Machine Learning Support for Time-Efficient Processing Dangerous Driving Detection Using Vehicle Inertial Data

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Abstract: Detection of dangerous driving behavior is a key component to improving road safety. It can be successfully carried out using data collected by sensors widely available in smartphones. Current work focuses on two groups: either they classify drivers in a binary way, into good and bad drivers, or they provide a scoring scale, allowing for a larger group of categories. This detection of dangerous driving behavior can be done with high granularity, evaluating a total distance covered by the driver on a trip, or with minute granularity, through the evaluation of small sections of driving, also making it possible to identify which maneuvers the driver is carrying out negligently. However, the process of collecting data for dangerous driving behavior is complicated because the driver needs to carry out these maneuvers, so that a classifier can later detect them, adding to situations of insecurity in traffic. Moreover, the solution needs to execute efficiently, so that the detection of dangerous driving behavior can be carried out in real time. Given this problem, we propose a time efficient dangerous driving detection system using vehicle inertial data. In contrast to other works, we collected data in a simulation environment with a model car that allows us to perform risky maneuvers, which would not be possible in a real environment. We identify in our small dataset the dangerous driving behavior pattern. Thus, given the established pattern, we applied a machine learning method to generate a classifier to enable the detection of dangerous driving behavior. The resulting system achieved a total average accuracy of 85.61% in our experiments using a small dataset as input towards efficient data processing.

1 INTRODUCTION

The use of motorized vehicles is augmenting more and more in our country (see Fig. 1). In fact, motor vehicles are key elements in urban mobility. In this context, even though there is a few tendency to improve over the last few years, the number of traffic accidents is still extremely relevant. Due to the driver behavior, lack of vehicle maintenance, bad road and bad environment conditions, accidents occur frequently, e and this impacts negatively people's quality of life and also on the economy of countries. The main causes of motor vehicle accidents are human factors, such as drowsiness while driving or driver distraction.

Given the human factor, detection of dangerous driving behavior is mandatory to improve road safety. It can be successfully carried out using data collected by sensors widely available in smartphones, such as accelerometer (ACC) and gyroscope (GYRO). These sensors can also be easily embedded in vehicles together with other sensors such as those to detect driver

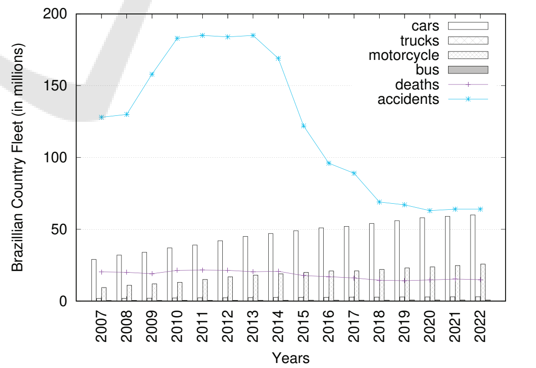

Figure 1: History data of the number of vehicles in circulation[1], the number of deaths due to traffic accidents[2], and the number of accidents on public highways in Brazil[3].

[a] https://orcid.org/0000-0001-6649-1488

[1] https://cidades.ibge.gov.br

[2] https://datasus.saude.gov.br

[3] https://cnt.org.br/painel-acidente

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alcohol ingestion (Abu Al-Haija and Krichen, 2022) (Willis et al., 2019) (Shreshtha et al., 2020), or cameras to capture the driver behaviour inside the vehicle or even outside the vehicle, which can be used to detect the use of smartphones (Wang et al., 2014) (Yasar, 2017), for example, or any other type of bad driver behavior during trips.

Moreover, classifying driver behavior can support commercial applications such as ride-sharing services and vehicle insurance services, provide information to authorities, or serve as support for Advanced Driver Assistance Systems (ADAS). However, the process of collecting data for dangerous driving behavior is complicated because the driver needs to carry out these maneuvers, so that a classifier can later detect them, adding to situations of insecurity in traffic.

In this paper, we propose a dangerous driving detection system with the support of machine learning approach which consumes inertial data extracted by ACC and GYRO devices, towards efficient data processing. The analysis of ACC and GYRO data, which is a feature easily captured through sensors embedded in the vehicle itself and even in smartphones, is one of the commonly investigated alternatives to detect dangerous driving behavior. In contrast to other works (Jeong et al., 2013) (Chen et al., 2015) (Nuswantoro et al., 2020), to conduct our experiments, we collected data in a simulation environment with a model car that allows us to perform risky maneuvers which would not be possible in a real environment. Typically, the use of data collected in real drive scenarios allows some form of driver anonymization, while image processing require filters to drive anonymization. However, as drivers are subject to complying with the law when driving on the streets, this represents a limitation on the driver's opportunities to perform risky maneuvers. Moreover, our solution seeks to perform efficiently in terms of classification time, so that the detection of dangerous driving can be carried out in real time.

Controversially, features associated with acceleration events did not play a significant role in drivers classification (Van Ly et al., 2013). Braking and turning events can be more significant potential in drivers classification. Time headway in high flow freeways can also impact the accident risk. Headway is the time interval between successive vehicles' head in a lane. Shorter headway corresponds to higher risk of accidents, and was found for drivers with prior accidents or violations, young drivers, male drivers, drivers with no passengers and as well as drivers not wearing seat belt (Evans and Wasielewski, 1983). With regard to the vehicles characteristics, shorter headway was associated with newer vehicles and vehicles of intermediate mass. Thus, a classifier for detecting dangerous driving needs to consider more parameters, such as headways, braking (Lattanzi and Freschi, 2021) and turning events, than just vehicle acceleration. We have not yet added the headway computing to our solution, but we take data from a complete trip in the analysis, precisely to consider braking and turning events in our classification approach.

This work is organized as following. In, Section 2, we describe and categorize previous related work. In Section 3, we present our methodology to detect dangerous drive behaviour. In Section 4, we discuss the obtained results. Finally, in Section 5, we present the paper conclusion.

2 RELATED WORK

Regarding the classification of drivers with regard to dangerous driving behavior, the detector's output can be binary (aggressive/non-aggressive behavior), or on a scale, with three or more distinct groups. In fact, proposed techniques for detecting dangerous driving behavior are nothing new. However, the concept of dangerous driving sometimes involves particular aspects of each country. For instance, some country legislation do not tolerate the drinking of alcoholic beverages by drivers (e.g. Brazil, Czech Republic, Romania, Slovakia), while others allows the ingestion of a low amount of alcohol. Blood Alcohol Content (BAC) drink driving limits across many Europe country usually is 0.5 grams per litre[4].

In academia, early works did not apply Machine Learning (ML) techniques for the detection of dangerous driving behavior. A popular metric for detecting dangerous driving has been the analysis of vehicle speed. Speed and acceleration data acquired with the support of sensors and GPS embedded in the vehicle can be used to model and analyze driver behavior with the support of data mining techniques (Constantinescu et al., 2010). Drivers were divided into 5 types: non-aggressive, slightly aggressive, neutral, moderately aggressive and very aggressive. Also, Dynamic Time Warping (DTW) can be used to binary classify drivers (non-aggressive and aggressive) using as input data ACC measurements, GYRO, magnetometer, GPS, and videos (Johnson and Trivedi, 2011). DTW is a method to calculate the optimal matching, usually with regard to time, between two data sequences. However, evaluation was conduced using a modest dataset. Vehicle speed can also be used to driver classification, such as in (Eboli et al.,

[4]https://etsc.eu/issues/drink-driving/blood-alcohol-content-bac-drink-driving-limits-across-europe/

2017). A percentage of the average vehicle speed (50-80%) can be used as parameter to categorize driving behaviors as safe, unsafe and safe, but potentially dangerous.

Nowadays, in the academia, Machine Learning (ML) techniques have been frequently applied to detect dangerous driving using ACC and GYRO achieved data. The most popular classifiers, with regard to dangerous drive detection, are Support Vector Machine (SVM) (Jeong et al., 2013) (Chen et al., 2015) (Nuswantoro et al., 2020) (Lattanzi and Freschi, 2021) e CNN, which has gain more attention is recent years (Baheti et al., 2018) (Shahverdy et al., 2020) (Masood et al., 2020) (Zhang et al., 2020).

SVM can be applied to detect lateral hazardous driving movements, such as lane changes and zigzag driving (Jeong et al., 2013). Data from 172 hazardous driving movements was collected using the vehicle's onboard GYRO. An average total accuracy of $\approx$85% was achieved in the experiments. A set of six types of abnormal driving behaviors was identified: weaving, swerving, sideslipping, fast U-turn, turning with a wide radius and sudden braking. Experiments were conducted in real driving environments with 20 volunteers driving during 4 months, and the proposed approach achieved an average total accuracy of $\approx$ 95%. Another work (Chen et al., 2015) also applied SVM classifier to detect the dangerous drive behaviour but using data from ACC and GYRO devices present in a smartphone.

Recent works also compared SVM with other classifiers, such as in (Nuswantoro et al., 2020) and (Lattanzi and Freschi, 2021). Artificial Neural Network (ANN) and SVM can be used for classifying a broad set of driver movements (normal behaviour, zig-zag, sleepy, turn right, turn left, U-turn, sudden braking, sudden acceleration, and speed bumps) performed by motorcycle drivers, such as in (Nuswantoro et al., 2020). Experiments were conducted in real driving environments with 5 volunteers driving all the movements. The proposed approach with ANN classifier outperformed the SVM classifier with an average total accuracy of $\approx$96% and $\approx$87%, respectively.

A combination SVM and Feed-Forward Neural Network (FFNN) classifiers were used to recognize safe and unsafe driving behaviors, such as in (Lattanzi and Freschi, 2021). Acceleration, braking and vehicle speed values were collected in the experiments with more than 26 hours of driving by 10 drivers. The conducted experiments shown an average accuracy above 90% for both classifiers with a slight advantage of the FFNN classifier.

Deep learning can also be applied to the detection of dangerous driving using inertial data from the vehicle, GPS and images captured by cameras, such as in (Khodairy and Abosamra, 2021). The classifier output was proposed in order to meet different demands such as driver protection, needs of the automotive insurance industry and ADAS requirements. Two classification outputs were used, one with three classes (normal, drowsy and aggressive behaviors) and a binary classification model (safe/unsafe).

A method for dangerous driving behavior prediction using a combination of cloud data and Elman neural network (CM-ENN), based on vehicle motion state estimation and passenger's scores about the drivers, was proposed by (Xiang et al., 2021). Experiments were conducted in real traffic scenarios and demonstrate that the proposed method is more accurate and robust than classical neural network approaches.

Convolutional Neural Networks (CNN) have been also widely applied to classify driver behavior using vehicle data (such as acceleration, gravity, RPM, speed, and throttle (the amount of accelerator pedal is pushed)) (Shahverdy et al., 2020), and/or images obtained obtained through in-vehicle cameras (Zhang et al., 2020) (Masood et al., 2020) (Baheti et al., 2018). In fact, the most recent academic works show a trend towards using the CNN classifier. A research question that is still under wide discussion is the need to divide drivers in a binary way or in a more detailed classification. In a recent work (Shahverdy et al., 2020), the CNN classifier is able to distinguish driver behaviour into five classes: safe or normal, aggressive, distracted, drowsy, and drunk driving. (Baheti et al., 2018) (Masood et al., 2020) (Zhang et al., 2020) divided driver behaviour in a much larger number of classes.

In this work, the classifier delivers a binary classification but the methodology can be easily adapted to deliver a more detailed classification. The classifier process data achieved from ACC and GYRO available in a GoPro 10 Black camera. In contrast to other works, which use data from real drivers, we use data achieved from a remote-controlled scale vehicle platform, which allows us to perform riskier maneuvers.

3 METHODOLOGY

In the following, we detail the methodology for classifying drivers' behavior into safe and unsafe, using the neural network as classifier.

3.1 Data Acquisition

In this project, a remote-controlled scale vehicle platform was used to obtain inertial and ranging sensors data. For this purpose, a GoPro 10 Black camera was attached to the rear face of the vehicle shell (see Fig. 2).

Figure 2: Assembly of the prototype for the remote-controlled vehicle used in the data acquisition process.

The GoPro camera has a 5.3K-maximum resolution imaging sensor, which is also capable of capturing video at 2.7K resolution with maximum frame rate at 240 Hz (Kirschenbaum, 2021). At the same time, it carries a Bosch BMI 260 inertial unit (Sensortec, 2019) alongside the image sensor, which provides the acceleration and turning rate data onto the video mp4-file metadata.

The GoPro 10 captures images in several resolutions and frame rates, configured with a 4K image at 60 Hz frame rate for generating videos and their metadata. The mp4 video files from the camera were interpreted through a bin2csv converter tool applied to binary data from the ffmpeg codec for extracting the embedded inertial data at a sampling rate of 400 Hz, with location data sampled at 10 Hz (Irache, 2020).

In order to successfully detect dangerous driving behaviour through the use of inertial data, it is essential to complement the hardware capability with software that can make the data useful. Therefore, a scheme of our data acquisition system setup is depicted in Fig. 3.

Raw data achieved from the system is post-processed to generate a set of features that are indicative of the driving behavior. The data collection process is iterative, involving initial data gathering, preliminary model training, and evaluation of the model's performance. Based on the model's performance, further data may be gathered to cover identified gaps or to improve performance in areas where the model currently underperforms.

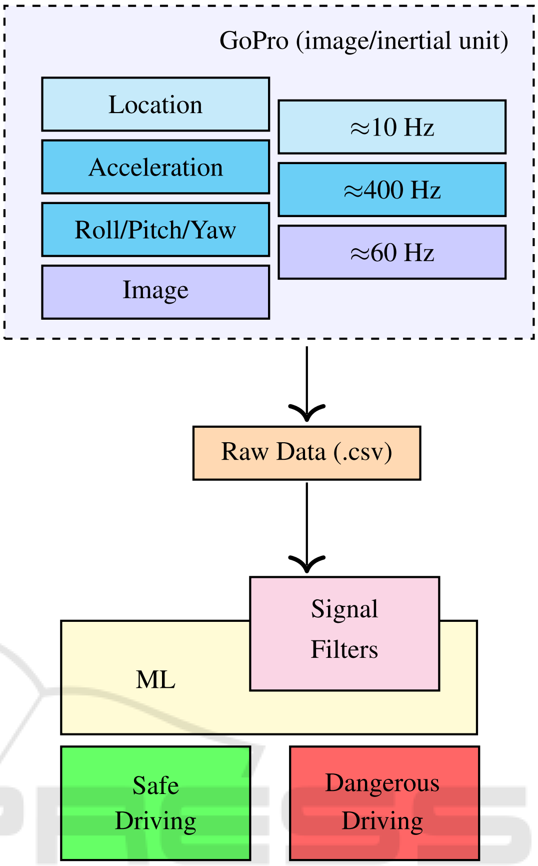


Figure 3: Data acquisition/filtering approach.

3.2 Driving Scenarios

The recognition of dangerous driving behaviour requires a dataset containing data about driving movements such as accelerating, braking, driving straight and cornering, with differentiating between safe scenarios with moderate driving and more complex and potentially dangerous maneuvers such as sharp turns, sudden braking, aggressive acceleration, and erratic lane changes. Varying road surface conditions can lead to changes in traction, leading to different degrees of tire slip and subsequently, changes in acceleration and angular velocity.

In the same manner, the track layout, whether it is straight or curved, and if the road has bumps and depressions, this significantly impacts the forces experienced by the vehicle and hence the data captured by the onboard sensors. The experimentation with driving scenarios was carried out in a flat track with rough tarmac with a total length of ≈30 m as represented in Fig. 4.

Each driver started riding around 15 m straight line to proceed performing curves over six poles spaced 3 m from each other, and then running back

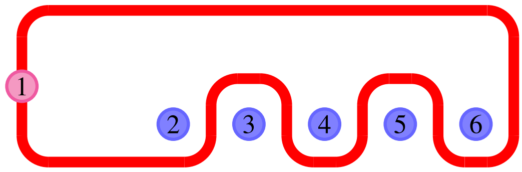


Figure 4: Schematic of the track on which driving scenarios were performed.

to the starting line after the sixth pole.

For the purpose of gathering data, 8 drivers using the remote-controlled vehicle platform performed laps following the track layout above with speeds up to 10 m/s. The driving sessions were organized in safe driving runs, and then in dangerous driving runs. Node 1 indicates the start/end of the route and each of the nodes 2-6 indicates a pole the driver should swerve around. The process of acquiring the dynamic driving data accounted for wet and dry tarmac conditions - there were two driving sessions - alongside the safe and dangerous driving scenarios, aiming to improve the output accuracy of the detection model.

3.3 Data Pre-Processing

The data pre-processing phase involves the identification and treatment of noise and situations that the data may manifest. Therefore, it is necessary to have the appropriate tools that help in the identification and processing of data.

Therefore, our dataset was reformatted and processed before the neural network processing. In this work, GoPro telemetry data was extracted using a free online tool, GoPro Telemetry Extractor[5].

When extracting data relating to ACC and GYRO by the tool, it is accompanied by data relating to the camera temperature, date and recording time in ms in a tabular .csv file. The columns are renamed to more accessible names and unnecessary data needs to be removed, leaving only the recording time and ACC and GYRO data in the 3-axes x, y and z. Additionally, the data on the vertical axis must have the gravity value (9.8) subtracted and the recording time is converted to seconds for convenience. Fig. 5 depicts a sample of the dataset after the conclusion of the pre-processing step.

In the data, there is still a lot of high-frequency noise, so it is necessary to filter it using a LowPass Filter (LPF). LPFs are a good way to remove noise (both mechanical and electrical) from the ACC. The LPF used is the Infinite Impulse Response (IIR) filter. The IIR filter is used so that the computing process can be carried out as quickly as possible. IIR filters do not have a phase delay, so there is no time delay. Fig. 6 depicts a sample of our data before and after the application of the IIR filters.

[5]https://goprotelemetryextractor.com/free/

	cts	acc1	acc2	acc3	gyr1	gyr2	gyr3
1	0.03610200	-0.0206235012	-0.30935252	0.165467626	-0.010649627	-0.072417465	0.027689031
2	0.04104942	0.0201438849	-0.29256595	0.199040767	-0.008519702	-0.075612354	0.022364217
3	0.04599683	0.0800959233	-0.31175060	0.131894484	-0.006389776	-0.074547391	0.019169329
4	0.05094425	0.0609112710	-0.30935252	0.160671463	-0.009584665	-0.071352503	0.015974441
5	0.05589166	0.0393285372	-0.33812950	0.148681055	-0.007454739	-0.063897764	0.015974441
6	0.06083908	0.0177458034	-0.33093525	0.139088729	-0.007454739	-0.060702875	0.013844515
7	0.06578650	0.0561151079	-0.33093525	0.007194245	-0.005324814	-0.055378062	0.012779553
8	0.07073391	0.0920863309	-0.37649880	-0.043165468	-0.003194888	-0.042598509	0.010649627
9	0.07568133	0.1088729017	-0.39328537	-0.086330935	-0.003194888	-0.026624068	0.008519702
10	0.08062874	0.1280575540	-0.39088729	-0.083932854	0.000000000	-0.006389776	0.004259851
11	0.08557616	0.1328537170	-0.33093525	-0.047961631	0.002129925	0.013844515	0.001064963
12	0.09052357	0.0872901679	-0.36690647	0.023980815	0.002129925	0.029818956	-0.001064963
13	0.09547099	0.0321342926	-0.37889688	0.105515588	0.001064963	0.041533546	-0.002129925

Figure 5: Sample of the dataset after the conclusion of the pre-processing step.

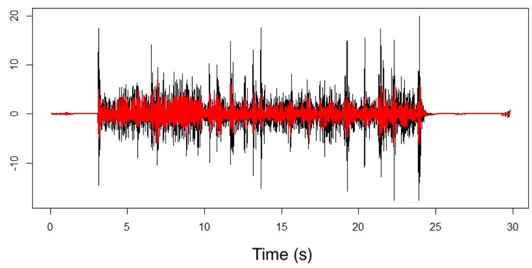


Figure 6: ACC data: in red, filtered data. In back, raw data.

Subsequently, downsampling in the data frequency must be carried out so that they can be processed quickly by the neural network. The GoPro collects data at a frequency of 200 Hz, which has been reduced to 10 Hz. Fig. 7 depicts a sample of our dataset after frequency downsampling to 10 Hz.

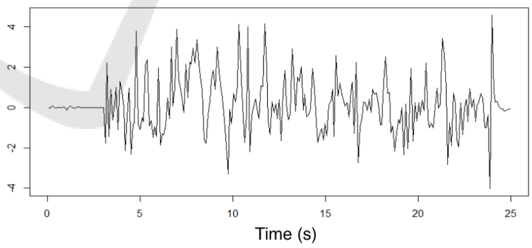


Figure 7: ACC data after downsampling to 10 Hz.

Finally, each 5s stretch within the dataset will become an observation labeled as safe or dangerous. To extend our dataset, the concept of sliding window was applied: between 0-5s will be considered a stretch, between 1-6s also and so on, as depicted in Fig. 8. A sample of the final dataset is depicted in Fig. 9.

3.4 Dataset Calibration

For experimental evaluation, a total of 374 cases were collected, of which 268 were safe and 106 (size) were

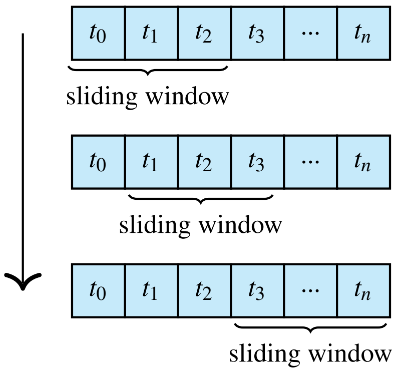
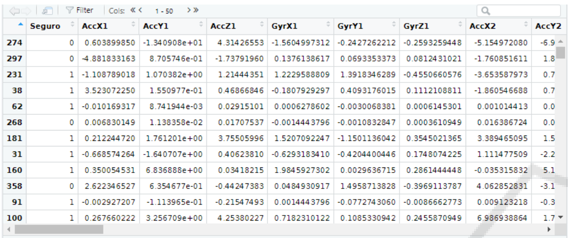


Figure 8: Sliding window approach.



	Seguro	AccX1	AccY1	AccZ1	GyrX1	GyrY1	GyrZ1	AccX2	AccY2
274	0	0.603899850	-1.340908e+01	4.31426553	-1.5604997312	-0.2427262212	-0.2593259448	-5.154972080	-6.9
297	0	-4.881833163	8.705746e-01	-1.73791960	0.1376138617	0.0693353373	0.0812431021	-1.760851611	1.8
231	1	-1.108789018	1.070382e+00	1.21444351	1.2229588809	1.3918346289	-0.4550660576	-3.653587973	0.7
38	1	3.523072250	1.550977e-01	0.46866846	-0.1807929297	0.4093176015	0.1112108811	-1.860546688	0.7
62	1	-0.010169317	8.741944e-03	0.02915101	0.0006278602	-0.0030068381	0.0006145301	0.001014413	0.0
268	0	0.006830149	1.138358e-02	0.01707537	-0.0014443796	-0.0010832847	0.0003610949	0.016386724	0.0
181	1	0.212244720	1.761201e+00	3.75505996	1.5207092247	-1.1501136042	0.3545021365	3.389465095	1.5
31	1	-0.668574264	-1.640707e+00	0.40623810	-0.6293183410	-0.4204400446	0.1748074225	1.111477509	-2.2
160	1	0.350054531	6.836888e+00	0.03418215	1.9845927302	0.0029636715	0.2861444448	-0.035315832	5.1
358	0	2.622346527	6.354677e-01	-0.44247383	0.0484930917	1.4958713828	-0.3969113787	4.062852831	-3.1
91	1	-0.002927207	-1.113965e-01	-0.21547493	0.0014443796	-0.0772743060	-0.0086662773	0.009123218	-0.3
100	1	0.267660222	3.256709e+00	4.25380227	0.7182310122	0.1085330942	0.2455870949	6.986938864	1.7

Figure 9: Sample of the final dataset.

dangerous. Since, each data in our dataset contains 6 kbytes, the total dataset size is 2244 kbytes or ≈ 2 Mbytes. The imbalance in the dataset occurred due to the speed at which the dangerous laps were performed, which ended up generating shorter videos.

The treatment of datasets with unbalanced data is a recent problem. Algorithms used to training neural networks have difficulty to learn in the presence of unbalanced data, i.e. when there is a large difference in the number of samples in each class (safe/unsafe). This difference can lead the classifier to have a biased output, favoring the outstanding class.

Because of this and to prevent the data from being trained in an unbalanced way in the neural network, 162 safe cases were removed from the dataset. The remaining 212 cases were divided between a training dataset containing 180 data and a testing dataset containing 32 cases.

3.5 Neural Network Model

Our classifier, which the code is depicted in Fig. 11, follows a neural network schematic model used in this work consists of three layers, as depicted in Fig. 10. In each network layer, with a set of artificial neurons, the network can learn about the data, by extracting its characteristics.

The input layer has 300 nodes (ACC and GYRO data for 5 seconds of the section at a frequency of 10 Hz). The two dense intermediate layers with the

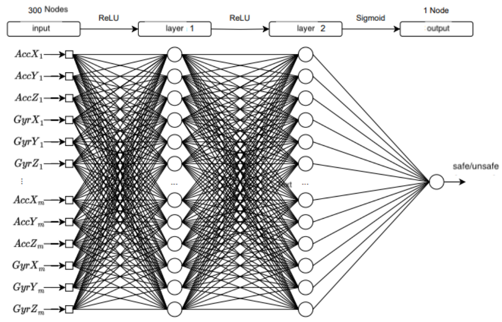


Figure 10: Neural network schematic model.

ReLU activation function, have 256 nodes and with 128 nodes, respectively. The output layer with the *sigmoid* activation function, the values close to 1.0 indicate a safe trip and values close to 0.0 indicate a dangerous trip.

3.6 Training

The training process of the neural network occurs every round or every epoch. During each epoch, the process of updating the weights takes place in order to improve the results obtained. The weights are adjusted in the neural network during the learning process.

After running all epochs, the trained model is obtained, which has learned features about the dataset used as input. Therefore, when displaying new information to this network, which is within the class in which the model was trained, in this case the detection of dangerous driving behavior, it is expected that the model will have the ability to correctly classify the information presented (in safe/unsafe).

All our experiments were conducted with a conventional entry-level laptop from 2016: Intel(R) Core(TM) i7-5500U CPU @ 2.40GHz, 8GB DDR3 RAM and a Nvidia GeForce 940M 2GB DDR3 GPU running Linux Mint 21.1. We divided our training dataset with 180 examples into batches of 16 examples. Training was carried out using 25 epochs (as depicts Fig. 12).

4 RESULTS

The proposed model achieved an accuracy rate of 85.61% for test cases that were not seen by the neural network during training (again see Fig. 12). The achieved accuracy rate indicates that there is a pattern to be found in the trips, however, it is not a high enough rate for the purpose of classifying and reporting dangerous driving, since it presents many false

```
model = tf.keras.Sequential([
preprocessing_layer,
tf.keras.layers.Dense(256, activation = 'relu'),
tf.keras.layers.BatchNormalization(),
tf.keras.layers.Dropout(0.1),
tf.keras.layers.Dense(128, activation = 'relu'),
tf.keras.layers.BatchNormalization(),
tf.keras.layers.Dropout(0.1),
tf.keras.layers.Dense(1, activation='sigmoid'),
])

model.compile(
loss='binary_crossentropy'
optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
metrics =['binary_accuracy']
)
```

Figure 11: Classifier implementation.

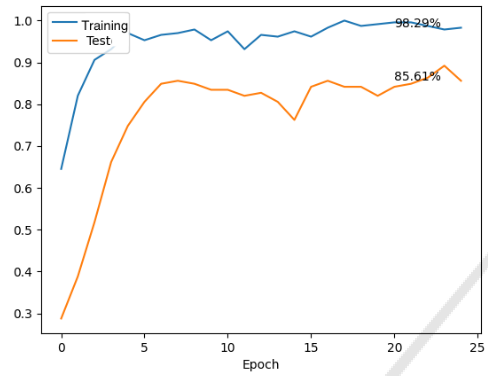


Figure 12: Neural Network Learning Curve with regard to the accuracy.

negatives. This happens because the dataset needs to be better calibrated. However, we want to keep the amount of data small, so that the neural network can readily process it. To achieve better accuracy results, possible solutions are (*i*) expanding the database, (*ii*) improving pre-processing phase and (*iii*) testing different hyper-parameters.

5 CONCLUSION

Data quality is one of the main concerns for ML algorithm's output. Most of the available methods induces knowledge strictly from the data, without using any external information. Thus, the quality of the algorithm's output largely determined by the quality of the input data.

In this way, future work includes to augment the database data and to improve data pre-processing phase, seeking precisely to improve the accuracy of the algorithm here applied. Furthermore, we aim to improve the neural network accuracy, using other techniques such as recurrent neural networks, in addition to evaluating the use of different neural network models to solve the given problem, such as multi-class classifiers for identifying maneuvers performed by the vehicle or for recognizing drivers. Finally, we aim to apply the classification of dangerous detection behavior in a real time environment to evaluate the performance of the solution given the computational power and resources available in the vehicle.

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