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Utilizing LSTM Networks for the Prediction of Driver Behavior

***Abstract**. The driving behaviour prediction system was extensively utilised for minimising traffic accidents especially in detection of abnormal driving behaviours such as rapid acceleration, emergency braking, and sudden lane changes. This paper proposes deep learning model based on LSTM to classify driving behavior using OBD-II data. Results suggest that the proposed model exhibits a natural capability to retain and utilize temporal information in the input data, surpassing conventional machine learning methods.*

***Streszczenie.** System przewidywania zachowania kierowcy był szeroko wykorzystywany do minimalizowania liczby wypadków drogowych, zwłaszcza do wykrywania nietypowych zachowań podczas jazdy, takich jak gwałtowne przyspieszanie, hamowanie awaryjne i nagła zmiana pasa ruchu. W artykule zaproponowano model głębokiego uczenia oparty na LSTM do klasyfikacji zachowań kierowców przy użyciu danych OBD-II. Wyniki sugerują, że proponowany model wykazuje naturalną zdolność do zatrzymywania i wykorzystywania informacji czasowych w danych wejściowych, przewyższając konwencjonalne metody uczenia maszynowego (**Wykorzystanie sieci LSTM do przewidywania zachowań kierowców**)*

Keywords: Driving behaviour prediction, long short-term memory (LSTM), vehicle sensors, acceleration.
Słowa kluczowe: Przewidywanie zachowania podczas jazdy, pamięć długotrwała (LSTM), czujniki pojazdu, przyspieszenie

Introduction

New standards for the transport industry have emerged because of the quick expansion of the need for movement of human and products, as well as the development of Information and Communication Technology (ICT). Furthermore, as sensor technology develops and matures, new transportation paradigms can be established that can provide a greater knowledge of driving behaviour. The increasing volume of vehicles in daily circulation, particularly in urban areas, presents fresh risks to both individuals and the environment. According to the World Health Organization (WHO), approximately 1.35 million lives were lost globally in car accidents in 2016, as reported in 2020 [1]. In addition to the rise in vehicle numbers and car accidents, it is crucial to examine the environmental impact of vehicles.

Most existing studies rely on clustering techniques and shallow learning methods. Shallow learning refers to the utilization of machine learning algorithms that are not as intricate or deep as architectures such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs). Shallow learning algorithms are typically simpler and have fewer layers compared to deep learning models. It is difficult to accurately identify the types of abnormal driving behaviours. Shallow learning approaches for driving behaviour monitoring systems lack the ability to capture complex patterns and nuances, leading to inaccurate analysis and unreliable predictions.

Shallow learning algorithms fail to accurately detect subtle signs of driver fatigue, leading to inadequate warnings or false alarms. In congested traffic scenarios, shallow learning models struggle to differentiate between aggressive driving behaviors and necessary maneuvers, resulting in misclassification. Shallow learning techniques struggle to adapt to individual driving styles, hindering the system's ability to provide personalized feedback and coaching. The societal drive to reduce fatalities has led to increased funding, research, and opportunities to enhance traffic safety. It is widely acknowledged that driving behavior plays a crucial role in ensuring safer roads [2]–[4]. With the ongoing digitalization within the transportation domain, analyzing and evaluating driver behavior becomes essential for leveraging emerging opportunities and making future traffic safer.

The advancements in the transportation domain are not only driven by new data processing methods but also by the substantial increase in data volume generated and collected. This is primarily due to the growing number of vehicle sensors, which provide valuable information about vehicles and driving performance [5]. The utilization of Cloud technologies, coupled with advanced data analysis, communication, and storage techniques, further accelerates this development. To address the emerging opportunities in this domain, a diverse array of methods and algorithms can be employed [6] as shown in Fig. 1.

Fig.1. In-Vehicle (telematics) data acquisition through OBD-II interface [3]

Related works

The driving style of everyone differs based on their vehicle handling techniques. Various factors can contribute to a driver's style, such as the frequency of brake and gas pedal usage, the amount of pressure applied to the brakes, or the adjustments made to the steering wheel angle when navigating curves. These characteristics of a driver's unique driving style are directly or indirectly reflected in the generated vehicle telematics data. By analyzing this data, one can gain insights into the driving behavior of individuals and assess their driving style attributes [7] [8].

Deep learning has been widely used in recent years to analyse and understand driving behaviour. Various research efforts have focused on detecting abnormal human driver behaviour, such as inattentive and aggressive driving, using deep learning techniques. These studies have addressed the challenges of automating real-time behaviour recognition while ensuring high accuracy in action classification. One approach to driver behaviour recognition is through interwoven deep convolutional neural networks (CNNs) with multi-stream inputs [9]. This method aims to improve the accuracy of action classification by integrating information from multiple sources, such as vehicle accelerometers and gyroscopes. Real-time data collection and analysis are crucial for effective driver behaviour recognition, as demonstrated by a study that collected real data from vehicle sensors to identify aggressive driver behaviours using statistical techniques [10].

Video-based abnormal driving behaviour detection has also been explored using deep learning fusions [11]. This approach involves analysing video footage of drivers to identify and classify abnormal behaviours. Similarly, a deep hybrid model has been proposed to detect safe driver behaviours and driving events using real-time smartphone sensor signals [12].

In addition to analysing driving behaviour, deep learning has also been used for driver identification and verification. One study addressed driver identification and verification through a deep learning approach using psychological behavioural data [13]. This method leverages psychological factors to enhance the accuracy of driver identification and verification processes. Despite the advancements in deep learning-based driving behaviour analysis, there are still open challenges and requirements for further improvement. These include the need for more comprehensive and diverse datasets, the development of robust models that can handle various driving scenarios, and the integration of real-time data collection and analysis for more accurate results [14].

In the driver identification task, traditional algorithms often necessitate extensive data preprocessing steps, which can either require domain expert knowledge or involve an extensive data exploration process. Additionally, conventional machine learning algorithms are not inherently equipped to effectively utilize sequential relationships present in time-series data from vehicle telematics sensors. On the other hand, end-to-end deep learning-based methods, such as Recurrent Neural Networks (RNN), offer advantages in this context. These methods can directly extract important features from the data without the need for extensive preprocessing and can leverage temporal relationships in a holistic data-driven manner [15], [16].

In terms of deep learning algorithms, LSTM [8] performs slightly better than MLP, but it comes with a higher execution time compared to MLP and other mentioned machine learning algorithms. It's important to note that the loss and validation loss values for both machine learning (ML) and deep learning (DL) algorithms show similarity, indicating that there is no occurrence of overfitting or underfitting during the training process [14].

Methodology

During driving behavior experiments, data collection takes place in an uncontrolled environment. To gather this data, an instrumented vehicle is used, equipped with sensors e.g. On-board diagnostics adapter (OBD-II) that detect various parameters such as vehicle speed, position, acceleration, deceleration, RPM, and total distance traveled. The data collection procedure entails the continuous observation and recording of driver behaviors across varying time intervals. For this case, Torque Pro mobile application software was used to monitor and analyze data related to acceleration, braking, and overall vehicle performance Within the data collection phase of this research, five drivers were enlisted, all utilizing the same vehicle model. The data collection transpired over three distinct time frames, and the experiment was conducted in proximity to the primary campus area as shown in Fig. 2. Notably, the selected participants for this study fell within the age bracket of 20 to 25 years. Furthermore, an additional cohort of five drivers was engaged to operate the same vehicle under identical scenarios, facilitating the collection of a separate testing dataset.

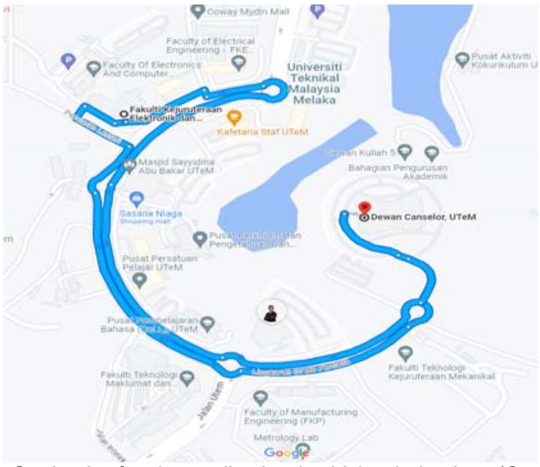

Fig.2. Study site for data collection in driving behaviour (Canselor Hall, UTeM – FKEKK – Canselor Hall, UTeM).

The acceleration measure is appropriate for categorizing driving behaviour since it offers insightful data on how a vehicle is being operated. First off, acceleration and variations in the vehicle's speed are strongly related in terms of safety. Rapid starts or abrupt acceleration manoeuvres are two examples of risky driving practices that might be indicated by sudden and forceful accelerations. These actions may suggest reckless driving or raise the danger of accidents. Smooth and gradual accelerations are typically associated with safe and comfortable driving. Monitoring acceleration patterns can help identify whether a driver is maintaining a steady and controlled driving style or if there are frequent accelerations or decelerations, which can impact fuel efficiency, passenger comfort, and overall driving experience. Aggressive driving behaviors, such as rapid accelerations, are often considered undesirable. By analyzing acceleration patterns, it is possible to detect aggressive driving events, such as harsh accelerations, which can be indicators of unsafe or reckless driving habits. This paper will categorize three types of drivers which are aggressive, moderate, and good drivers.

Deep learning model

The model proposed in this project is a pattern recognition model for labeled (supervised) deep learning data-based. The best results are then obtained by tuning the topology and hyperparameters in the evaluation process (the real test). A long short-term memory (LSTM) [8] model was built to account for variations in parameter values and the output was evaluated to determine if the design was optimal for the condition. The original dataset is then splitted into three parts which is training, validation, and test. The 'Sequential' class from the 'tensorflow.keras.models' module is used to create the LSTM model. The model architecture consists of an input shape of (time_steps, 1) and an LSTM layer with 128 units. To generate the final output probabilities for each class, the LSTM layer's output is connected to a dense layer with a softmax activation function. For multi-class classification tasks, the SoftMax function assigns probabilities to each class. The outputs are transformed into a probability distribution, allowing the model to predict data for various classes.

To optimize the LSTM model, an optimization algorithm called ADAM (Adaptive Moment Estimation) is used in deep learning to train neural networks. The stochastic gradient descent (SGD) optimization technique is extended to include adaptive learning rates and momentum. The ADAM optimizer upholds adaptive learning rates for various neural network parameters. The first and second moments (estimates of the mean and uncentered variance of the gradients) are used to compute the adaptive learning rates. Based on the strength and direction of the gradients, these moments are updated throughout the training process to modify the learning rates. The combination of adaptive learning rates, momentum, and bias correction in ADAM allows for efficient and effective optimization of neural networks. By iteratively adjusting the parameters based on the gradients computed during backpropagation, ADAM helps the neural network converge towards a set of optimal weights that minimize the loss function.

Results and discussion

This section presents the outcomes derived from the coding process, specifically focusing on the assessment of the LSTM model's performance. As depicted in Fig. 3, the results pertaining to the LSTM model's evaluation encompass critical metrics, such as precision, recall, F1-score, and overall accuracy. This evaluation transpired following an iterative process encompassing 400 epochs, which was undertaken to ascertain the accuracy of the training data across various label ranges. Notably, the precision values, which span from 0.96 to 0.99, within the classification report signify the LSTM model's remarkable precision across all distinct classes. This observation underscores the model's competence in minimizing the occurrence of false positive predictions, affirming its aptitude in correctly categorizing instances as positive solely when they genuinely pertain to their respective classes. Essentially, the LSTM model exhibits a pronounced capacity for ensuring the veracity of classification outcomes by effectively mitigating the occurrence of false positive predictions, a pivotal aspect in the pursuit of dependable classification results.

	precision	recall	f1-score	support
AGGRESSIVE	0.98	1.00	0.99	58
MODERATE	0.96	0.96	0.96	72
SAFE	0.99	0.99	0.99	334
accuracy			0.98	464
macro avg	0.98	0.98	0.98	464
weighted avg	0.98	0.98	0.98	464

Fig.3. Model Evaluation result with Recall, Precision and F1-Score

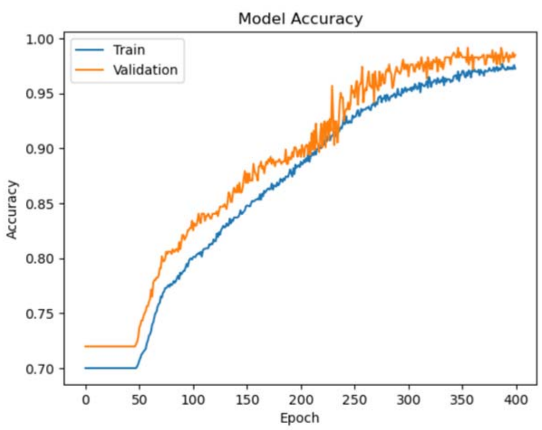

Fig.4. Result for Training and Validation Accuracy using LSTM.

Fig. 4 represented the results of the training and validation accuracy, getting the range for each label, calculating the percentage of each range label, and determining the driver behavior by the highest percentage calculated. The better accuracy may be attained utilising the LSTM algorithm within two to three minutes of the driving session. The model would be provided based on two minutes between two and three minutes due to the close proximity of three minutes and two minutes. In this report, the accuracy is 0.99, indicating that the model achieves a high overall accuracy

Fig. 5 displays the printed results of minimum and maximum values for each range label. The minimum value for the "AGGRESSIVE" range label is -1.64920, and the maximum value is 1.64655. The least value for the "MODERATE" range label is -0.50708, and the highest value is 0.5891. Finally, the "SAFE" range label's minimum and maximum values are -0.28300 and 0.3930 respectively. The following section provides the percentage of each range label in the dataset. It indicates that the "SAFE" range label accounts for approximately 70.41% of the dataset, the "MODERATE" range label represents about 17.21%, and the "AGGRESSIVE" range label comprises approximately 12.38%. Based on the highest percentage, it is determined that the driver behavior is labeled as "SAFE." This shows that most of the dataset's cases fall into the "SAFE" category.

```
                  min       max
Range Labels
AGGRESSIVE   -1.64920  1.64655
MODERATE     -0.50708  0.5891
SAFE         -0.28300  0.3930
Percentage of each range label:
SAFE          70.405522
MODERATE      17.213115
AGGRESSIVE    12.381363
Name: Range Labels, dtype: float64
Driver behavior: SAFE
Model saved successfully.
```

Fig.5. Results for Range, Percentage and Classification of each Range Label.

Analysis for driving behavior classification.

From Table 1, the results analysis reveals noteworthy patterns among the drivers' behavioral categories. Drivers 1, 3, and 4 exhibit a predominant inclination towards "AGGRESSIVE" driving behavior, encompassing a substantial 99.44% of the dataset. This suggests that these drivers consistently engage in aggressive driving practices. In contrast, Driver 2's dataset is notably skewed towards the "SAFE" driving behavior category, comprising approximately 68.88% of the data points, indicating a strong proclivity for safe driving practices. Conversely, Driver 5's dataset is marked by a prominent presence of the "MODERATE" driving behavior category, representing the highest percentage at 48.93% of the data points. This observation underscores Driver 5's characteristic inclination towards a moderate driving style.

The LSTM model demonstrated commendable proficiency in the prediction of driving behavior across all three distinct classes, namely "AGGRESSIVE," "MODERATE," and "SAFE." This proficiency is readily apparent through the attainment of elevated precision, recall, and F1-scores for each individual class, in addition to the model's impressive overall accuracy. These outcomes underscore the substantial importance of addressing and comprehending aggressive driving behaviors, as they contribute significantly to advancing road safety initiatives and fostering a culture of responsible driving practices.Overall, the results provides valuable insights into the driving behaviors exhibited by different drivers and highlight the effectiveness of the LSTM model in accurately predicting these behaviors. By understanding and categorizing driving behaviors, appropriate interventions and measures can be implemented to improve road safety and promote a culture of responsible driving.

Table 1. The parameters of the sensor

Driver	Behaviour result
Driver 1	Percentage of each range label: AGGRESSIVE 94.444444 MODERATE 3.838384 SAFE 1.717172 Name: Range Labels, dtype: float64 Driver behavior: AGGRESSIVE
Driver 2	Percentage of each range label: SAFE 68.888889 MODERATE 20.190476 AGGRESSIVE 10.920635 Name: Range Labels, dtype: float64 Driver behavior: SAFE
Driver 3	Percentage of each range label: AGGRESSIVE 74.940334 MODERATE 21.336516 SAFE 3.723150 Name: Range Labels, dtype: float64 Driver behavior: AGGRESSIVE
Driver 4	Percentage of each range label: AGGRESSIVE 99.148859 MODERATE 0.633828 SAFE 0.217313 Name: Range Labels, dtype: float64 Driver behavior: AGGRESSIVE
Driver 5	Percentage of each range label: MODERATE 48.938224 AGGRESSIVE 47.538610 SAFE 3.523166 Name: Range Labels, dtype: float64 Driver behavior: MODERATE

Conclusion

Within this research paper, a comprehensive driver behavior analysis was systematically conducted, encompassing iterative procedures encompassing data collection, preprocessing, formatting, LSTM model development, training, and subsequent evaluation. The implementation phase involved the utilization of Python, scikit-learn, and TensorFlow. Remarkably, the LSTM model adeptly harnessed temporal information inherent in the input data, thus obviating the need for extensive preprocessing steps. In sum, this project successfully realized precise driver behavior analysis by leveraging LSTM neural networks in conjunction with real-world data, reflecting a significant accomplishment in the field.

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