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Towards IoT-based Smart Mobility Framework for Proactive Road Stress Detection in Individuals with ASD

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Abstract. Autism Spectrum Disorder (ASD) is a neurodevelopmental disability that significantly increases the difficulties and risks associated with driving. Individuals with ASD often face a variety of challenges, such as increased sensory sensitivities, difficulty adapting to changing environments, and struggles with unexpected situations on the road. These difficulties can lead to sensory overload, panic attacks, and impaired decision-making, all of which increase the risk of accidents and make driving an especially overwhelming task. In this paper, we propose a novel IoT-based smart mobility framework for predictive stress detection in drivers with ASD, enabling the early identification of potential stressors before they encounter them on the road. This approach leverages AI-based models, including LSTM and CNN-based architectures. Unlike existing methods that focus on reactive stress detection, which may be too late, our approach predicts stress triggers in advance, enabling timely and preventive support.

Keywords: Proactive stress detection · smart mobility · ASD · IoT · deep learning

1 Introduction

"*Since obtaining my driver's license, I have not touched a steering wheel again. I am too afraid of either killing myself or someone else*". This testimony comes from an individual with Autism Spectrum Disorder (ASD), a disability with an estimated global prevalence of 1 in 100⁴. For adults with ASD, driving remains a top priority [14]. Many actively avoid public transportation due to sensory sensitivities and social challenges, making the use of personal vehicle not just a preference but a necessity for daily mobility.

⁴ <https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorders>

However, modern cars and road environments are primarily designed for individuals with typical neurodevelopment, often overlooking the unique needs of people with ASD. They frequently experience sensory hypersensitivity, an intense focus on details, and executive function difficulties, including challenges with attention, planning, decision-making, and cognitive flexibility.

Driving is an intricate task that requires a seamless integration of cognitive and motor skills, the ability to perceive and process the surrounding environment, filter and prioritize relevant information, regulate emotional and motor responses, and manage potentially overwhelming sensory stimuli, such as loud noises or flashing lights. For individuals with ASD, these demands pose significant challenges, amplifying cognitive and emotional strain and heightening the risk of stress, which can lead to dangerous situations on the road.

Stress is an adaptive response to perceived threats, activating the body’s fight, flight, or freeze reactions [16]. In individuals with ASD, these stress responses are often heightened, resulting in impaired decision-making, reduced situational awareness, and compromised motor control, all of which are critical for safe driving [12]. Accurate and timely stress detection is essential to mitigating these risks. By providing early alerts, such systems can help alleviate driver stress, reduce sensory overload, and enhance decision-making, ultimately improving both driver well-being and overall road safety.

Stress detection has attracted significant research attention in recent years [1, 9, 17, 21]. Mainly, existing approaches identify stress only after it has already manifested, typically through reactive real-time monitoring and analysis of physiological parameters such as heart rate. While these methods offer valuable insights, reactive stress detection alone is insufficient to prevent the cascading effects of stress on ASD driving performance. These limitations highlight the need for context-aware, proactive stress prediction systems that can anticipate rising stress and enable timely interventions to enhance both driving safety and comfort.

The Internet of Things (IoT) presents a promising avenue for addressing these challenges in the smart mobility domain. By enabling seamless data collection and real-time processing through interconnected sensors and intelligent services, IoT coupled with Artificial Intelligence (AI) can transform the way we approach stress detection and intervention in driving contexts. In this paper, we propose a novel solution that goes beyond traditional reactive stress detection by introducing a proactive IoT-based framework capable of predicting stress before it fully manifests. Our approach leverages advanced predictive models and real-time contextual analysis to assess surrounding environmental events that may impact the driver, even before he reaches the event location. By forecasting how these events could affect the driver’s stress in advance, our system can proactively send timely alerts, allowing the driver to take preventive actions before stress is triggered. The proposed framework is built upon a Deep Neural Network (DNN)-based model that harnesses the power of Long Short-Term Memory (LSTM) [10], and Convolutional Neural Networks (CNN) [13]. LSTM networks, a specialized type of Recurrent Neural Network (RNN), are highly effective in

capturing long-term dependencies, making them well-suited for handling sequential data. In this work, LSTM is used to predict heart rate variations in response to upcoming road events. Once the heart rate variations are predicted, they are processed by the CNN, which classifies them as either stressful or non-stressful based on identified patterns. This combined approach enables accurate prediction and real-time classification, significantly improving the model’s ability to proactively detect and mitigate stress in dynamic driving environments.

The main contributions of this paper can be summarized as follows: 1) We propose a novel IoT-based smart mobility framework dedicated to individuals with ASD, 2) We introduce a deep-learning-based approach for proactive stress detection, tailored to the context of road events, 3) We implemented and evaluated the proposed solution, demonstrating its practical effectiveness in real-world driving scenarios.

The remainder of the paper is structured as follows. Section 2 introduces a real-life scenario. Section 3 provides a review of related works. Section 4 presents a comprehensive overview of the proposed framework. Section 5 details the proposed approach for proactive stress detection. Section 6 discusses the experimental results, and Section 7 concludes the paper.

2 Motivating example: ASD driving challenge

Let us consider a real-life case shared by a collaborating psychologist. It concerns a woman with ASD, referred to here as Anna. Anna had a scheduled appointment with her psychologist and, as part of her usual routine, meticulously planned her journey in advance to minimize any potential disruptions. To ensure a timely arrival, she left early and carefully followed a familiar, well-rehearsed route, anticipating a smooth and predictable experience. However, as Anna approached a roundabout, she unexpectedly encountered significant traffic congestion. The abrupt change in traffic conditions disrupted her sense of control and routine. The combination of auditory stimuli, such as honking from impatient drivers and sudden lane changes, contributed to a rapid escalation in Anna’s stress levels. Unable to manage this situation, she abruptly stopped her vehicle in the middle of the roundabout, experiencing a state of emotional overload. As panic took over, she exited the vehicle and walked away, leaving the car stationary and obstructing the traffic flow. This situation poses a significant safety risk, not only for Anna but for other road users as it increases the likelihood of traffic accidents and contributes to broader roadway disruptions.

This scenario highlights the critical need for a proactive stress prediction system within intelligent transportation frameworks. If Anna’s vehicle had been equipped with an IoT-enabled, context-aware stress anticipation mechanism, it could have detected the risk of increased stress before she encountered the congested roundabout. By analyzing real-time road conditions and estimating their potential impact on the driver’s stress levels, such a system could have provided timely alerts. This would have enabled Anna to navigate the situation with increased confidence, reduced stress, and improved safety.

3 Related works

Several initiatives have been defined to contribute to ongoing development of inclusive mobility solutions that address the diverse needs of ASD users, promoting safer and more accessible environments. A substantial body of research has focused on designing solutions tailored to the unique cognitive, sensory, and behavioral characteristics of individuals with ASD across various domains. For example, Cecchini et al. [5] proposed a comprehensive framework of micro-scale interventions, including sensory-friendly pedestrian pathways, and traffic-calming designs, aimed at enhancing the navigability and inclusivity of mobility spaces for individuals with Autism. Padmanaban et al. [15], through a design-thinking approach with caregiver input, developed a personalized system that includes customizable interiors, emotional regulation tools, and an intuitive companion mobile app. This solution has demonstrated a significant enhancement in trust and autonomy for neurodiverse passengers, offering a tailored experience that supports their unique needs and promotes greater independence during mobility.

Other works have studied the stress experienced by individuals with ASD during driving. Cox et al. [6] demonstrated that newly licensed drivers with ASD exhibit greater physiological stress responses and poorer performance in driving simulations compared to their neurotypical peers. Fok et al. [8] conducted a study showing that emerging drivers with ASD report elevated emotional stress and greater difficulty managing challenging driving situations, which these difficulties strongly correlating with their perceived struggles in completing driving tasks. Other smart mobility systems dedicated to individuals with ASD have also been proposed. In this context, wearable technologies have been increasingly employed to monitor and support individuals with ASD. Bessassi et al. [3] reviewed assistive devices such as smart glasses and proximity sensors, highlighting their potential to enhance real-time social interaction and sensory regulation while pointing out limitations related to usability, feedback design, and ethical implementation. D. Bian et al. [4] introduced a novel adaptive Virtual Reality (VR) driving simulator for individuals with ASD, which infers user engagement from physiological signals and dynamically adjusts task difficulty in real-time to foster emotionally safe and personalized learning experiences. All these efforts aim to create an ecosystem of mobility solutions that empower individuals with ASD, enhancing their autonomy and inclusivity. However, they fall short in proposing proactive solutions for detecting and anticipating stress states.

Stress detection through physiological signals has been extensively studied. In particular, deep learning techniques have significantly advanced the performance of stress detection models [1, 9, 18, 19, 22]. Rastgoo et al. [17] developed a method to process electrocardiogram (ECG) signals for real-time driver stress classification. Similarly, Amin et al. [1] used ECG signals alongside deep transfer learning with fuzzy logic to classify driver stress. Ke Wang et al. [21] presented an ensemble classification model using autoencoders and the AdaBoost framework to classify driving stress levels based on various physiological signals.

While these works have made significant contributions to detecting stress reactively by analyzing observed physiological data, they primarily rely on real-time signals such as ECG to classify stress levels after the stress response has already been triggered. This reactive approach, though effective in many scenarios, presents limitations, particularly within the context of mobility, where it is crucial to anticipate and prevent stress induced by road events and environmental factors before they arise.

4 Global Overview of the IoT-based smart mobility system

Fig. 1 illustrates the IoT-based smart mobility framework designed to enable proactive stress detection for drivers with ASD. The system leverages Multi-Access Edge Computing (MEC) servers, which facilitate the acquisition of real-time road event data from geographical areas that the driver is likely to traverse, supporting timely and context-aware decision-making. In this framework, two

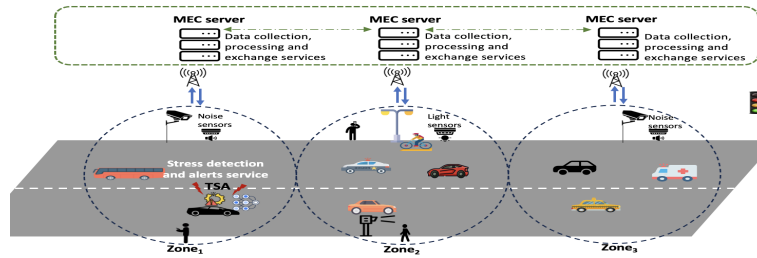


Fig. 1. IoT-based framework for proactive stress detection service

main categories of data are utilized:

- *Road event data*: Through IoT-enabled services, external environmental and traffic-related conditions, such as noise levels, lighting conditions, weather changes (e.g., fog, rain), and traffic density, are continuously monitored and transmitted to the ASD vehicle analysis system. Moreover, contextual data are also monitored. They refer to information related to the driver's situation and journey progression, such as acceleration patterns, distance traveled, and time elapsed since the start of the trip.

- *Physiological responses*: Stress levels are commonly assessed through various physiological signals, with electrocardiogram (ECG) data being the most widely used due to its reliability in capturing autonomic nervous system responses [23]. In this paper, we leverage two key ECG-derived metrics to assess physiological stress responses: heart rate (HR) and heart rate variability (HRV). HR provides a basic measure of cardiac activity and is expressed in beats per minute (bpm): $HR = \frac{60}{\overline{RR}}$, where \overline{RR} is the mean of the RR intervals in seconds (i.e., the time between successive R-wave peaks in the ECG signal).

To gain a deeper understanding of autonomic nervous system regulation, we also consider two well-established HRV metrics, each offering complementary insights into stress dynamics [11]:

- *Root Mean Square of Successive Differences (RMSSD)*: It quantifies short-term fluctuations in heart rate, primarily driven by parasympathetic activity, making it a highly sensitive marker for detecting acute stress responses.

$$\text{RMSSD} = \sqrt{\frac{1}{N-1} \sum_{i=2}^N (RR_i - RR_{i-1})^2}$$

- *Standard Deviation of NN Intervals (SDNN)*: measures overall HRV and is considered a robust indicator of long-term stress adaptation : $\text{SDNN} = \sqrt{\frac{1}{N} \sum_{i=1}^N (RR_i - \overline{RR})^2}$, where RR_i represents the i^{th} RR interval and N is the total number of RR intervals.

Under stress conditions, HR tends to increase, while RMSSD and SDNN typically decrease [20].

Each ASD vehicle is equipped with an onboard AI-driven predictive stress detection model designed to assess the potential impact of context-aware road events on drivers with ASD. The primary objective is to proactively anticipate stress responses triggered by these events, thereby enabling timely interventions and promoting safer, more adaptive driving experiences.

5 Predictive stress detection driven by event roads

Fig. 2 presents the architecture of the proposed model for proactively assessing stress responses in ASD drivers in the presence of upcoming road events. The framework includes two core components: (1) an LSTM-based prediction module to predict physiological biomarkers (HR, RMSSD, SDNN) in response to road and contextual conditions, and (2) a CNN-based classification module to infer the driver’s stress state from these predicted biomarkers. Each component is described in the subsequent sections.

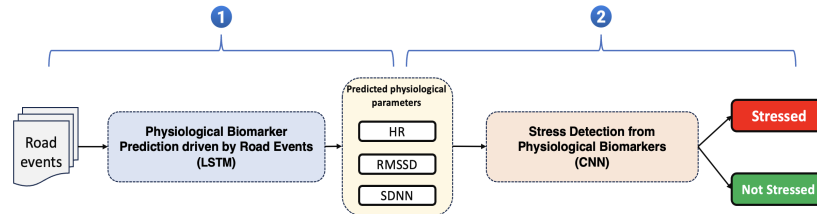


Fig. 2. Global architecture of the proposed stress prediction model

5.1 LSTM-based physiological biomarkers prediction driven by road events

The proposed LSTM-based model is illustrated in Fig. 3. It captures temporal dependencies and contextual patterns within the input stream of road events and contextual data. A notable advantage of using LSTM in this setting lies in its capacity to model both immediate and delayed physiological responses. For instance, acute stimuli such as sudden loud noises may trigger instantaneous stress reactions, whereas prolonged exposure to traffic congestion may lead to gradual physiological changes. The model comprises two main components : the *LSTM network* and *a dense layer*, presented below.

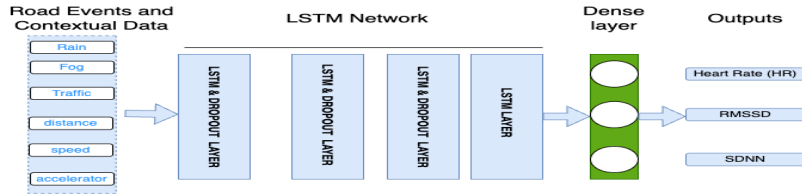


Fig. 3. Architecture of the LSTM-based model

LSTM network-based context and road events encoding: The model takes as input a sequential stream of road events, each characterized by contextual and environmental factors such as traffic dynamics (e.g., congestion levels), environmental conditions (e.g., noise levels, lighting variations, weather changes), and emergency events (e.g., roadblocks, sirens, and accidents). These features are encoded as normalized numerical vectors and processed sequentially to reflect their temporal relationships.

Example: Let us consider an ASD driver on a 15-minute urban journey. At a specific moment in time, denoted as t , the vehicle collects and transmits a set of contextual features: Fog (500 m visibility) normalized to 0.92 (assuming a range of 20 m to 6000 m), Rain intensity: 0 (no rain), Noise level (70 dB) normalized to 0.70, Lighting level (40 lux) normalized to 0.45, Traffic: “heavy” as 1.0, Acceleration: -0.4 m/s^2 normalized to 0.35, Driving distance: 2.5 km normalized to 0.42 (assuming a maximum of 6 km trip), and Time elapsed: 6 minutes normalized to 0.40 (assuming a maximum of 15 minutes). Considering these subset of features, the feature vector x_i at time t_i is then represented as $x_i = [0.92, 0, 0.70, 0.45, 1.0, 0.35, 0.42, 0.40]$.

The normalized input vectors $x_{t_i} \in R^d$, where d is the number of input features, are fed into an LSTM-based model, capturing temporal dependencies to forecast physiological responses. The LSTM architecture consists of stacked layers that progressively capture temporal patterns. A Dropout layer is used to reduce overfitting by randomly deactivating a subset of neurons during training.

The output of the final LSTM layer consists of hidden states $\{h_1, \dots, h_n\}$, where each $h_n \in R^d$ encodes the learned temporal and contextual representation of the input at time step t_i .

Final mapping of physiological biomarkers output through a dense layer: The model incorporates a fully connected *Dense* layer that maps the last hidden state output vector $h \in \mathbf{R}^{d_h}$, where d_h is the dimensionality of the final LSTM hidden state, to the final output space corresponding to the predicted physiological biomarkers: HR, RMSSD, and SDNN.

This transformation is defined as: $\hat{y} = W \cdot h + b$, where W is the weight matrix connecting the last hidden state vector h to the output layer, b is the bias vector. The output vector \hat{y} represents the predicted values of the three physiological biomarkers HR, RMSSD, and SDNN.

5.2 Stress classification based on predicted physiological biomarkers

The predicted physiological biomarkers HR, RMSSD, and SDNN are used to infer stress states through a structured pipeline that includes directional alignment to standardize biomarker interpretations, statistical feature extraction to capture relevant physiological patterns, personalized labeling based on individual stress score distributions, and deep learning-based classification to distinguish between stressed and non-stressed conditions. The different steps are presented below.

Directional alignment: Given that HR is positively correlated with stress, whereas RMSSD and SDNN are negatively correlated, we applied a transformation to invert the negatively correlated biomarkers: $1 - \hat{X}_i(t)$, where $\hat{X}_i(t)$ denotes the normalized value of the biomarker X_i at time t . This transformation ensures that all biomarkers contribute consistently to the overall stress estimation, with higher values uniformly indicating higher levels of stress.

Example: Consider a sample where the normalized physiological parameters at time t are : $\hat{\text{HR}}(t) = 0.80$, $\hat{\text{RMSSD}}(t) = 0.75$, $\hat{\text{SDNN}}(t) = 0.60$. Since HR is positively correlated with stress, its normalized value is used directly. However, RMSSD and SDNN are negatively correlated with stress-higher values typically indicate lower stress. To ensure directional consistency across features, we apply the following transformation: $\tilde{\text{RMSSD}}(t) = 1 - \hat{\text{RMSSD}}(t) = 1 - 0.75 = 0.25$ and $\tilde{\text{SDNN}}(t) = 1 - \hat{\text{SDNN}}(t) = 1 - 0.60 = 0.40$.

The directionally aligned values are : $\hat{\text{HR}}(t) = 0.80$, $\tilde{\text{RMSSD}}(t) = 0.25$, $\tilde{\text{SDNN}}(t) = 0.40$. These values can now be interpreted consistently: higher values uniformly indicate a higher level of physiological stress activation.

Stress indicators and stress scores: To quantify stress, we computed four descriptive statistics: *mean*, *first quartile*, *median*, and *third quartile*, for each of

the three biomarkers HR, RMSSD, and SDNN within each sample of the output dataset. These statistics, derived from the distribution of each biomarker within the sample, are referred to as *stress indicators*.

So, for each sample, a set of 12 stress indicators $I_i = \{I_i^{(1)}, I_i^{(2)}, \dots, I_i^{(N)}\}$ was generated. Here, $N = 12$ represents the total number of stress indicators, with each $I_i^{(n)}$ denoting the n -th stress indicator corresponding to the i -th sample. These indicators capture essential characteristics of the physiological responses across the three biomarkers, providing a multi-dimensional representation of the individual's stress profile.

Subsequently, an overall *stress score* S_i for each sample was computed by averaging these 12 stress indicators. This aggregation yields a single scalar value that summarizes the stress level for the sample, representing the combined impact of the various biomarkers' behaviors within the observed time window. The stress score S_i is calculated using the following formula: $S_i = \frac{1}{N} \sum_{n=1}^{N=12} I_i^{(n)}$. A higher value of S_i reflects a higher stress level, as all output biomarkers were aligned to be positively correlated with driver stress.

Stress Labeling: To account for individual variability in physiological stress responses, a personalized, distribution-based approach was used to label stress levels for each driver. Specifically, labels were assigned by analyzing the statistical distribution of stress scores S_i within each driver's dataset. This method avoids reliance on fixed thresholds and instead uses intra-subject variability as a reference as follows [22]:

1. Samples with stress scores greater than the third quartile (Q_3) but below the upper outlier boundary ($Q_3 + 1.5 \times IQR$) were labeled as *stressed*.
2. Samples with stress scores lower than or equal to the third quartile but above the lower outlier boundary ($Q_1 - 1.5 \times IQR$) were labeled as *not stressed*.

Where Q_1 and Q_3 represent the first and third quartiles of the stress score distribution for a given driver, and $IQR = Q_3 - Q_1$ is the interquartile range.

Example: Let us assume that, based on the descriptive statistics computed for each normalized biomarker within the sample window, we obtain the following values:

Statistic	HR	RMSSD	SDNN
Mean	0.82	0.30	0.40
First Quartile (Q_1)	0.78	0.25	0.36
Median	0.81	0.29	0.39
Third Quartile (Q_3)	0.85	0.34	0.43

From these statistics, the 12 stress indicators $I_i^{(n)}$ for this sample are: $I_i = \{0.82, 0.78, 0.81, 0.85, 0.30, 0.25, 0.29, 0.34, 0.40, 0.36, 0.39, 0.43\}$. The overall stress score S_i is then computed as the average of these 12 indicators: $S_i = \frac{1}{12} \sum_{n=1}^{12} I_i^{(n)} = \frac{0.82+0.78+\dots+0.43}{12} = 0.487$.

To determine the stress label for this sample, we compare the computed score to the statistical distribution of stress scores for the corresponding driver.

Assume the following quartile values based on the driver’s stress score history: First Quartile (Q_1) = 0.420 and Third Quartile (Q_3) = 0.530. The interquartile range is: $IQR = Q_3 - Q_1 = 0.530 - 0.420 = 0.110$. From this, we compute the outlier boundaries:

$$\text{- Lower Bound} = Q_1 - 1.5 \times IQR = 0.420 - 1.5 \times 0.110 = 0.255$$

$$\text{- Upper Bound} = Q_3 + 1.5 \times IQR = 0.530 + 1.5 \times 0.110 = 0.695$$

Now we compare the current sample’s stress score $S_i = 0.487$ to the distribution. Since $S_i = 0.487 \leq Q_3 = 0.530$ and $S_i \geq Q_1 = 0.420$, the sample is labeled as *not stressed*.

CNN-Based Stress Classification: Fig. 4 illustrates the architecture of the proposed CNN-based model, designed to classify an individual’s stress state based on predicted physiological biomarkers HR, RMSSD, and SDNN. The model employs a series of one-dimensional convolutional layers to extract hierarchical temporal features from the input sequences, followed by pooling and flattening operations to reduce dimensionality and prepare the data for classification. Fully connected layers then integrate the learned features to produce a binary stress classification.

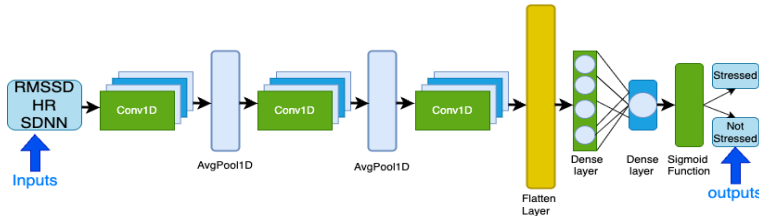


Fig. 4. Architecture of the classification CNN-based model

Once stress is proactively detected, the system can be extended to propose adaptive responses, such as suggesting an alternative route. If rerouting is not possible, it instead describes the road-related threat to help the driver anticipate and prepare for it, offer step-by-step coping strategies to assist in navigating the situation, or initiate a return home or a stop at a nearby rest area. In cases of extreme stress, the system may also trigger an alert to designated caregivers or family members.

6 Experiments and evaluation

The proposed approach has been implemented and thoroughly evaluated. In the following sections, we present dataset acquisition, experimental setup, and the results obtained across different evaluation metrics.

6.1 Dataset acquisition and implementation setup

Driving simulator: Data were collected using the *SimulAuto*⁵ driving simulator at the University of Toulouse 2, depicted in Fig.5, featuring a Renault Zoe car and a 360° visual setup. Several scenarios and simulations were built and executed using SCANer™ studio 9.8⁶, capturing data at 500 Hz.



Fig. 5. The car simulator *SimulAuto*

Participants: Ten participants (7 women, 3 men; aged 22–28), all licensed drivers with no heart issues, took part. All participants passed the RAADS-14 [7], a screening test designed to identify adults presenting behavioral traits associated with autism. Participants 1, 2, 3, and 10 scored above the cutoff of 14, indicating strong autistic traits; participant 10 was diagnosed with ASD. We note that the study was approved by the University of Toulouse Ethics Committee (CER-2023_709), with consent obtained in line with the Declaration of Helsinki [2].

Implementation setup: The approach was implemented in Python 3.11 using PyTorch and tested on a MacBook Pro (M3 Max, 36GB RAM). Data were split into 75% for training and 25% for testing. The Adam optimizer was used for training.

Evaluation metrics: For the LSTM model, we used Mean Absolute Error ($MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$) and Mean Squared Error ($MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$). For CNN-based classification, metrics included accuracy, recall, and AUC. Recall (TPR) and AUC (based on ROC curve) were computed based on true positive (TP), false positive (FP), true negative (TN), and false negative (FN) rates as follows: $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$, $TPR = \frac{TP}{TP+FN}$, $FPR = \frac{FP}{FP+TN}$, $AUC = \int_0^1 TPR d(FPR)$. These metrics help evaluate model performance, especially under class imbalance.

6.2 Experimental evaluations

LSTM model: Fig.6 and Fig. 7 show the substantial reduction in MAE and MSE, respectively, along with rapid convergence during training for each one of the ten users.

⁵ <https://miroir.univ-tlse2.fr/2019/05/27/com-simulauto-le-simulateur-de-conduite-de-la-plateforme-ccu/>

⁶ <https://www.avsimulation.com/en/simulators/full-cab/simreal/>

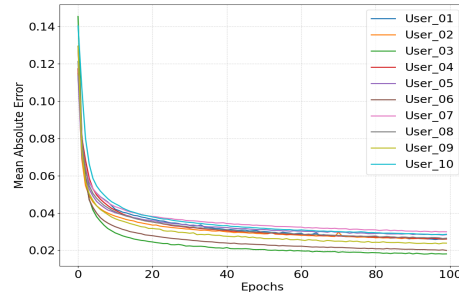


Fig. 6. Training MAE loss of the LSTM model

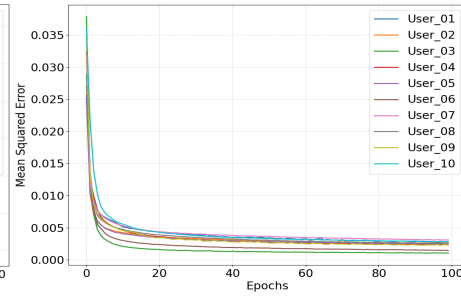


Fig. 7. Training MSE loss of the LSTM Model

Table 1 presents the performance of the LSTM model for each of the ten users, showing both training and validation losses. Overall, the model achieves low error values across all users, with average MAE and MSE of 0.0249 and 0.0023 for training, and 0.021 and 0.00247 for validation, indicating good generalization and consistent predictive accuracy

Table 1. The MSE and MAE losses

Users	MAE	MSE	MAE_val	MSE_val
user_01	0.026	0.0028	0.026	0.0031
user_02	0.025	0.0026	0.022	0.020
user_03	0.018	0.001	0.014	0.007
user_04	0.026	0.0023	0.020	0.0015
user_05	0.028	0.0025	0.023	0.0017
user_06	0.019	0.0014	0.016	0.001
user_07	0.03	0.003	0.025	0.0023
user_08	0.026	0.0025	0.023	0.0021
user_09	0.024	0.0024	0.02	0.0022
user_10	0.028	0.0028	0.023	0.0022
Average	0.0249	0.0023	0.021	0.00247

A Mann-Whitney U test comparing participants with low versus high ASD features across all performance metrics (MAE, MSE, MAE_{val}, MSE_{val}) revealed a single statistically significant difference: MSE_{val} was significantly higher in the high-ASD-feature group compared to the low-ASD-feature group ($U = 1.50$, $p < 0.032$).

CNN classification model: Fig. 8 shows the progressive decrease in binary cross-entropy loss across epochs, reflecting effective learning and convergence of

the CNN model. Additionally, Fig. 9 presents the AUC scores for each driver, demonstrating the model’s strong discriminative capability in accurately classifying stress versus non-stress conditions.

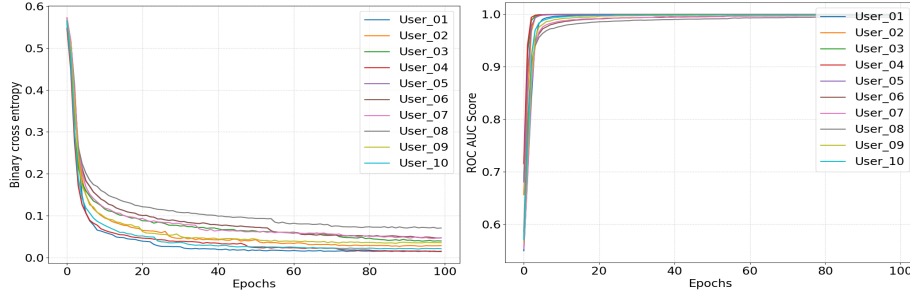


Fig. 8. CNN training binary cross-entropy

Fig. 9. CNN training AUC score

Table 2 summarizes the performance of the CNN classification model for each user during the validation phase. It reports accuracy, recall, and AUC scores, showing consistently high performance across all users. On average, the model achieved 0.987% accuracy, 98.3% recall, and an AUC of 99.8%, highlighting its robustness and reliability in stress classification.

Table 2. The Performance metrics of each user during the validation phase

Users	Accuracy	Recalls	AUC
user_01	0.994	0.994	0.998
user_02	0.990	0.989	0.999
user_03	0.986	0.979	0.998
user_04	0.994	0.990	0.999
user_05	0.982	0.970	0.998
user_06	0.997	0.995	0.999
user_07	0.983	0.975	0.997
user_08	0.975	0.959	0.994
user_09	0.987	0.983	0.998
user_10	0.992	0.987	0.999
Average	0.987	0.983	0.998

The evaluation results demonstrate the effectiveness of the proposed approach in predicting physiological biomarkers HR, RMSSD, and SDNN and detecting stress accurately, while improving stress detection reliability, particularly for ASD drivers.

7 Conclusion

This paper introduces a novel IoT-based smart framework specifically designed to address the unique needs of individuals with ASD in driving contexts. By integrating LSTM and CNN, our approach goes beyond conventional reactive models, enabling the proactive detection of stress responses before they are physiologically observed. The system leverages real-time environmental data to forecast the potential impact of road events. Experimental results demonstrate the model’s robustness and accuracy across a diverse range of users and scenarios.

In our future work, we plan to extend the proposed framework by advanced intelligent models capable of further personalizing stress prediction and intervention strategies. Specifically, we aim to refine the system to dynamically adjust preventive actions based on the ASD driver’s unique profile, the specific road context, and individual driver constraints. To support this, we will define and incorporate a wider spectrum of driving scenarios and environmental conditions. Furthermore, expanding the participant pool will be crucial to improving the generalizability and robustness of our findings. We also intend to incorporate additional features, such as jerk (the rate of change of acceleration), pedal pressure, steering variability, and headway distance, to enhance both the accuracy of stress detection and the system’s sensitivity to contextual nuances.

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