**An LSTM-Based Approach for Detecting Specific Harsh Driving Events Using Multi-Sensor Data**

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# Abstract

Harsh driving behaviours, including sudden acceleration, abrupt braking, and aggressive lane changes, pose significant risks to road safety as road traffic crashes are the sixth leading cause of disability-adjusted life years worldwide. This study presents a novel approach to detecting these specific harsh driving events using a Long Short-Term Memory (LSTM) model trained on time-series data from inertial sensors. A publicly available dataset, collected under controlled conditions, was used for model development. The dataset was preprocessed with a robust pipeline that included missing value removal, noise reduction using a Kalman Filter, and min-max normalization of magnetometer readings. Sensor measurements were generated with a sliding window technique to capture temporal dependencies in the data. The LSTM model, featuring three hidden layers and trained over 100 epochs with a cross-entropy loss function and Adam optimizer, demonstrated high performance in classifying seven types of driving behaviours. Achieving accuracy, AUC, and F1 scores of 84%, 0.97, and 0.84, respectively, on the test set, the model showcases the potential of LSTM-based architectures for real-time harsh driving detection. These findings highlight the feasibility of leveraging sequential sensor data for more granular event detection, paving the way for advanced driving safety applications.

**Index Terms—** Harsh Driving, Telematics Data, Driving Behaviour, Sensor Data, LSTM Model, Time-Series Data

# 1. Introduction

Driving behaviours such as speeding, sudden braking, aggressive lane changes, and inattentiveness are significant contributors to road traffic incidents. Road traffic crashes are the sixth leading cause of disability-adjusted life years (DALYs) worldwide and the only non-disease cause among the top 15 contributors to this metric. [1]. With approximately 1.3 million fatalities annually, road traffic crashes exceed major global health threats such as HIV/AIDS, tuberculosis, and diarrheal diseases. [2]. They are also the leading cause of death for children and young adults aged 5–29 years. [3].

Recent advancements in telematics and sensor technologies have revolutionized the study of driving behaviour. The term "telematics" refers to the integration of informatics and telecommunications, which has evolved into "automotive telematics.” Telematics systems, which integrate global positioning systems (GPS), accelerometers, and wireless communication technologies, enable the collection of high-resolution data on vehicle dynamics and driver actions [4], [5]. One significant advancement is the increase of in-vehicle driving data from large-scale naturalistic driving studies (NDS) [6]. These datasets provide continuous, objective information on driver behaviour, vehicle dynamics, traffic conditions, and environmental factors leading up to crashes. This has paved the way for the application of advanced analytical methods, including machine learning and artificial intelligence, to identify patterns of risky driving [7], [8], [9]. However, the high cost and rarity of crash data in NDS have necessitated the use of measures, such as harsh driving events, to predict crash risks and assess risky driving behaviours [10].

Harsh driving events, caused by actions like hard braking, sharp swerving, and sudden accelerations, occur more frequently than crashes and are easily captured by vehicle sensors. These events have been widely validated as substitutes for crash risk prediction and driver behaviour evaluation, with research showing their strong predictive value for crash likelihood [11], [12]. For example, hard-braking events, defined by significant deceleration along the vehicle’s longitudinal axis, are critical metrics for assessing evasive maneuvers or collision scenarios.

Moreover, understanding the human factors behind driving behaviours is critical. Studies reveal that human errors, including improper lookout, excessive speed, and inattention, are primary contributors to over 90% of crashes [13], [14]. By leveraging telematics data and computational models, researchers can evaluate these behaviours in real-time, offering opportunities for proactive interventions and improved safety measures.

While most existing studies focus on classifying overall driving behaviour into categories such as safe and harsh driving, they often overlook the identification and classification of specific harsh driving events such as sudden acceleration, sudden braking, sharp turning, and aggressive lane changing. These individual events are critical for a detailed understanding of driving behaviour and real-time risk detection. Our study addresses this gap by developing a novel system that not only classifies driving behaviour as safe or harsh but also detects and classifies specific harsh driving events using advanced LSTM-based machine-learning techniques. This approach enables a more granular and actionable understanding of driving behaviour compared to the broader categorizations used in prior work.

# 2. Related WORK

Early research in driving behaviour analysis often relied on statistical models and subjective evaluations by human observers, focusing primarily on assessing general driving risks [15]. Recent advancements in machine learning have enabled the development of predictive models that analyze historical data to identify risky driving behaviours, such as speeding, abrupt acceleration, lane changes, and near-collision events [16]. Trajectory-based acceleration indicators and accelerometer data have been particularly effective in detecting abnormal driving patterns, enhancing the precision of such analyses [17]. These studies often relied on acceleration and braking thresholds to identify events where predefined values were used to classify behaviours as risky [18]. While effective to some extent, threshold-based approaches can oversimplify the complexity of driving patterns and may miss nuanced behaviours.

Clustering and pattern recognition algorithms have been employed to categorize driving behaviours into clusters like aggressive, cautious, or routine driving, linking these clusters to accident risk levels [19]. Neural networks such as MLP have also shown promise in predicting driving features, such as acceleration distribution, but face challenges in visualizing and interpreting features in high-dimensional datasets [20], [21].

Much of the existing research has focused on monitoring drivers' gaze behaviour or analyzing general driving styles that may pose risks [20]. However, fewer studies have concentrated on specific features of aggressive driving, such as sudden acceleration, sudden braking, sharp turning, or abrupt lane changes. These behaviours, which are direct indicators of hazardous driving, are less frequently addressed in studies leveraging machine learning and data-driven techniques.

Additionally, many algorithms rely on data from smartphones, surveys, simulations, or controlled experiments. These approaches often face limitations, as real-world driving behaviours can differ significantly from those observed in simulated environments. Smartphone-based data analysis is also constrained by factors like device positioning, data inconsistency due to user interactions, and limited sensors, such as GPS and accelerometers [21], [22], [23], [24], [25]. This highlights the need for more robust methodologies to analyze specific risky driving features in naturalistic settings.

# 3. MATERIALS AND METHODS

3.1 Dataset Description

The dataset used in this study was sourced from an online repository [26]. The dataset is labeled and publicly available, making it an ideal benchmark for evaluating the effectiveness of our model in detecting and classifying harsh driving events. The dataset used in this study was designed to detect and classify harsh driving behaviours during a complete driving trip. Data was collected on a 4-lane paved road with no traffic, using a 2003 Mehran car driven by a single driver. The dataset includes six primary types of harsh driving events:

1. Sudden Acceleration
2. Sudden Braking
3. Left Sudden Turning
4. Right Sudden Turning
5. Left Aggressive Line Changing
6. Right Aggressive Line Changing

Each of these events is labeled as either safe or harsh, with safe driving instances labeled as 0 and harsh driving instances labeled as 1. The data is organized into multiple files, each corresponding to a specific type of harsh driving event, with variations in starting acceleration values to provide a diverse dataset for training and analysis.

3.2 Data Collection Method

The data was collected using an Arduino Uno microcontroller paired with an MPU9250 inertial sensor. The inertial sensor provides data on vehicle acceleration, gyroscopic movements, and angular velocity, which are essential for identifying various driving behaviours. This allows us to capture the dynamics of the vehicle and detect specific events such as sudden acceleration, braking, and aggressive turns. Fig. 1 shows the devices and axis orientations.

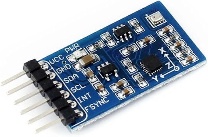
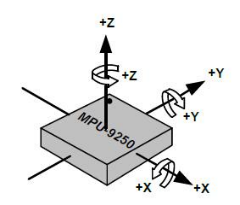


Fig. 1 MPU9250 inertial sensor (Left), MPU9250 inertial sensor axis orientation (Center), and an Arduino Uno microcontroller (Right)

3.3 Key Features and Parameters

The primary features used for classifying harsh driving events in this dataset include:

* Sudden Acceleration: Instances where the vehicle's acceleration exceeds a predefined threshold within a short time period.
* Sudden Braking: Instances where the vehicle decelerates rapidly, indicating hard braking or emergency stop scenarios.
* Aggressive Line Changing: Abrupt or high-speed lane changes.
* Sudden Turning: Sharp turns involving significant changes in direction at high speeds.

These key features are critical for identifying risky driving behaviours that could lead to accidents or hazardous driving conditions.

3.4 LSTM Model for Event Detection

In this project, a Long Short-Term Memory (LSTM) model was developed to detect harsh driving behaviour events. The LSTM model was chosen for its ability to effectively handle time-series data, such as vehicle motion and acceleration, as well as its capability to learn long-term dependencies from sequential data. While LSTM models have been used previously to classify driving behaviours, such as aggressive, drowsy, and normal driving [27], this study focuses on detecting and classifying specific harsh driving events within the dataset. The model was trained using the mentioned dataset, which contained time-series data from inertial sensors. Unlike the attempts made by the collector of that dataset, which was the identification of safe or harsh driving, we developed the model so that it can identify what type of harsh driving behaviour is evident from the data. In other words, instead of having 2 classes as output, we have 7 total distinct classes. Based on the increased complexity of the task, this requires the usage of all parameters at the same time as input parameters; Hence, the modeling algorithm must also accommodate for this increased complexity in data dimensions and output labels. The mentioned reasons are why we decided to use the LSTM model instead of more conventional and simpler algorithms.

3.5 Dataset Structure

The dataset consists of multiple files, each containing driving data from a complete trip, with varying driving speeds including 20 km/h, 40km/h, and 60km/h. Each file contains acceleration (m/s2), gyroscope (rad/sec), and magnetometer (µT) measurements from the three axes in the x, y, and z directions. The label of the current event type is also recorded for each measurement sample based on the beginning and ending times of these events. Some files only have measurements of a specific event separated from the main measurement records, while some have multiple labels in the same file.

3.6 Data preparation and model development

To ensure the reliability and accuracy of the sensor data, a data filtering and preprocessing pipeline was implemented. The raw driving data, collected from accelerometers, gyroscopes, and magnetometers, was initially checked for missing values, which were removed to avoid inconsistencies in subsequent analysis. Noise reduction was achieved using a Kalman Filter, a recursive algorithm for smoothing time-series data [28]. By leveraging this filter, the inherent noise from real-world conditions, such as road vibrations or environmental interference, was effectively minimized. Finally, the magnetometer readings were normalized using min-max scaling to bring all values within a standardized range of ([0, 1]). The output classes (i.e., driving event type) were encoded from string values to number format, during which some labels that referred to the same event were merged to further clean the data.

After data pre-processing, we generated data sequences of parameter measurements and the label corresponding to the end of this sequence. We decided to use a sequence length of 100 which is roughly 3 seconds of data. To make sure that our model is not overfitting, and we do not provide overly similar samples to the algorithm, we created these sequences with a moving window of 15 timestamps which roughly equals 0.4 seconds in real life. After generating the samples, we split the dataset into three subsets for training, validation, and testing. These subsets consist of 60%-20%-20% of the total samples, respectively. We used stratified sampling to ensure that the number of samples from each event type is roughly equal in all subsets and we have no bias in model development and assessment.

Using the measurements from all the three-axis (x,y,z) data from the accelerometer, gyroscope, and magnetometer sensors, we trained the model to classify the exact type of driving behaviour corresponding to that sequence. For dangerous driving, we used samples from 6 different behaviours. For safe driving, we used samples of diverse driving behaviours that were considered safe. In other words, multiple driving maneuvers were done in both safe and dangerous ways and their data was used to train this model, which improves the detection of safe and dangerous variations of common maneuvers. The cross-entropy loss function was used alongside an Adam optimizer to train the model for 100 epochs. The model’s architecture was designed to have 3 hidden LSTM layers, each comprised of 100 nodes. The input layer consists of 9 nodes for the 9 input parameters, and the output layer has 7 nodes corresponding to our driving type classes. Fig. 2 shows a flowchart of the model development and assessment process.

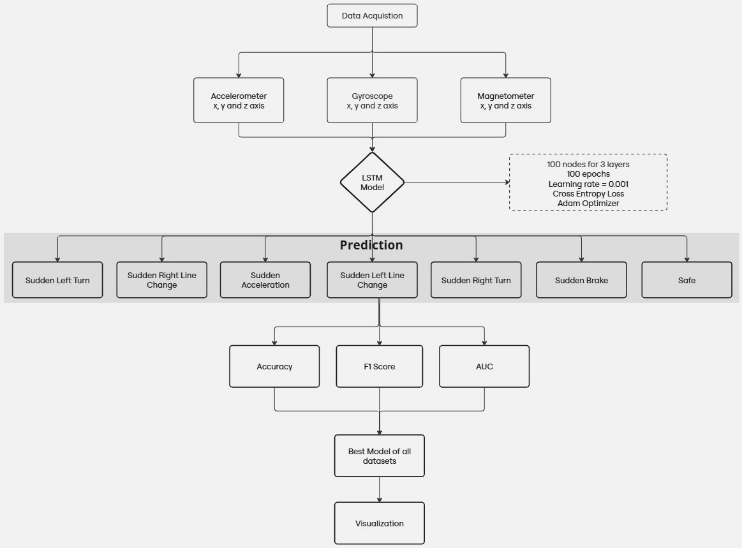


Fig. 2 Model development workflow

# 4. RESULTS AND DISCUSSION

Table 1 Summarizes the predictive performance of the model after the training and evaluation process. The results demonstrate that the LSTM model effectively detects specific harsh driving events, such as sudden acceleration, harsh braking, abrupt turning, and aggressive lane changes, from time-series data.

Table 1 Performance assessment results

|  |  |  |  |
| --- | --- | --- | --- |
| **Metrics** | **Accuracy** | **AUC** | **F1** |
| **Training Set** | 100% | 1.000 | 1.000 |
| **Validation Set** | 89.446% | 0.985 | 0.895 |
| **Testing Set** | 83.947% | 0.974 | 0.839 |

The best model’s performance on the training dataset was good which indicates that the model has successfully learned the patterns within the training data, showcasing its capability to identify harsh driving events. Moreover, the validation and testing dataset showed good results, highlighting the model’s ability to generalize to unseen data. These metrics, while lower than the training set, indicate that the model can still identify harsh driving behaviours in novel scenarios with reasonable precision. Finally, the high AUC values indicate that with careful classification threshold determination, the model can demonstrate even better performance in correctly classifying driving behaviour types. Therefore, the LSTM model is well-suited for capturing temporal dependencies in time-series data, such as sequential driving behaviours.

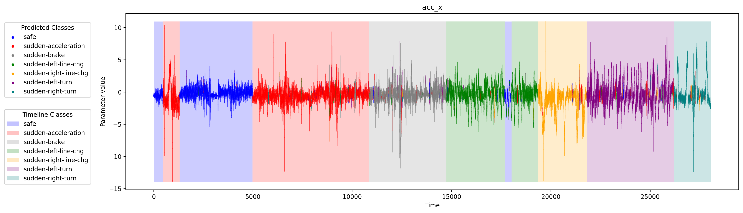


Fig. 3 Prediction results across the whole dataset against true labels (x-axis acceleration)

A graph of a graph

Description automatically generated

Fig. 4 Prediction results across the whole dataset against true labels (z-axis gyroscope)

For visualization purposes, we then process the whole dataset and predict event types for every sequence possible. The results can be seen in the above figures. Fig. 3 provides a detailed visualization of the acceleration in the x-axis signal, and Fig. 4 Visualizes gyroscope measurements in the z-axis. The plots are segmented by different driving behaviours such as sudden acceleration, sudden braking, sudden turning, and aggressive lane changing, highlighted in different colors. Plot points where the plot color is the same as the background of its timeline indicate correct classification, and vice versa. Most classes are predicted with high accuracy, while a few have more misclassified samples which could indicate difficulty in identifying their pattern, high similarity with other event classes, or lack of data samples for properly training the model for that event.

Each type of event is represented by distinct patterns in the acceleration data. For example, sudden acceleration is characterized by sharp, upward spikes in the signal, indicating rapid increases in forward motion, whereas sudden braking features abrupt drops, reflecting rapid deceleration. Sudden turning, on the other hand, introduces oscillatory or irregular patterns, reflecting lateral forces due to the rapid change in vehicle direction. Similarly, aggressive lane changes exhibit rapid variations in acceleration, indicative of quick swerves. In contrast, normal driving segments exhibit relatively stable and consistent acceleration values with minimal fluctuations, serving as a clear baseline for comparison.

4.1 Limitations

While the proposed LSTM model demonstrates strong performance in detecting harsh driving events, there were some limitations. First, this study relied on a sample dataset collected under controlled conditions, which may not fully represent the variability of real-world driving scenarios, such as diverse road conditions, vehicle types, and driver behaviours. Second, this dataset was relatively small, limiting the model's ability to generalize across broader populations and environments. Finally, while the model achieved high-performance metrics, further evaluation is required to assess its robustness under extreme driving scenarios. Addressing these limitations in future work could significantly enhance this model's applicability in real-world settings.

# 5. CONCLUSION

This study presents an LSTM-based method to identify specific harsh driving events, such as sudden acceleration or abrupt braking, instead of just labeling driving as safe or unsafe, marking a significant advancement in driving behaviour analysis. The data preprocessing process effectively removed noise, standardized sensor readings, and created sequences needed for training the model. The LSTM model performed well on training, validation, and testing datasets, showing its ability to learn and predict detailed driving events using data from multiple sensors. Unlike general classifications, this approach provides more detailed insights, making it useful for targeted safety systems. While the results are promising, further work is needed to address limitations, to improve its performance in real-world driving scenarios. This research sets the groundwork for scalable, real-world deployment of advanced driving behaviour detection systems

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