Aggressive Driving Detection Using Deep Learning-based Time Series Classification

Youness Moukafih
International University of Rabat
Faculty of Engineering, TICLab
Morocco
youness.moukafih@uir.ac.ma

Hakim Hafidi
International University of Rabat
Faculty of Engineering, TICLab
Morocco
hakim.hafidi@uir.ac.ma

Mounir Ghogho
International University of Rabat
Faculty of Engineering, TICLab
Morocco
mounir.ghogho@uir.ac.ma

***Abstract*—Driver aggressiveness is a major cause of traffic accidents. Aggressive driving detection is an important application in the field of intelligent transportation systems (ITS). Developing systems capable of automatically detecting aggressive driving behavior should help improve traffic safety. In this paper we propose a novel solution to the problem of drivers' behavior classification based on a Long Short Term Memory Fully Convolutional Network (LTSM-FCN) to detect if a driving session involves aggressive behavior. We formulate the problem as a time series classification and test the validity of our approach on the UAH-DriveSet, a public dataset that provides a large amount of naturalistic driving data obtained from smartphones via a driving monitoring application. The proposed solution is compared to other deep learning and classical machine learning models for different processing time window sizes. It is shown that the proposed system outperforms the other methods in terms of the F-measure score, which reaches 95.88% for a 5 minutes window length.**

***Index Terms*—Aggressive driving, Deep learning, Smartphone**

I. Introduction

With the increase in the world car fleet, traffic accidents became a major concern. They cause the death of about 1.35 million people each year [1]. Human factors are among the main causes of accidents. Indeed, according to the World Health Organization, driver's behavior is the principal cause of traffic accidents; it is responsible for nearly 90% of accidents. Within the behavioral realm, one phenomenon in particular captures the attention of researchers from different fields, which is aggressive driving [2] [3].

It is difficult to find a consensus on the meaning of aggressive driving. However, in general, researchers agree on two main aspects in its definition: danger and intentionality. Moreover, aggressive driving appears as one of the factors involved in road accidents. A study conducted in different countries concluded that aggressive road behavior is correlated with a larger number of accidents [4] .

Researchers have identified multiple behaviors that may be representative of aggressive driving, namely excessive speed driving, hard braking and acceleration, horn-honking latency. [5]. Given the complexity of defining this phenomenon and precisely determining the behaviors to be used to illustrate this type of driving, psychologists have been interested in its different components. The authors in [6] investigated the relationship between aggressive behavior and personality traits. In [7], the authors conclude that there is a positive correlation between anger and aggressive driving. In other studies, different cognitive functions have been studied in connection with aggressive and dangerous driving. A study found that a driver with low inhibitory capacity has a higher probability of perpetrating violations of the rules and of being involved in road accidents [8].

Although it is difficult to understand precisely the mechanisms that lead to aggressive behavior, some factors are believed to increase its incidence. More specifically, in a study conducted for the National Highway Traffic Safety Administration, aggressive driving was associated with dangerous behaviors such as speeding and tailgating [9].

In recent years, several methods are reported in the literature to address the problem of aggressive driving detection. They can be distinguished by the types of data or by the models they use to classify drivers' behavior. Some studies use vehicle dynamics. In [10], the authors use lateral and longitudinal accelerations and speed to detect drivers' aggressiveness. A more recent study uses a fusion of visual and sensors data to decide if a driving session involves aggressive driving [11]. In a different perspective, the authors in [12] extracted features from video recordings to detect dangerous driving.

To our knowledge, with the exception of the work presented in [13], most of the methods proposed for the classification of driver behavior are based on machine learning models that use hand-crafted features. One major drawback of this approach is the disconnection between the feature engineering step and the model learning algorithms.

In this paper, we use deep learning models to extract relevant features for aggressive driving detection from a fusion of data coming from the vehicle (e.g. speed, acceleration) and its environment (e.g. car position relative to lane center, time of impact to ahead vehicle). More specifically, we adapt and use a state of the art model for time series classification, namely the LSTM-FCN model [14], to the problem of detecting aggressive driving. The combination of convolutional neuron networks (FCN) and recurrent neural networks (LSTM)

978-1-7281-1862-8/19/$31.00 ©2019 IEEE

TABLE I: List of drivers and vehicles in the dataset [15]

Driver	Genre	Age range	Vehicle Model	Fuel type
D1	Male	40-50	Audi Q5 (2014)	Diesel
D2	Male	20-30	Mercedes B180 (2013)	Diesel
D3	Male	20-30	Citröen C4 (2015)	Diesel
D4	Female	30-40	Kia Picanto (2004)	Gasoline
D5	Male	30-40	Opel Astra (2007)	Gasoline
D6	Male	30-40	Citröen C-zero (2011)	Electric

has enabled us to significantly improve the performance of aggressiveness detection on the roads.

The rest of the paper is structured as follows. The next section gives information about UAH-DriveSet, the dataset to which we applied our approach. It provides also a description of the different data preparation and preprocessing techniques that we applied to the overall data. In section III, we describe our proposed methodology to tackle the problem of aggressive driving detection. In section IV, we present the results of the performed experiment. Finally, conclusions are drawn in Section V.

II. Data

A. Dataset description

The dataset (UAH-DriveSet) that we use to detect aggressive behavior has been collected and put online by the university of Alcalà [15].

The data were collected using the DriveSafe application which takes advantage of the main sensors of the phones (e.g. gyroscopes, cameras, GPS). The camera of the smart phone was used as the vehicle front view camera.

UAH-DriveSet provides driving data of 6 different drivers on two types of roads of the community of Madrid (Spain). The first road is a 120km/h maximum speed motorway, the second is a 90km/h secondary road. Table I gives details about the drivers and the used vehicles. Each driver repeats the same route by simulating each time a different behavior (aggressive, drowsy or normal). For each path and driver, the dataset provides several types of data: raw data from the GPS and accelerometer as well as pre-processed data from video recordings. A detailed description of all the features can be found in [15].

The differences between the four classes of driving styles can be seen in Fig.2, where acceleration on the X axis (i.e., axis along the driving direction), is plotted against time.

B. Data preprocessing

In this section, we give a detailed description of how we processed the data (see Fig.1), before feeding them to the machine learning model.

1) Data preparation: The present work is based on the UAH-DriveSet dataset. As mentioned in previous sections, this dataset consists of data collected from smartphone cameras alongside some built-in sensors (GPS and accelerometer) sampled at different frequencies (1Hz, 10Hz, 30Hz, 100Hz).

First a cleaning phase was necessary to remove redundant data like correlated and identical features, duplicated rows (with the same timestamp) from the raw data. Then the replacement of missing values is done using the K-nearest-neighbor (KNN) algorithm by approximating a point value using the points that are closest to it, based on other features. A synchronization phase followed in order to output a data with a unified sampling frequency (i.e., 10Hz).

Data from each driver were provided originally in separate files based on the driving behavior and the road type. Due to this fact, a merging phase was implemented to be able to work on a single file data based on the timestamp column and get a synchronized data relative to each driver. Furthermore, data belonging to each behavior class were then merged into a single file.

2) Data augmentation: Before injecting data into the algorithm, the data were divided into overlapping segments using a sliding window with a fixed length. This data augmentation trick was applied to improve the accuracy of the model by providing a better understanding of the driving behavior. For instance, with a fixed sliding window of 4 min of data, the first record, of duration 240 seconds, starts at the 0^{th} second, the second record starts at the 20^{th} second instead of starting from the 240^{th}. Using this method allows us to obtain more information from the raw data than choosing disjoint data segments.

3) Data normalization: Normalization of the data in deep learning is generally useful to obtain a good model. Since the features have different scales, we used the following equation to obtain a data with features values between 0 and 1:

$$X_i = \frac{X_i - min(X_i)}{max(X_i) - min(X_i)} \tag{1}$$

where X_i denotes the i

III. Methodology

A. Proposed system

Our objective is to detect driving style (normal driving or aggressive driving) for each driver automatically based on data coming from the vehicle (in-vehicle sensors or phone sensors, and front view camera).

As shown in Fig.3, the system starts working as soon as the driver starts driving. The video recordings are used to extract information about the environment, e.g. the car position relative to the lane center, the distance to the ahead vehicle, etc. The obtained features are then fed to the classification model which has 4 classes (C1 = Aggressive driving in motorway road, C2 = Aggressive driving in secondary road, C3 = Normal driving in motorway road and C4 = Normal driving in secondary road).

B. Classical machine learning algorithms

For the classical machine learning algorithms we used two ensemble supervised machine learning algorithms. The first is Random Forest [16], which applies the technique of bagging (Bootstrap-based trees generation) and random feature selection. The second is Adaboost [17], short for Adaptive Boosting, which sets weights to both classifiers (weak learners)

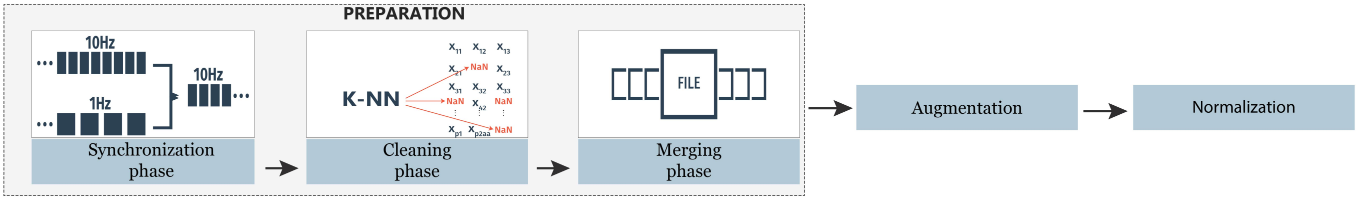
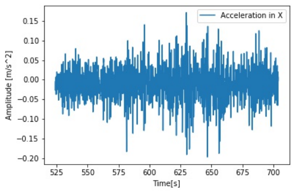
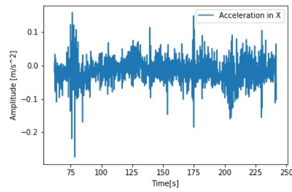


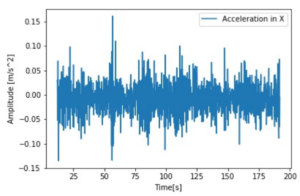
Fig. 1: Preprocessing phases.



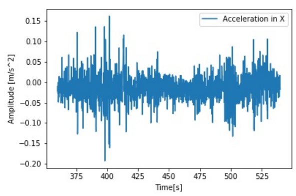
(a) Aggressive in Motorway



(b) Aggressive in Secondary



(c) Normal in Motorway



(d) Normal in Secondary

Fig. 2: Acceleration signal along the x-axis for different driving behavior and different type of roads.

and observations in a way that forces classifiers to concentrate on samples that are difficult to correctly classify.

Since we are dealing with time series data, we compute descriptive statistics (average, standard deviation and maximum value) for each feature in order to aggregate data. Cross validation technique (5 folds) was used for both algorithms to evaluate the model and fine-tune the hyper-parameters. Forward-selection was used to select the most contributing features.

C. Deep Learning algorithms

In this paper, we use the FCN-LSTM architecture, which combines the benefits of two powerful models used in time series classification tasks: Long Short-Term Memory network (LSTM), and Fully Convolutional Network (FCN) [18].

The first part of the model is a FCN network composed of several temporal convolutional layers that act as its feature extraction modules. Each FCN block contains sequentially a convolution layer, a batch normalization, and an activation function. The second part is an LSTM network. The latter is a category of Recurrent Neural Networks (RNN) that addresses the vanishing gradient problem.

Both networks take the same input. Nevertheless, each network has its specific input shape. For instance, the FCN receives time series data in a multi-step univariate fashion, while the LSTM network receives the same data but in a multivariate way. To give a more detailed illustration, a 30 seconds-long time series would be read from the FCN side in a 30 time steps process, whereas for LSTM the same data would be read completely in single time step. We will compare the performance of this architecture against ResNet [19] and LSTM [20].

D. Feature selection

Feature selection is a process used in machine learning and data processing. It consists, given data in a large space, to find a subset of relevant variables by trying to minimize the loss of information from removing all other variables. It is a method of dimensionality reduction.

We used a feature selection method that fits a model and recursively eliminate the weakest feature until it reaches a specified number of features by removing dependencies that may exist in the model. It is called recursive feature elimination. To specify the number of features to keep, we use cross-validation to score different subsets and select the best possible collection based on the accuracy metric.

After applying this method to the preprocessed data, we are left with the following features.

- Speed
- Acceleration in X
- Acceleration in Y
- Acceleration in Z
- Roll
- Pitch
- Yaw
- Car position relative to lane center
- Car angle relative to lane curvature
- Road width
- Distance to ahead vehicle in current lane
- Time of impact to ahead vehicle

E. Model validation technique

One of the most important and challenging aspects of machine learning is the validation step. The model must generalize with the appropriate bias-variance trade-off to mitigate the over-fitting problem. In this work, the model was trained and vaildated by a data collected from five randomly selected drivers with different driving behaviors. The data related to the sixth driver were used for the testing phase. The fine-tuning of the hyper-parameters (optimizer, learning rate and batch size) were chosen based on the categorical cross entropy loss function. In this work we used the Adam optimizer [21] with learning rate of 0.05 for training the FCN-LSTM model.

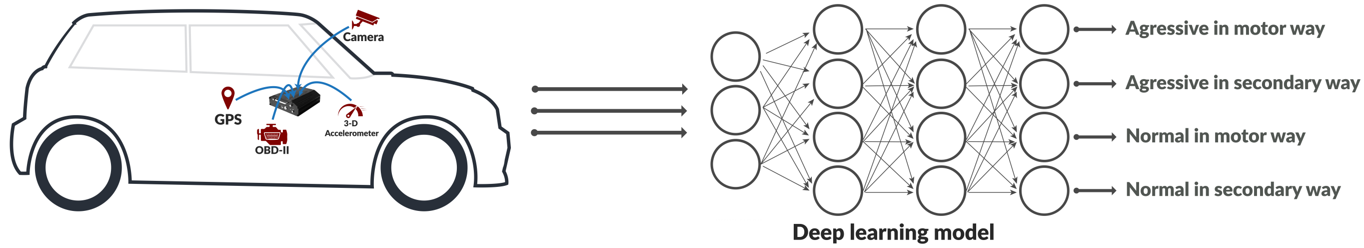


Fig. 3: Aggressive driving detection system

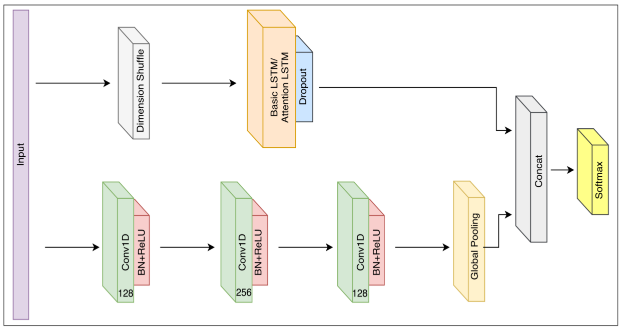


Fig. 4: The LSTM-FCN architecture [14]

IV. Results

To put the model's results into perspective, Table II compares the model's performance with those of the ResNet, LSTM, Random Forest and Adaboost models for different time window sizes.

TABLE II: The F1 score

Window size	1 min	2 min	3 min	4 min	5 min
Random Forest	0.7358	0.8323	0.8452	0.9116	0.9411
Adaboost	0.7217	0.7844	0.8105	0.8914	0.9275
ResNet	0.8344	0.8311	0.8326	0.8713	0.8829
LSTM	0.7363	0.75	0.819	0.7963	0.8522
FCN-LSTM	**0.9168**	**0.9213**	**0.9209**	**0.9321**	**0.9588**

To demonstrate the merits of the proposed method, we use the F-measure, which is defined as follows

$$F - measure = \frac{(1+\beta^2) \times Recall \times Precision}{\beta^2 \times (Precision + Recall)} \tag{2}$$

Which combines the precision and the recall as a measure of effectiveness of classification.

It is shown that the FCN-LSTM model provides better performance in differentiating between the 4 classes of driving behaviors. The best performance was obtained with a time window length of 5 minutes. It is also shown that the performance deteriorates for larger window sizes. This is due to the fact that when the time window size increase, the size of the input to the FCN-LSTM increases, which causes overfitting.

V. Conclusion

The goal of the proposed approach was the detection of aggressive driving by using deep learning and formulating the driving behavior classification task as a time-series classification. The time series were obtained from speed and acceleration sensors and a vehicle front view camera. The extracted features were used to train a FCN-LSTM model in order to provide classification scores (normal in motorway road, normal in secondary road, aggressive in motorway road and aggressive in secondary road). The proposed solution is shown to give good performance.

VI. Acknowledgement

This work was supported by the HowDrive project funded by the Moroccan Ministry of Equipment, Transport, Logistics and Water via the National Center for Scientific and Technical Research (CNRST).

References

[1] W. H. Organization *et al.*, "Global status report on road safety 2018," 2018.

[2] T. Lajunen and D. Parker, "Are aggressive people aggressive drivers? a study of the relationship between self-reported general aggressiveness, driver anger and aggressive driving," *Accident Analysis & Prevention*, vol. 33, no. 2, pp. 243–255, 2001.

[3] É. Berdoulat, "La prise de risque dans lespace routier: lexemple de la conduite agressive," *Le Journal des psychologues*, no. 8, pp. 30–35, 2018.

[4] T. Özkan, T. Lajunen, D. Parker, N. Sümer, and H. Summala, "Aggressive driving among british, dutch, finnish and turkish drivers," *International journal of crashworthiness*, vol. 16, no. 3, pp. 233–238, 2011.

[5] D. A. Hennessy and D. L. Wiesenthal, "Traffic congestion, driver stress, and driver aggression," *Aggressive Behavior: Official Journal of the International Society for Research on Aggression*, vol. 25, no. 6, pp. 409–423, 1999.

[6] E. R. Dahlen, B. D. Edwards, T. Tubré, M. J. Zyphur, and C. R. Warren, "Taking a look behind the wheel: An investigation into the personality predictors of aggressive driving," *Accident Analysis & Prevention*, vol. 45, pp. 1–9, 2012.

[7] S. M. Nesbit, J. C. Conger, and A. J. Conger, "A quantitative review of the relationship between anger and aggressive driving," *Aggression and Violent Behavior*, vol. 12, no. 2, pp. 156–176, 2007.

[8] Z. Tabibi, H. H. Borzabadi, D. Stavrinos, and A. Mashhadi, "Predicting aberrant driving behaviour: The role of executive function," *Transportation research part F: traffic psychology and behaviour*, vol. 34, pp. 18–28, 2015.

[9] N. H. T. S. Administration *et al.*, "Aggressive driving enforcement: Strategies for implementing best practices," *DOT HS*, vol. 809, p. 031, 2000.

[10] A. B. R. González, M. R. Wilby, J. J. V. Díaz, and C. S. Ávila, "Modeling and detecting aggressiveness from driving signals," *IEEE Transactions on intelligent transportation systems*, vol. 15, no. 4, pp. 1419–1428, 2014.

[11] O. Kumtepe, G. B. Akar, and E. Yuncu, "Driver aggressiveness detection via multisensory data fusion," *EURASIP Journal on Image and Video Processing*, vol. 2016, no. 1, p. 5, 2016.

[12] G. Jian-Qiang and W. Yi-ying, "Research on online identification algorithm of dangerous driving behavior," in *2014 Fifth International Conference on Intelligent Systems Design and Engineering Applications*. IEEE, 2014, pp. 821–824.

[13] K. Saleh, M. Hossny, and S. Nahavandi, "Driving behavior classification based on sensor data fusion using lstm recurrent neural networks," in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017, pp. 1–6.

[14] F. Karim, S. Majumdar, H. Darabi, and S. Chen, "Lstm fully convolutional networks for time series classification," *IEEE Access*, vol. 6, pp. 1662–1669, 2018.

[15] E. Romera, L. M. Bergasa, and R. Arroyo, "Need data for driver behaviour analysis? presenting the public uah-driveset," in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2016, pp. 387–392.

[16] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[17] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Journal of computer and system sciences*, vol. 55, no. 1, pp. 119–139, 1997.

[18] Z. Wang, W. Yan, and T. Oates, "Time series classification from scratch with deep neural networks: A strong baseline," in *2017 International joint conference on neural networks (IJCNN)*. IEEE, 2017, pp. 1578–1585.

[19] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[20] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[21] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.