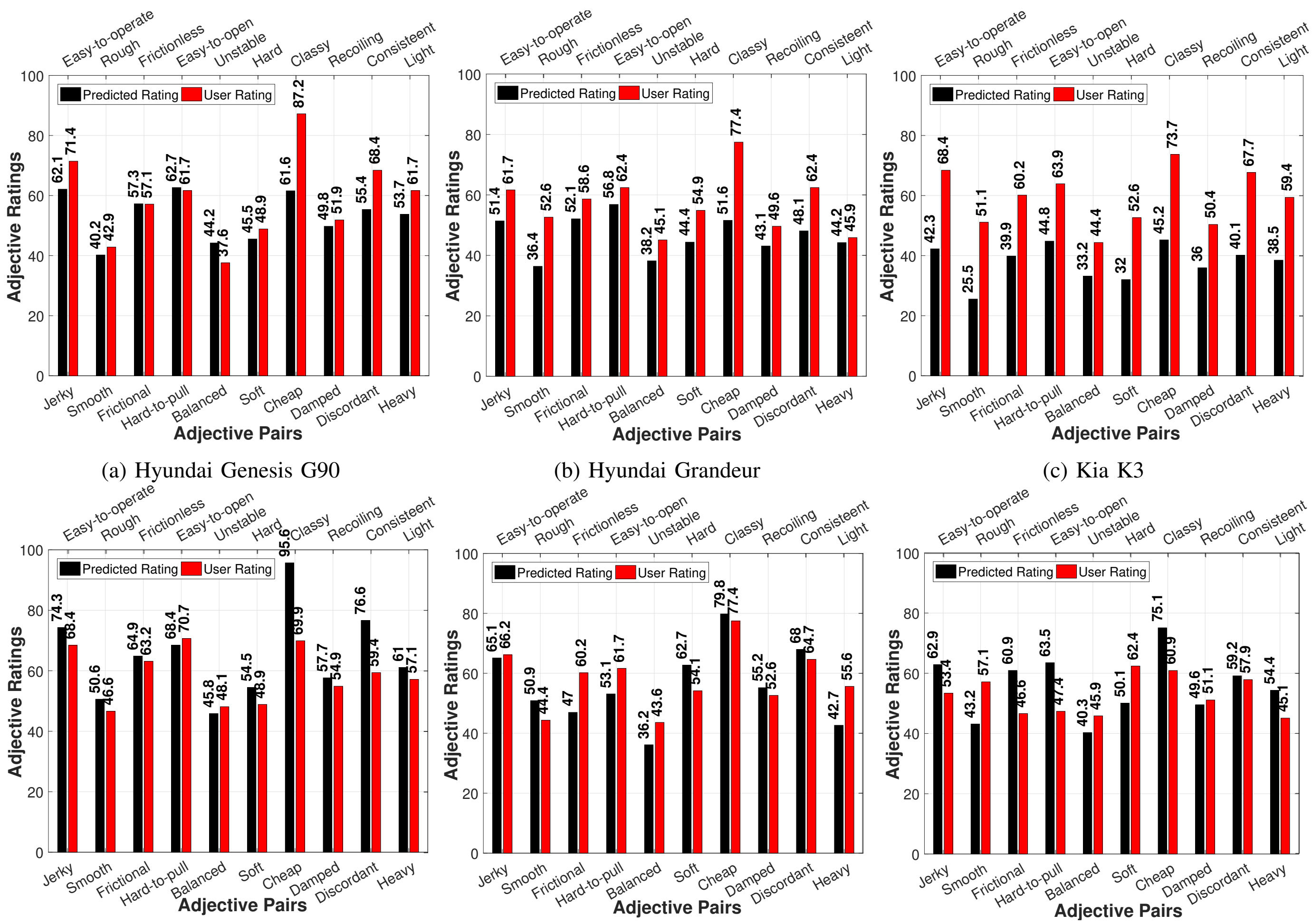
In order to fuse the extracted spatial and temporal features from 1D-CNN and LSTM networks respectively, flattening operation before concatenation is applied to form a single feature vector. Two subsequent dense layers with 64 and 32 nodes are then employed as shown in Fig.6, followed by a final regression output layer utilized to conclude the model prediction. Moreover, RelU was set as an activation function for all the employed layers in this study while Root means square error (RMSE) is selected as a loss function. The number of epochs was set to 200 and the Adam optimization algorithm was utilized to boost the model performance. Nonetheless, the learning rate, considered one of the most crucial hyper-parameters while training the model, is selected after a series of experiments [40]. A lower learning rate can lead to slower model convergence and can require longer training time, whereas, a larger learning rate can prevent the loss function from converging. In this study, we trained our model with 0.05, 0.01, and 0.001 learning rates. After cross-validation, we found a 0.001 learning rate as the optimal choice for this model.

VII. Evaluation

The purpose of the system under consideration is to precisely predict the haptic perception of opening a car door through the analysis of its force profile. Ensuring that the prediction errors remain beneath the human perception threshold is of utmost importance. In order to gauge the model's ability to predict door-opening attributes for unseen force profiles, a numerical evaluation is conducted using Leave-One-Out Cross-Validation (LOOCV). This evaluation gauges the system's ability to predict haptic attribute values for force profiles it has not encountered before, measuring its predicting proficiency.

A. Leave-One-Out Cross Validation

Cross-validation is a powerful technique for assessing a model's predictive performance on unseen data. It evaluates the model's ability to generalize its learning from the training data to new, unseen data. One form of cross-validation is k-fold cross-validation, where the data is divided into k subsets and a fixed number of subsets are used for training while the rest are used for testing. This process is repeated until all subsets have been used for testing. Leave-One-Out Cross-Validation



(a) Hyundai Genesis G90 (b) Hyundai Grandeur (c) Kia K3

(d) Kia k5 (e) Hyundai Santafe (f) Kia Sorento

Fig. 7: Leave-one-out Cross-Validation results for each of the six cars used in this study. The predicted and human-rated values are presented for ten adjective pairs.

TABLE III: Mean absolute error (MAE) For all Cars and Adjective Pairs using the LOOCV method.

	Jerky Easy-to-operate	Smooth Rough	Frictional Frictionless	Hard-to-pull Easy-to-open	Balanced Unstable	Soft Hard	Cheap Classy	Damped Recoiling	Discordant Consistent	Heavy Light	**Error %**
Grandeur	10.25	16.25	6.55	5.56	6.92	1.51	25.86	6.51	14.30	1.63	**10.43**
Genesis	9.30	2.63	0.12	1.01	6.62	3.32	25.63	2.11	13.01	7.91	**7.17**
K3	26.15	25.58	20.28	19.09	11.17	20.60	28.43	14.41	27.52	20.90	**21.41**
K5	5.88	3.98	1.70	2.24	2.30	5.63	25.72	2.78	17.24	3.89	**7.14**
Santafe	1.05	6.52	13.19	8.53	7.45	8.56	2.36	2.56	3.31	12.97	**6.65**
Sorento	9.46	13.98	14.32	16.12	5.57	12.30	14.20	1.57	1.26	9.23	**9.80**
Error %	**10.35**	**11.49**	**9.36**	**8.76**	**6.60**	**10.15**	**20.36**	**4.99**	**12.78**	**9.42**	**10.43**

(LOOCV), a specific type of k-fold cross-validation with k = 1, trains the model on all instances except for one, which is used as the test data. This method offers a comprehensive and fair evaluation of the model, as every item in the dataset is used for testing at least once. LOOCV can be considered as a computation-heavy evaluation method, however, it was selected for this study's in-depth evaluation of the proposed model, as the dataset used is not considered large in the machine learning field.

The dataset described in the Sec: IV-A, consisting of force profiles and user adjective ratings for six cars, was employed for LOOCV. According to LOOCV, the model should be trained using five of the cars in the dataset, with the remaining one serving as the test set. However, after running initial tests, it was noted that the force profile of Kia K3 was significantly different from all other profiles, and the prediction accuracy was reduced if K3 was used for training. Therefore, K5 was not used in training the model, instead, the model was trained using the data of four cars at a time, and the fifth one was used as the test set (with K3 being left out every time). K3 was also used as a test set, where the model was trained using only four other cars to keep the training data size consistent (Santafe was randomly chosen to be excluded). This process was repeated until all cars had been used as test sets. The prediction results from LOOCV for the proposed model are illustrated in Fig. 7.

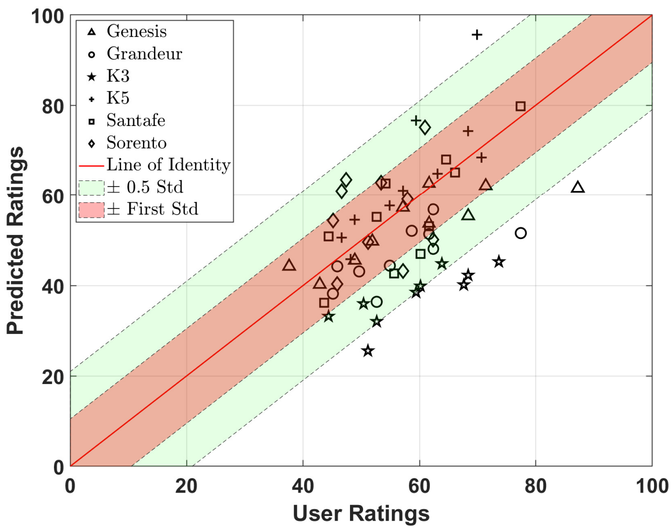


Fig. 8: Analysis of the predicted ratings based on standard deviation in user ratings from the perspective of different cars in the dataset. The red line indicates a perfect prediction of the user rating by the algorithm. The red and green bands represent a half and the first standard deviation of the user ratings.

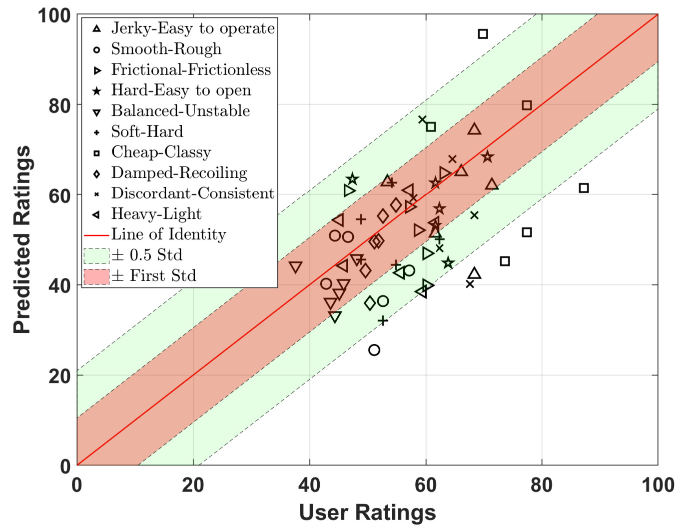


Fig. 9: Analysis of the predicted ratings based on standard deviation in user ratings from the perspective of the adjective pairs. The red line indicates a perfect prediction of the user rating by the algorithm. The red and green bands represent a half and the first standard deviation of the user ratings.

The Mean Absolute Error (MAE) was calculated for all the adjective pairs and all the cars to better understand the prediction results, as shown in Table III. The MAE offers a more direct and intuitive summary of the prediction results. Table III shows the individual prediction accuracy for each car against each of the adjective pairs. The error % column on the right shows the averaged prediction error for each car, while the error % column at the bottom shows the averaged prediction error for each adjective pair. It can be seen that the average prediction accuracy for most of the cars and adjective pairs is around 10 % or below. The only outliers (high prediction error) are the averaged results for K3 (21.41 %), and the adjective-pair of Cheap-Classy (20.36 %).

B. Error Analysis

Figures 8 and 9 show an analysis of the predicted results in terms of the standard deviation of user ratings. The x-axis represents the user ratings, and the y-axis represents the corresponding prediction by the algorithm. In an ideal scenario all the data would be located on the diagonal line of identity (red line), shown in Figs. 8 and 9, where the predicted values and the user ratings would be the same. However, in the current case values are scattered around this trend line due to prediction errors. A point above the line of identity would signify that the algorithm under-predicted the user rating, while a point below the line of identity means that the predicted value was above the user rating.

Analysis of the user ratings from Sect. IV-D shows that the user ratings contained variations across participants. These variations are expected as haptic perception can vary from one person to another. In order to account for these variations, the average standard deviation across the six cars and the adjective pairs was calculated for all participants. The standard deviation for the cars was 22.0 for Genesis G90, 22.89 for Grandeur, 20.95 for K3, 19.30 for K5, 20.54 for Santafe, and 20.11 for Sorento. Similarly, the average standard deviation for the adjective pairs was 22.17 for Jerky-Easy to operate, 21.54 for Smooth-Rough, 22.20 for Frictional-Frictionless, 23.48 for Hard-Easy to open, 18.31 for Balanced-Unstable, 22.46 for Soft-Hard, 13.34 for Cheap-Classy, 21.73 for Damped-Recoiling, 20.88 for Discordant-Consistent, and 23.57 for Heavy-Light. The standard deviation averaged for all cars or all adjective pairs was 20.96. The red and green bands in Figs. 8 and 9 highlight the half and first standard deviation from the ideal prediction line. It can be seen that a majority of the data points fall within the first standard deviation across both figures. The consistent outliers in both cases are the data points for K3 among cars, and Cheap-Classy among adjective pairs, as expected.

VIII. Discussion

In our current study as an initial proof of concept, we utilized a limited dataset for the training and evaluation of our machine-learning algorithm. The model relies on force profiles and user evaluations, and these inputs dictate the quality and reliability of the model. The number of adjectives used in this study was extensive, however, the number of cars could be a limiting factor. The use of six different cars provided a reasonable diversity, but increasing the dataset to include more cars could further improve the model's generalizability. One of the future directions is to develop a door simulator that could render manually generated force profiles as a function of different door dynamics. A significant amount of data could be generated using the simulator, without the need for acquiring different cars. As more data becomes available the efficiency and performance of the system are likely to improve, therefore, justifying the choice of a complex machine learning algorithm in the current study.

The results in Fig. 7 and Table III show that most of the predictions had an error of around 10 % or lower. It is difficult to adjudicate the impact of a 10 % error in haptic attributes, as the JND (Just Noticeable Difference) for haptic attributes is not available in the literature. However, an earlier study showed that the boundaries of perceptual similarities are rather diffused [47]. The average standard deviation for all participant responses was calculated in order to approximate how much of an error is acceptable in perceptual ratings for adjectives. It can be hypothesized that a prediction error of less than or equal to the standard deviation will be considered perceptually similar. The mean standard deviation for user ratings across all cars (or adjective pairs) was 20.96. Based on the mean standard deviation, it can be safely assumed that an error of around 10 % should be perceptually insignificant.

One observation from our results is the presence of a few instances where the model's predictions were significantly different from the ground truth. A possible explanation for these discrepancies could be that the underlying relationships between the input features and the output adjective pairs are non-linear or more complex than what our model could capture. It could also be the result of the user's bias towards a specific adjective pair or a car. Such as a lack of understanding of adjective pairs, or difficulty in differentiating cars based on an adjective pair. Similarly, prejudice or admiration for a car model could also skew the results.

A limitation of the present study is that the perceptual rating experiments were carried out using real cars. Although using real cars provided an authentic experience, it was difficult to mask the visual stimuli (the car itself) from participants. The participants were instructed to ignore the visual appearance of the cars, but it is possible that the presence of visual stimuli may have introduced unwanted bias and noise into the perceptual ratings. One potential way of addressing this issue is to use a controlled environment, such as a door simulator. The users could be blindfolded and the simulator would allow the interactions to be consistent and standardized. Such a method would produce data that is more representative of the true relationships between force profiles and perception.

The current study used raw force profiles as input for the 1D CNN-LSTM network. It could prove beneficial to use methods that capture the unique characteristics of force profiles in relation to perception or employ hand-crafted features that specialize in describing the haptic attributes of opening a car door.

IX. Conclusion

The current study presents a deep learning model for predicting the perceptual properties of opening a car door by analyzing force profiles. The perceptual attributes were provided by human participants, whereas the force profiles were recorded by sensors attached to a car door. The performance of the model was evaluated using LOOCV, and the results indicated a significant degree of accuracy in predicting perceptual haptic attributes in most cases. These findings highlight the potential applications of the model in the automotive industry for the design evaluation of car doors from a perceptual point of view. Future work in this domain could focus on expanding the dataset, including more adjectives, studying external factors that influence a user's perceptual ratings, refining the deep learning model or replacing it with a more suitable one, and considering more robust features from the force profile.

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This should be a simple paragraph before the References to thank those individuals and institutions who have supported your work on this article.

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