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Prediction of driver stress under different conditions on habitual routes

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Stress is a growing problem in recent years. It causes a deterioration of cognitive skills. The result is a worsening in the driving style and an increase in the likelihood of traffic accidents. In this context, prediction models allow us to avoid or to minimize the negative consequences.

An algorithm based on Deep Learning is proposed in this paper to predict the stress in advance. This type of algorithms detects complex relationships between variables. At the same time, it avoids the overfitting. The prediction of the upcoming stress level is made taking into account the driving behaviour (acceleration, deceleration, speed) and the previous stress level.

The algorithm has been validated under different conditions in three routes in Spain and the United Kingdom. Results show that upcoming stress states can be accurately predicted by 88% when the driver is not fatigued. The model also presents a good behavior when the visibility is poor. However, the prediction is complex when there is heavy traffic or the driver is tired. In these cases, the percentage of success for the stress prediction is 82%. But, the main problem is the number of false positive (23% on average).

Introduction

Sely [1] was the first researcher to refer to the term “stress” in a biological context. According to this author, the stress includes an inappropriate physiological response to any kind of demand [2]. The “Stress” term refers to the condition while stressors are the stimulus causing it. Currently, there are many definitions of stress. However, all authors are in agreement in that the stress can have a negative effect on the intelligence, health and making decisions [3] [4] [5].

The data presented in [U.S. Department of Transportation, 2008] categorizes the major risk factors responsible for traffic accidents as follows (according to their impact): human factors (92%), vehicle factors (2.6%), road/environmental factors (2.6%), and others (2.8%). Among these, drivers’ human factors consist of cognitive errors (40.6%), judgment errors (34.1%), execution errors (10.3%), and others (15%). Stress is one of the causes of human errors. Stress degrades the cognitive capabilities of driver.

In the literature, there are many proposals on measuring and quantifying the driver’s cognitive load and stress levels. There are two major types of proposals to measure the stress:

- Questionnaires
- Physiological signals

Questionnaires allow us to assess a large part of the population. However, the result is based on the subjective perception of the participant. One of the most important research work [7] is "The Perceived Stress Questionnaire (PSQ)". This measurement employs the subjective perception of things and the emotional reaction. This questionnaire can be used regardless of age, gender or profession of the participants. Other questionnaires relevant to measure the stress: The Stress Appraisal Measure (SAM) [8], the Impact of Event Scale (IES) [9] and the Perceived Stress Scale (PSS) [10].

The proposals based on the physiological signals allow us to objectively and continuously determine the stress level of a user. However, they require the use of sensors, increasing the cost and reducing the number of possible participants. In addition, these solutions can cause discomfort if they are intrusive or heavy.

However, these problems are being minimized with the proliferation of the wearable devices in the recent years. Currently, a simple wristband can monitor several physiological signals. One example is the Empatica E4 [11] wristband is an unobtrusive, wearable, lightweight, wireless, multisensory signal acquisition device. It has four inbuilt sensors for continuously reporting Galvanic Skin Response (GSR), Photoplethysmograph (PPG) data, Skin Temperature (ST), and Tri-Axial Acceleration (ACC). It also reports Inter-Beat Interval (IBI) at discrete intervals.

The driver’s workload and the perceived capacity for handling it are major contributors to stress levels while driving. In [12], Itoh et al. measured electrocardiogram (ECG) signals as well as head rotational angles, pupil diameters, and eye blinking with a faceLAB device installed in a driving simulator to calculate the driving workload. In the study captured in [13], the driver’s workload was estimated from lane changing and measurements were taken through simulation test driving. In [14], the authors proposed a multiple linear regression equation to estimate the driving workload. The model employs variables such as: speed, steering angle, turn signal, and acceleration.

In [15] the authors propose a method for detecting stress based on facial expressions. They employed a near-infrared (NIR) camera to capture the near frontal view of the driver's face. Tracking face is made using a supervised descent method (SDM) [16]. In [17], the research analyzed the suitability of the heart rate variability (HRV) to measure the driving workload. The results conclude that the HRV could be used as a good workload indicator, although it is also affected by many other factors that may have an influence on it.

In [18], the authors presented a solution to evaluate some emotional states (high stress, low stress, disappointment, and euphoria) of car-racing drivers. Support vector machines (SVMs) and adaptive neuro-fuzzy inference system (ANFIS) were used for the classification The proposed approach performs an assessment of the emotional states using facial electromyograms, electrocardiogram, respiration, and electro dermal activity. The system was validated by using data obtained from ten subjects in simulated racing conditions. The maximum predictive rate was 79.3% using support vector machine (SVM).

As we have seen above, the proposal to detect current stress levels are getting very promising results. However, the stress prediction is a more complex task. Firstly, it is difficult to label stress perception levels by each driver in a generic way because the effects of events and stressors change depending on the driver profile and their current state. In addition, drivers tend to forget stress situations and details if filling in a questionnaire some time later. On the other hand, the physiological signals that have proven higher correlation levels with stress are very sensitive to noise and are influenced by other factors apart from stress. Finally, the combination of all the data collected by different sensors is not trivial.

Estimation of stress level on drivers

The objective of this work is to analyze how a set of factors (driver state, traffic, and visibility) affect the prediction of the upcoming driver stress levels. In order to make the stress level prediction, we use a model based on Deep Learning. Deep Learning is a set of algorithms that allow to design Multilayer Neural Networks.

The training process is different from classic neural networks algorithms, avoiding the overtraining. These methods detect the complex relationships among variables. Currently, this type of algorithms is used in many commercial applications such as: keyboard from IOS, Android Operating System's speech recognition system or identifying objects in Google Photos. In the following subsections, we are going to describe each of the elements of our prediction model.

Input variables

In this work, the input variables can be classified into two groups: variables related to the stress level and variables associated with the driving behavior.

Measurements of stress level

The Heart Rate signal is many times used as an indicator or proxy for the Autonomic Nervous System (ANS) activity for normal, fatigued and drowsy states because the hearth rate is influenced by the sympathetic - and parasympathetic nervous systems which adapt to the user's perceived stress. This indicator is not intrusive. A decrease in the heart variability correlates with the driver experiencing stress.

Among the different physiological signals which correlate with stress levels previously captured in the existing literature we have used the Heart Rate Variability (HRV) [19] [20] since it has been assessed as one having a higher correlation with stress levels together with Skin Conductivity (SC).

One major limitation of the HRV signal in order to estimate the level of stress and cognitive load is that there are other factors such as the physical exercise that also impact the measured values. In order to avoid this problem, the experiment has been designed to minimize the impact that factors outside the study have on the measurements. In this way, only data from drivers driving in similar situations each day (same hour, same traffic conditions, with moderated previous walking to get into the car and a relaxation period of 30 seconds before driving, with the mobile phone muted, with the radio switched off and without using any navigation system) have been taken.

In addition to the HRV signal, we analyze some driving behavior related data. The combination of these two groups of variables (HRV and driving behavior) allows us to build a model to predict the stress on drivers accurately. The idea is that the different stressors on the road that the user is currently facing will have a short term impact on the way the driver reacts (accelerating or pressing the brake for example) and a longer term impact on upcoming stress levels. Measuring current driving behavior and monitoring current levels of stress should therefore contain information about upcoming levels of stress.

We can compute stress related features from the Heart Rate Variability (HRV) signal in two different domains: Time and Frequency. Time domain analysis of HRV implicates quantifying the mean or standard deviation of RR intervals (time between beat and beat given in milliseconds). Frequency domain analysis means calculating the power of the respiratory-dependent high frequency and low frequency components of HRV. In our case, we are going to use measures on the time domain. There are many HRV features that can be defined on this domain which are correlated with the perceived stress levels such as: mean RR interval (mRR), mean heart rate (mHR), standard deviation of RR interval (SDRR) or standard deviation of heart rate (SDHR).

We have chosen the following variables based on real tests:

- Average HeartRate (b.p.m): This variable has a high value when the driver experiences high levels of stress.
- Average RR (ms): It measures the time between beat-beat (consecutive heartbeats). Its value decreases when there is an event that causes stress on the driver. On the contrary, a high value means that the driver is relaxed.
- Standard deviation of RR intervals (ms): the variation between beat and beat (inter-beats period) decreases when the driving workload is high.
- RMSSD: The square root of the mean of the squares of the successive differences between adjacent RRs.
- RR50: It is the number of pairs of successive RRs that differ by more than 50 ms. A high number allows us to detect stress situations.

Driving behavior

Maximum acceleration (positive and negative): The accelerations and decelerations capture reactions to different stressors that have an impact on stress levels and imply changes in the HRV signal such as a decrease in the time between heartbeat and heartbeat. The percentage depends on the intensity of these accelerations. The sudden accelerations significantly increase the driving workload. Figure 1 captures the RR and the vehicle speed when driver is braking. We can observe how RR value decreases by 12.22%. Figure 2 shows the results when the driver is accelerating. In that case, the RR value is also reduced by a 10.89%. The values have been normalized using the following equation:

$$N = \frac{a - \min(A)}{\max(A) - \min(A)} \quad (1)$$

In which a is the current value of the variable (vehicle speed or RR) that we want to normalize and A is the dataset (where a value is included)

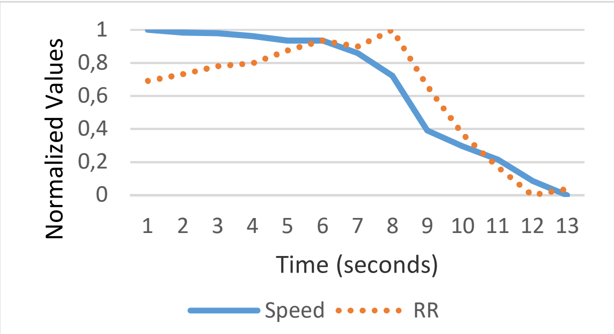

Figure 1 RR values (normalized between 0 and 1) while driver was braking.

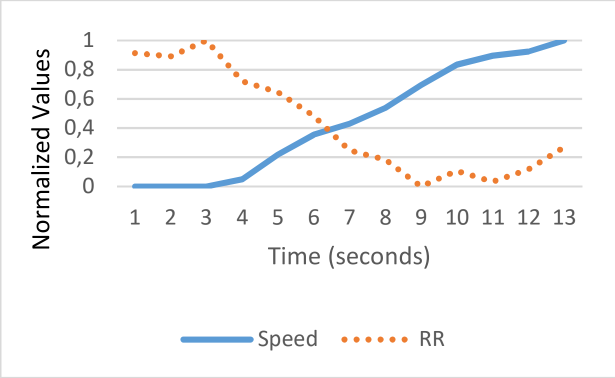

Figure 2 RR values (normalized between 0 and 1) while driver was speeding up.

The current acceleration of the vehicle is calculated based on the measured speed as follows:

$$a_i = \frac{v_i - v_{i-1}}{t_i - t_{i-1}} \quad (2)$$

In which v_i represents the speed at the sample number i, a_i the estimated acceleration at that sample and the derivative of the speed is estimated by dividing the increment in speed by the time elapsed between the consecutive samples i-1 and i. Vehicle speed was obtained using the GPS data from the system's smartphone.

Standard deviation of vehicle speed: The workload decreases when the driver is driving at steady speed. High deviations of speed capture reactions of the driver to different stressor that cause stress to the driver. He or she has to do several tasks at the same time such as: looking at the surrounding road, pressing the accelerator pedal or turning the steering wheel. Figure 3 shows the RR values obtained in two different cases by the same driver using a 60 seconds time window. In the first case, the standard deviation of vehicle speed was 19.33. In the second case, the value was 2.71. We can observe that in the first case the RR values are higher than in the second case. In conclusion, we can see that there is a strong relationship between standard deviation of vehicle speed and the inter-beats time.

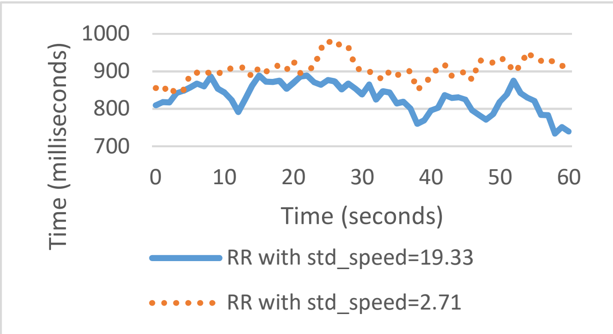

Figure 3 Comparison of RR values according to the standard deviation of vehicle speed.

Positive Kinetic Energy: This variable measures the aggressiveness of driving. Its value depends on the intensity and frequency of the accelerations. If it is high, it means that the driver accelerated sharply and frequently. This driving style has a negative impact on the stress level. He or she has to make faster decisions in order to avoid accidents.

The PKE is estimated over a period of time as follows:

$$PKE = \frac{\sum(v_i - v_{i-1})^2}{d};\ v_i > v_{i-1} \qquad (3)$$

Where the sum is performed for the period considered and d is the cumulated distance traveled during this time

The intensity of turning: We detected during testing that the tension increased in the majority of the drivers when there were curves on the road. The degree of impact depends on the road angle (intensity of turning required). Figure 4 captures the RR values when the driver was driving over a curve. We can see that the inter-beats time decreases.

The intensity of turning is estimated using the following formula:

$$TI_i = \cos^{-1}\frac{\overline{l_i}\cdot\overline{l_{i-1}}}{\|\overline{l_i}\|\|\overline{l_{i-1}}\|};\ v_i > th \qquad (4)$$

Where the numerator represents the dot product between the average direction vectors in the last 5 seconds and the average direction vectors in the next 5 seconds and the denominator captures the norm of such averaged vectors. The direction vectors are calculated from the GPS coordinates. The average over a period of 5 seconds is used to minimize the impact of random errors in the GPS signal. In order to eliminate the errors introduced at low speeds, a threshold in the speed is used. This threshold has been empirically evaluated and a value of 1 m/s has been found to perform well and therefore selected for the experiment. It depends on the device.

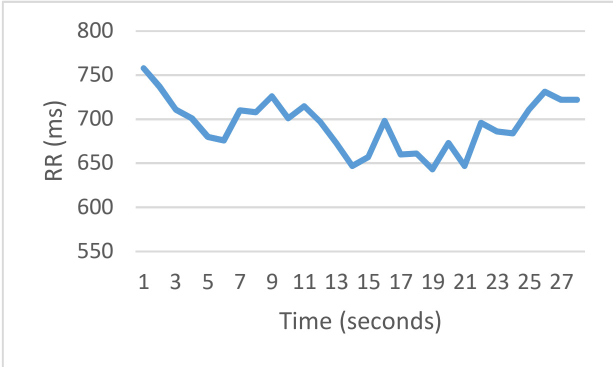

Figure 4 RR values when the driver was driving over a road curve.

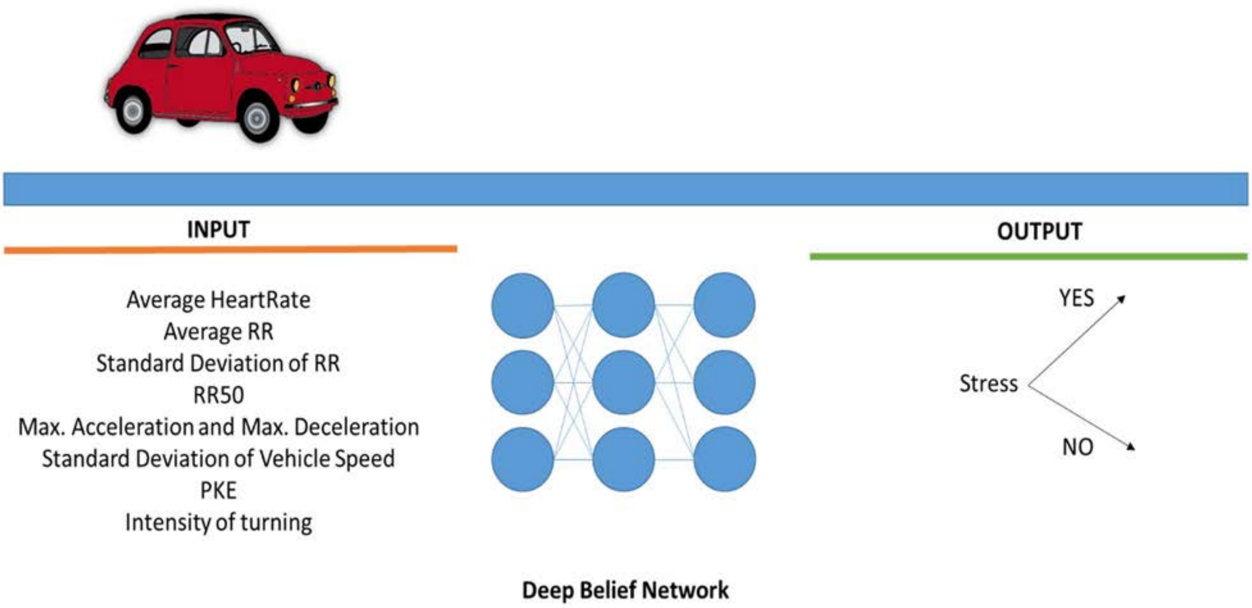

Figure 5 Proposal to estimate the upcoming stress.

Output variable

The output of the algorithm is the stress state in the next minute. In order to label the driving samples, the HRV signal has been translated into 2 different levels of cognitive load: stress or not stress. The HRV signal depends on the cognitive workload and the particular driver features and characteristics. Therefore, we take into account the usual values of the driver to make accurate predictions (intra-user prediction).

In this work, we have defined stress as a state in which the measures related to the heart rate signal suffer a significant change compared to the usual values of the driver for a road type. On the other hand, no-stress state has been defined as the driver state when his or her heart rate signal presents a similar pattern to the obtained when there are not events that can alter the mental state.

Table 1 captures the values of the heart rate signal in two scenarios for the same driver and route. However, the driving test in the first case took place on Monday at rush hour. In addition, the driver was stressed because had to go to the work. Driving test in the scenario 2 was made on Sunday. There was no traffic and the driver did not have any obligation. We can see as there is a change very meaningful in the variable. We have chosen the RMSSD measure to label the driving samples because it is the most recommended [21] in order to analyze the heart rate variability in short term.

We compared the usual RMSSD (taking into account the road type) with the value obtained in the last 60 seconds. If the current RMSSD value is lower and the difference exceeds a threshold, we will label the driving sample as "stress". In our case we set the threshold at 7. This value was obtained empirically and it depends on many variables such as: heart rate band, driver age, diseases, and lifestyle. Figure 5 shows a schema of the proposal.

	Case 1 (Commute on Monday at rush hour)	**Case 2 (Driving on Sunday)**
Average Heart Rate (b.p.m)	98.46	83.16
Average RR (milliseconds)	622.8	737.03
Std. RR (milliseconds)	16.41	33.21
RR50	1	0
RMSSD (milliseconds)	11.10	19.08

Table 1 *Heart Rate measures with and without stress events.*

Deep Belief Network

A deep-belief network (DBN) [22] is defined as a stack of restricted Boltzmann machines (RBM), in which each RBM layer communicates with both the previous and subsequent layers. The nodes of any single layer don’t communicate with each other laterally. The end of DBN is a classifier. We employ gradient-descent algorithm to revise the weight matrix of the whole network. The error is propagated in the opposite direction. Therefore, the parameters of RBMs change slightly. DBN has the following steps:

Layer-wise Unsupervised Learning: We train the first RBM using the original data without the labels (unsupervised) and fixing up the parameters of this RBM. Then, the first layer configuration is frozen. We train the second layer using the output of the first layer. Finally, we get a DBN with several layers, whose parameters are appropriate to extract the features of data. This method avoids the overfitting. In addition, we can take advantage of unlabelled data.

Fine-Turning: We unfreeze all weights, and train full DBN with supervised model (SoftMax classifier) to fine-tune weights. Gradient-descent algorithm is employed to update the weight matrix of the whole network. This solution avoids drastic changes because the error is propagated in the opposite direction.

Restricted Boltzmann Machine (RBM)

Restricted Boltzmann Machine are bipartite graph with a layer of “hidden” neurons and a layer of "visible" neurons, without connections between neurons in the same layer. Each node represents a random variable and each edge a dependency between variables that connects.

We employ energy function (E) and probability distribution to describe a RBM. The energy of a configuration (pair of boolean vectors) (v,h) is defined as:

$$E(v,h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_i \sum_j v_i w_{i,j} h_j \qquad (5)$$

where a_i is the bias weight (offset) for the visible unit v_i, b_j is the bias weight for the hidden unit h_j, and $w_{i,j}$ the weight associated with the connection between hidden unit h_j and visible unit v_i.

Probability Distribution:

$$p(v,h) = \frac{1}{Z} e^{-E(v,h)} \qquad (6)$$

where Z is a partition function defined as the sum of $e^{-E(v,h)}$ over all possible configurations. The aim is to ensure the probability distribution sums to 1.

Through summation we can get the marginal distribution of visible layer $\boldsymbol{v}$:

$$p(v) = \frac{1}{Z} \sum_h e^{-E(v,h)} \qquad (7)$$

SoftMax Classifier

There are a set of training samples such as: $\{(x^1, y^1), (x^2, y^2), \ldots, (x^m, y^m)\}$, $y^i \in \{1,2,\ldots m\}$. The classifier is used in order to estimate the probability that x is a sample of j class. The activation function is:

$$h_\theta(x) = \begin{bmatrix} P(y=1|x,\theta) \\ P(y=2\,|x,\theta) \\ \dots \\ P(y=k\,|x,\theta) \end{bmatrix} = \frac{1}{Z}\begin{bmatrix} e^{\theta_1 \times X} \\ e^{\theta_2 \times X} \\ \dots \\ e^{\theta_k \times X} \end{bmatrix} \quad (8)$$

Where $Z = \sum e^{\theta_j \times X}$ is normalization factor.

The cost function to train the classifier is:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{n} 1\{y^{(i)}\}log\frac{e^{\theta_j^T x(i)}}{\sum_{s=0}^{n}\theta_s^T x(i)}\right] \quad (9)$$

In the equation, $1\{y(i) = j\}$ is indicative function, whose value is 1 when $y(i) = j$ and 0 when not. The aim is to minimize the cost function adjusting the parameters. We employ gradient-descent algorithm to make this task.

Validation of the prediction model

In this section, the proposed prediction algorithm is validated under different conditions. The solution was deployed on a Nexus 6 and Samsung Galaxy Note 4. These devices support Bluetooth Low Energy. The solution requires this protocol in order to get the heart rate signal. A Polar H7 band [23] is used to monitor the stress.

Tests were made in three different regions: Madrid (Route A-Spain), Seville (Route B-Spain), and Sheffield (Route C-United Kingdom). Route A has a length of 8.3 Km. The trip time estimated by Google under normal conditions is 18 minutes. Route B has a length of 16 Km. In this case, the trip time estimated by Google under normal conditions is 32 minutes. Finally, route C has a length of 22.4 Km. In this case, the trip time estimated by Google under normal conditions is 44 minutes.

Three different drivers participated. Each driver completed 150 test drives using their own cars. Their ages are between 38 and 41. All drivers were active and with unknown disease history. The experiment has been designed to minimize the impact that factors outside the study have on the measurements. We have only taken into account data from drivers driving in similar situations each day (same hour, same traffic conditions, with moderated previous walking to get into the car and a relaxation period of 30 seconds before driving, with the mobile phone muted, with the radio switched off and without using any navigation system) have been taken. The only exceptions are when we analyze the algorithm in low visibility conditions and heavy traffic.

The algorithm was validated using 10-fold cross-validation. The Deep Belief Network consisted of 6 hidden layers with 200 units per layer. The algorithm was run with the following parameters:

- Learning rate: 0.5
- Momentum: 0.2
- Epochs: 30

Driver state

In order to know the fatigue level, the drivers filled in a questionnaire with the following data:

- Working time
- Times Awakened
- Sleep Time

Tables 2-4 capture the results taking into account the driver state. The proposed algorithm is able to predict the stress levels by 88% when the driver is not tired. However, the results obtained when the driver is tired are worse. In this case, the proposal predicts stress by 80%. The main limitation of the approach is with false positives (the prediction of stress when driver will not suffer it). The algorithm classified 45 out of 150 non-stress samples as stress.

This happens because the user experience a worsening of the driving style due to fatigue. The proposal confuses the fatigue with stress. Therefore, the results are less accurate. This problem could be solved by adding personal features (working time and sleeping time) to the prediction model.

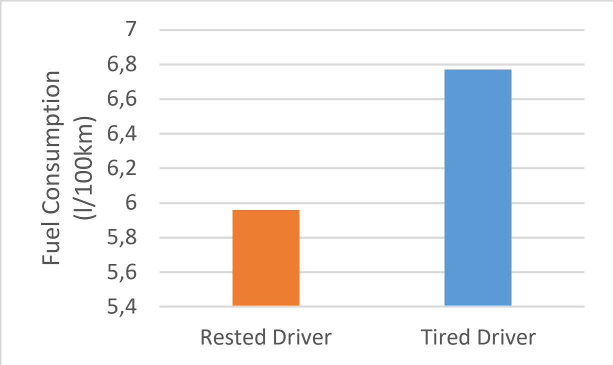

Figure 6 Comparison of fuel consumption (l/100km) according to the driver state (rested or tired).

The change in the driving behavior is also reflected on fuel consumption. Figure 6 compares the average fuel consumption (10 laps) according to the driver state under the same road conditions (weather, traffic, and route) for a driver. We can see that the fuel consumption improves by 11.96 % when the driver is rested.

	Rested		Tired	
Actual/Predicted	**No**	**Yes**	**No**	**Yes**
No	96 %	4 %	62 %	38 %
Yes	14%	86 %	20 %	80 %

Table 2 *Stress prediction on Route A.*

	Rested		Tired	
Actual/Predicted	**No**	**Yes**	**No**	**Yes**
No	100 %	0 %	70 %	30 %
Yes	15 %	85 %	18 %	82 %

Table 3 *Stress prediction on Route B.*

	Rested		Tired	
Actual/Predicted	No	Yes	No	Yes
No	88 %	12 %	78 %	22 %
Yes	7 %	93 %	21%	79 %

Table 4 *Stress prediction on Route C.*

Heavy traffic

Tables 5-7 present the results obtained in the three routes when traffic was dense. In this scenario, the proposal makes the stress prediction correctly by 84% on average. We can see that the results are worse than when the road conditions are good and the driving tests are made when the drivers are rested. The driving behavior is not as good as the usual. The accelerations and decelerations are more frequent. The consequences are an increase in error rates:

$$\frac{stress\ samples\ classifed\ as\ non\_stress}{stress\ samples} = \frac{35}{150}$$

$$\frac{non\_stress\ samples\ classifed\ as\ stress}{non\_stress\ samples} = \frac{24}{150}$$

Actual/Predicted	No	Yes
No	86 %	14 %
Yes	30 %	70 %

Table 5 *Stress prediction under heavy traffic on Route A.*

Actual/Predicted	No	Yes
No	90 %	10 %
Yes	22 %	78 %

Table 6 *Stress prediction under heavy traffic on Route B.*

Actual/Predicted	No	Yes
No	76 %	24 %
Yes	18 %	82 %

Table 7 *Stress prediction under heavy traffic on Route C.*

Visibility conditions

In is subsection, we analyze the algorithm behavior when the visibility is poor due to fog. Table 8 captures the results when there is fog on the road. In this situation the stress increases. However, the model response is accurate because the driver does not get worse driving. He only slows down. Therefore, sudden accelerations and heart rate are related to the future stress. The model is able to predict the stress by 88%.

$$\frac{stress\ samples\ classifed\ as\ non\_stress}{stress\ samples} = \frac{6}{50}$$

$$\frac{non\_stress\ samples\ classifed\ as\ stress}{non\_stress\ samples} = \frac{5}{50}$$

Actual/Predicted	No	Yes
No	90 %	10 %
Yes	12 %	88 %

Table 8 *Stress prediction foggy.*

Conclusions and future work

In this work, we have analyzed a model to predict the stress under different conditions. The proposed algorithm is based on deep learning. The proposal uses information about the road geometry, current driving behavior and the previous driving stress to infer the upcoming stress levels in advance.

The solution has been evaluated in four different scenarios: rested driver, tired driver, heavy traffic, and poor visibility. The results show that the model predicts accurately stress when the driver is rested. We also obtain a good hit rate when visibility is poor. However, the number of false positives is high when the driver is tired or the traffic is dense. The reason is that under these conditions the driver worsens the driving behavior. However, the causes are not the appearance of stress.

As future work, we want to introduce new variables in the model to improve the accuracy such as: working time, sleeping time or the air quality inside the vehicle. The proposal allows us to predict stress by assessing the driving and the previous stress level. We could use this algorithm to warn the driver in advance if he or she is making driving actions that are going to cause a high stress level. E.g.: if the solution predicts stress and we observe that the driver is speeding up strongly, the driving assistant would notify that he or she should smooth the accelerations.

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