**Driver Behaviour Classification Using Neural Networks**

**Abstract**

Global road safety is a pressing issue with approximately 1.19 million people dying each year due to road traffic accidents, these incidents also being the leading cause of death for children and young adults aged 5–29 years. The economic impact of road traffic crashes is significant, costing most countries about 3% of their GDP. Considering these statistics understanding driver behaviour is crucial for enhancing road safety and reducing the number of accidents. Through this paper we present a comprehensive analysis of driver behaviour classification using advanced neural network models. By leveraging the capabilities of deep learning, we aim to capture and analyse the complex patterns and nuances of driver actions particularly classifying driver behaviour into three distinct classes: drowsy, normal, and aggressive. To achieve this classification, we used long short-term memory networks, leveraging its unique capabilities to interpret complex patterns, as for the data source we have used the UAH DriveSet dataset because of its comprehensive feature set, high quality data and real word driving scenarios. The results appear promising, achieving an overall F1 score of 0.98 with Long Short-Term Memory Networks.Through this work, we underscore the importance of leveraging AI and deep learning in tackling the challenges of road safety and driver behaviour analysis.

**Keywords**

Driver Behaviour, LSTM, Neural Networks, Machine Learning.

**Introduction**

In the realm of road safety, the staggering statistics of traffic accidents present a grim reality that demands innovative solutions. According to the World Health Organization, approximately 1.35 million people lose their lives each year because of road traffic crashes, with tens of millions more sustaining injuries that often lead to long-term disability. These figures not only reflect the immense human suffering but also highlight a significant economic burden on global healthcare and social systems. Amidst this critical challenge, the advent of advanced machine learning techniques, offers a promising horizon for enhancing road safety. By accurately classifying driver behaviours, machine learning models hold the potential to identify risky driving patterns and predict possible hazardous scenarios before they occur. This research paper delves into the application of LSTM networks in driver behaviour classification, aiming to contribute to the reduction of road traffic accidents and pave the way for safer driving environments. Through a meticulous analysis of driver behaviour data, this study seeks to demonstrate how LSTM-based models can serve as a pivotal tool in the ongoing effort to mitigate traffic-related fatalities and injuries, marking a significant stride towards the intelligent transportation systems of the future.

This research utilizes the capabilities of the UAH DriveSet [6], an extensive and meticulously curated dataset, designed explicitly for the facilitation of advanced investigations into driver behaviour analytics and the enhancement of driver assistance systems. UAH-DriveSet utilizes the DriveSafe app, developed by the authors, to collect a comprehensive set of data across various driving conditions. The dataset encompasses over 500 minutes of driving, covering six different drivers in six vehicles including one fully electric vehicle, demonstrating three distinct driving behaviours—normal, drowsy, and aggressive—across five types of roads - motorways, motorway links, primary roads, primary link roads and tertiary link roads. This rich dataset includes raw data from smartphone sensors like GPS, accelerometers, gyroscopes and video recordings of the trips, providing both raw and processed data for detailed analysis. In this study we are specifically focusing on the vehicle dynamics measurements and GPS tracking data to accurate classify driver behaviour into three categories namely Normal, Drowsy, Aggressive.

The entire process unfolds in stages, beginning with data collection, followed by data pre-processing, then model creation and training, and finally evaluating the performance of the model.

**Literature Survey**

We referred several prior studies in the field of driver behaviour classification, which are discussed below.

In study [1] researchers employ machine learning classification methods to identify drivers’ behaviour and distraction situations based on real world data acquired through the UAH DriveSet dataset. Results in the study demonstrated that gradient boosting algorithms outperforms the other used algorithms.

Logistic Regression, Gradient Boosting Classifier, and Random Forest Classifier methods are applied on the UAH DriveSet dataset to classify driver behaviour into normal, drowsy, and aggressive states in study [2]. The study concludes that the Gradient Boosting algorithm exhibits the highest performance among the evaluated classifiers in identifying driver behaviour states.

Driver behaviour analysis tool that uses data from in-vehicle sensors from CAN-BUS, an Inertial Measurement Unit , and GPS to detect aggressive driving behaviours is proposed in paper [3].The proposed system integrates data from these sources using advanced data fusion techniques. Extensive analysis is done on this fusion data to classify the driver behaviour.

In study [4] Driver Behaviour Profiles are constructed through detailed GPS and spatiotemporal data analysis—and highlights the findings that spatiotemporal contexts significantly influence driver behaviour patterns, which are crucial for road safety analysis and interventions.

Study [5] focuses on advancing understanding of driving behaviour within the Driver–Vehicle–Environment (DVE) system by outlining a conceptual framework and conducting a systematic literature review of machine learning applications in Driver Behaviour analysis.

The UAH-DriveSet, a publicly available dataset aimed at facilitating driving behaviour analysis through machine learning is introduced in study [6]. The dataset comprises of over 500 minutes of naturalistic driving data from 6 different drivers performing normal, drowsy, and aggressive driving behaviours across motorway and secondary roads.

A comprehensive methodology for modelling intelligent driving behaviours using a driver behaviour model that integrates multiple modules for data acquisition, classification, and driver ride profiling is proposed in paper [7]. It employs an Artificial Neural Network utilising static and dynamic non-linear autoregressive approaches for accurate behaviour prediction.

Study [8] presents an approach to calculating drivers' risk profiles using predictive modelling based on supervised machine learning techniques. The study identifies 13 behavioural risk predictors to develop a feature matrix, various machine learning models are then evaluated for their performance in risk prediction.

Classification system for identifying core driving profiles of Heavy Goods Vehicle drivers in the UK, using data from 2014 to 2016 is proposed in study [9]. The study employs a 2-stage classification framework involving consensus clustering and classification to identify 11 driving profiles, which are then refined into 7 core profiles. These core profiles are used to train decision trees that classify drivers with high accuracy.

Study [10] introduces a driver identification system employing Support Vector Machine and Universal Background Model schemes. The methodology focuses on analysing accelerator and brake pedal signals from a vehicle's CAN bus. The system demonstrated over 95% accuracy in driver identification, with UBM schemes.

The application of Support Vector Machine and K-Nearest Neighbours machine learning techniques to classify driving behaviours into safe and unsafe stopping at signalised junctions during the yellow signal phase is explored in study [11]. The findings indicate SVM with a linear kernel, outperforms other methods, achieving high accuracy in classifying driving behaviours.

A mobile application designed to predict driver behaviour using classification techniques like K-Nearest Neighbour, Support Vector Machine, and Decision Trees, leveraging data from GPS, accelerometer, gyroscope, and magnetometer sensors is discussed in study [12]. The study found Decision Trees to be the most effective classifier for identifying safe and unsafe driving behaviours, such as harsh acceleration and turns, enabling real-time mobile alerts to drivers to enhance road safety.

Classifying driving behaviour using short-term and long-term summaries of sensor data (acceleration and speed) from telematics devices is presented in study [13]. The authors utilised k-Nearest Neighbours, Support Vector Machines, and decision trees as classification approaches. The results demonstrated that decision trees achieved the highest classification accuracy, significantly outperforming Recurrent Neural Network (RNN)-based approaches.

**Methodology**

**Data Collection**

In this step we concatenated the UAH DriveSet, organising data by drivers and their conditions, including various driving behaviours on secondary roads and motorways. Functions are defined for parsing and pre-processing different datasets such as GPS, accelerometer, lane detection, vehicle detection, and OpenStreetMap data, where unnecessary columns are removed, and appropriate column names are assigned. Then the datasets are merged into a single data frame based on timestamps to ensure temporal alignment, adding a 'Behaviour' label to classify driving conditions. This merging process is repeated for each driver across different conditions, ultimately concatenating these into a comprehensive dataset that combines all drivers' data for subsequent analysis and model training, demonstrating a methodical approach to prepare a driving behaviour dataset for in-depth studies.

**Data Pre-processing**

We pre-processed the concatenated UAH DriveSet by initially loading the dataset and dropping unnecessary columns, such as indices and timestamps. We eliminated duplicated and irrelevant columns, focusing particularly on those related to GPS speed and OSM queries, to streamline the dataset. Furthermore, we refined the data by filtering out implausible speed, accelerometer readings, and GPS accuracy values to ensure the dataset accurately reflects realistic driving conditions. We managed the encoding of categorical variables like road type and driving lane by applying one-hot encoding which is a technique used to convert categorical variables into a binary representation, where each category is represented by a binary vector with only one element set to 1 indicating the presence of that element and all others set to 0 indicating their absence. This method enables algorithms to better understand and process categorical data.To mitigate multicollinearity, we identified features with high intercorrelations through heatmap analysis and subsequently dropped them. Our final steps included removing selected binary columns to further prevent bias and multicollinearity, culminating in the export of a cleaned and pre-processed dataset, now ready for analytical or modelling purposes.

**Model Creation and Training**

Long Short-Term Memory (LSTM) networks constitute a specialized class of recurrent neural networks (RNNs) meticulously engineered to address the challenges of learning long-term dependencies in sequential data. Characterized by their intricate architecture featuring memory cells and gating mechanisms, LSTMs possess the ability to retain and selectively update information over extended temporal sequences. These networks employ a suite of gating units, including forget, input, cell state update and output gates, which facilitate the regulation of information flow within the network.

The forget decides the information the cell should discard from the previous state. Equation 1 determines which information the cell will discard from the previous state. *W\_f*​ and *b\_f*​ are the weights and bias for the forget gate, *h\_t*−1​ is the previous hidden state, *x\_t*​ is the input at time step *t*, and *σ* represents the sigmoid function.

The input gate decides which new information is stored in the cell state, in equation 2 and 3 represents the candidate values that could be added to the state.

The cell state update represents the internal memory of the LSTM unit, updated based on the input and forget gates information. Equation x+3 updates the cell state by combining the old state (Ct-1 ​) and the new candidate values, modulated by the forget gate (ft​) and input gate (*it*​) respectively.

Output gate controls the amount of information from the cell state to output at the current time step. Equation 5 and 6 determines the next hidden state (*ht*​), which is based on the cell state but filtered by the output gate.

These equations succinctly encapsulate the operations within an LSTM cell, detailing the mechanisms by which it regulates information flow and memory.

In the investigation of driver behavior classification using the LSTM model, a meticulous approach to data division and preprocessing was adopted, utilizing K-Fold cross-validation to ensure robust model validation across diverse subsets of the dataset. A crucial step in this process involved the computation and application of class weights because of the imbalance in instances for each class as shown in table [1], thereby ensuring a fair representation and consideration of all classes during the model's learning phase. Further, the data underwent normalization through MinMaxScaler, aligning feature values within a standardized range of 0 to 1, a vital precondition for enhancing model convergence. Additionally, the data was reshaped to meet the LSTM model's input specification, signifying a singular time-step per sample, a configuration pivotal for the subsequent modeling phase.

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| --- | --- | --- |
| Sr. No. | Behaviour | No. of Instances |
| 1 | Normal | 12,998 |
| 2 | Drowsy | 9,903 |
| 3 | Aggressive | 7,839 |

Table 1. No of instances for each driving behaviour

The architecture of the LSTM model was intricately designed, comprising a series of LSTM layers, each characterized by a distinct count of units, return sequences settings, and the tanh activation function. This layered arrangement was deliberately engineered to adeptly capture the temporal dependencies inherent in the dataset, a feature crucial for decoding the nuanced patterns of driver behavior. Interspersed between these LSTM layers were Dropout and BatchNormalization layers, integrated to forestall overfitting and ensure model training stability. Culminating the model architecture was a Dense layer equipped with a softmax activation function, tailored for the multi-class classification task at hand.

For model compilation and training, the Adam optimizer was selected, paired with the categorical crossentropy loss function, and augmented by metrics including accuracy, precision, and recall, reflecting their conventional application in multi-class classification scenarios, providing a balanced framework for evaluating the model's capability to classify driver behaviours accurately. The introduction of an early stopping mechanism, aimed at ceasing training upon validation loss stagnation, further underscored the preventative measures against overfitting. Training was conducted over an extensive span of 600 epochs. The application of class weights during training adjusted the significance of samples based on their class, a methodological process addressing the prevalent issue of class imbalance.

**Results**

Upon the culmination of training across each fold, predictive performance was analyzed, including the F1 score—a harmonic mean of precision and recall, serving as a critical indicator of the model's balanced performance, especially in scenarios of class imbalance. Precision, delineating the model's accuracy in predicting positive instances, and recall, indicating the model's ability to capture all relevant positive samples, were also individually examined.

The scikit-learn classification report provides these metrics for each class in the classification problem, as well as an overall weighted average.

Table 2 provides a breakdown of the model's performance across different folds in the cross-validation process, showing consistency in training and validation accuracy, precision, and recall. This consistency across folds validates the model's robustness and its generalizability to new, unseen data, ensuring its reliability in practical applications for enhancing road safety through the classification of driver behaviour.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Fold** | **Training**  **Accuracy** | **Training Loss**  **(Crossentropy)** | **Training**  **Precision** | **Training**  **Recall** | **Validation**  **Accuracy** | **Validation Loss**  **(Crossentropy)** | **Validation**  **Precision** | **Validation**  **Recall** |
| 1 | 97.68 | 0.06371 | 0.977128 | 0.976334 | 97.66 | 0.07645 | 0.977055 | 0.976578 |
| 2 | 97.44 | 0.06822 | 0.975009 | 0.974097 | 96.15 | 0.11159 | 0.962058 | 0.960963 |
| 3 | 97.52 | 0.06498 | 0.975463 | 0.974789 | 98.24 | 0.06164 | 0.982590 | 0.982271 |
| 4 | 97.96 | 0.05398 | 0.979980 | 0.979343 | 98.63 | 0.04812 | 0.986819 | 0.986337 |
| 5 | 97.65 | 0.06195 | 0.977122 | 0.976049 | 98.08 | 0.06282 | 0.981120 | 0.980481 |

Table 2. Fold wise model performance.

Table 3. provides the evaluation metrics for each class i.e. normal, drowsy, and aggressive. The high precision values indicate that the model is highly accurate in its positive predictions for each class, meaning that when it predicts a class, it is correct most of the time. The high recall values indicate that the model is excellent at identifying all instances of each behaviour class within the dataset.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| **Class 1** | 0.97 | 0.98 | 0.98 | 1625 |
| **Class 2** | 0.98 | 0.98 | 0.98 | 1995 |
| **Class 3** | 0.98 | 0.98 | 0.98 | 2528 |

Table 3. Evaluation metrics of each class.

**Conclusion**

The study on driver behaviour classification using Long Short-Term Memory (LSTM), demonstrates a promising approach to enhancing road safety by categorizing driver behaviour into normal, drowsy, and aggressive states. Leveraging the UAH DriveSet dataset, the research achieved notable results, including precision, recall, and F1-scores nearing perfection (97% for precision and recall, and 98% for F1-score across all classes) as detailed in the results section. These outcomes, indicative of the models' efficacy in capturing and analysing complex driver behaviour patterns, underscore the significant potential of applying advanced neural networks in developing intelligent driver assistance systems and contributing to the reduction of traffic accidents through real-time behaviour classification and intervention.

**References**