2022-01

A Practical Deep Learning Approach to Detect Aggressive Driving Behaviour

Talebloo, Farid

UNIVERSITY OF CALGARY

A Practical Deep Learning Approach to Detect Aggressive Driving Behaviour

by

Farid Talebloo

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF SCIENCE

GRADUATE PROGRAM IN ELECTRICAL ENGINEERING

CALGARY, ALBERTA

JANUARY, 2022

Abstract

Accidents while driving might result in minor injuries. Alternatively, it might result in a loss of life, which is highly detrimental to society. The loss of an expert due to fatalities can have a tremendous influence on humanity's scientific growth. Three factors can lead to accidents on the road: 1) The human, 2) the road, and 3) the vehicle. We look at the first element in our analysis, accounting for 93 percent of all accident causes. We will not look at the psychological aspects of driving behaviour in this study. The first step is to classify the vehicle; Self-driving vehicles and regular automobiles, both of which may be used to evaluate driving, are the two types of vehicles that can be checked. Aggressive driving behaviours have been identified as one of the most critical subcategories of human factors that contribute to accidents. To prevent road accidents, constant monitoring of drivers' driving behaviour can modify the driver's driving behaviour or notify the driver of a potential hazard. As a result, it is vital to devise a method of detecting aggressive driving behaviour.

Aggressive driving is every day among American drivers. According to AAA Foundation for Traffic Safety data from 2019, approximately 80% of drivers displayed severe anger, hostility, or road rage while driving at least once in the preceding 30 days. Aggressive driving has been a significant source of concern for many road users.

There are numerous methods for detecting aggressive driving behaviour, including changes in vehicle speed, lane shifts, eye and hand movement analyses, and others. We conducted this study using deep machine learning approaches rather than classic time series analysis methods. We analyzed roughly sixty similar publications to learn the procedures employed in the prior studies. The CNN was utilized in most publications to determine how to drive. We used RNN algorithms

to execute this experiment since the vehicle GPS data is a time series. We employed an external test technique during the experiment that was not used in earlier studies that dealt with the same data set. The provided model produced satisfactory results incorporated in the dissertation's conclusion.

Preface

The submissions by the author of this dissertation which include materials and ideas presented in this thesis are listed in this preface. We consider that these articles have not been peer-reviewed yet; we are trying to publish them in upcoming journals and conferences.

Chapter 2 of this thesis has been submitted as "Dynamic and Systematic Survey of Deep Learning Approaches for Driving Behavior Analysis," Farid Talebloo, Emad A. Mohammed, Behrouz H. Far,

https://arxiv.org/abs/2109.08996

Chapter 3 of this thesis has been submitted as "Deep Learning Approach for Aggressive Driving Behaviour Detection," Farid Talebloo, Emad A. Mohammed, Behrouz H. Far

https://arxiv.org/abs/2111.04794

Acknowledgements

During my study, the pandemic happened, and many other students and I undoubtedly went through horrible circumstances. Professor Far was always a supportive professor; they never left me alone with difficulties. It was an honour for me to learn not just sciences but also personality and humanity from them. I want to express my sincere gratitude to Professor Far for allowing me to work in their lab on such a great project. Without their guidance and kind helps, this project would not have been possible.

I would also thank my co-supervisor, Dr. Emad A. Mohammed, for his extremely nice technical supports along with the project. I will never forget his quick and very helpful responses to the emails. They work compassionately to teach and guide me.

It is an honour to thank Dr. M. Gregory Tweedie for their thoughtful suggestions on scientific and editorial points. It was a great opportunity to work with them on an interdisciplinary (English linguistic and AI) project.

I would like to thank Dr. Amir Sanati Nezhad (and their colleagues) and Dr. Moshirpour, who helped me be a suitable mentor for a capstone project that led to a practical application (to help covid-19 detection).

And all my instructors, faculty members, lab colleagues, friends who have always tried to survive me in difficult situations. Without all your help, this would not have happened.

Dedication

To my mother, to my father.

Table of Contents

List of Tables

List of Figures and Illustrations

List of Symbols, Abbreviations and Nomenclature

DBA	Driving Behaviour Analysis
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
WHO	World Health Organization
GPU	Graphic Processing Unit
AE	Auto Encoder
IEEE	Institute of Electrical and Electronics Engineers
ACM	Association for Computing Machinery
DL	Deep Learning
ML	Machine Learning
AI	Artificial intelligence
CNN	Convolutional Neural Networks
DBC	Driving Behaviour Classification
GPS	Global Positioning System
GRU	Gated Recurrent Unit

Chapter One: Introduction

1.1 Background

Each year, over 1.3 million individuals are killed in automobile accidents. Road traffic accidents cost most countries 3% of their GDP. More than half of all road traffic fatalities occur among vulnerable road users, such as pedestrians, cyclists, and motorcyclists. Despite having about 60% of the world's automobiles, low- and middle-income nations account for 93 percent of road deaths. Road traffic accidents are the leading cause of mortality for children and young people aged 5 to 29 [1]. Road traffic accidents have been a significant source of injury and death in most countries. Road accidents are the eighth-most significant cause of mortality worldwide, according to the World Health Organization [2]. Only human factors accounted for roughly 90% of road crashes, aside from vehicle and environmental variables [3].

It is possible to help the driver be more confident in the decision he makes at any given moment due to obstacles and crossings. Ryder et al. [4] discovered that in-vehicle warnings about accident hotspots enhance driver behaviour over time. As a result, they show that DSSs and design research may be useful in the field of connected automobiles, which has traditionally not been a critical focus of DSSs and information systems research. Research has been conducted that confirms the relationship between psychological tests and driving behaviours. Psychological tests can help score drivers' driving behaviour regarding Marjana et al. [5] proposed an assessment and decision support model. They believed using their model when a driver should be examined about their propensity for traffic accidents, based on an estimation of their psychological traits.

There may be issues or perspectives that are not obvious at first glance, but extensive research has measured them. For example, being familiar with the road (the experience of driving on the road before) is one of those examples. Intini et al. [6] have proved road familiarity as an influential factor in accident risk, presumably due to distraction and more unsafe behaviours caused by overconfidence. In this work, we employed a database that requested drivers to drive aggressively, then fed the data into the model to uncover its in-depth patterns. The model will be able to find those patterns in the test dataset to be evaluated. They believed that while crashes involving unfamiliar drivers may cluster in locations with substantial summer traffic variation and maybe more common during the summer months, several correlations between accident-related variables and the measured drivers' unfamiliarity remain unknown (such as the proneness to different accident types) [6].

On the other hand, Kalsi et al.'s [7] study support that sleep deprivation is a significant risk of fatal car accidents. They confirm that sleep deprivation is a health-related issue on its own. After a period of sleep deprivation, anyone can fall asleep unknowingly. Drivers should be more aware of the dangers of sleep deprivation in terms of road safety. As a general guideline, one should sleep at least 6 hours before driving for an extended amount of time [7]. There are different definitions for aggressive behaviour. In the belief of Archer et al. [8], a behaviour is aggressive when there is a desire to inflict harm, and if the persuasion is successful, it will result in psychological pain. However, there is a problematic dividing line between using such a method openly to harm someone and using it covertly, for example, to advance oneself in an organizational context [8], or in our context, the way of driving that will harm others. Aggressive driving presents itself in various ways, including vocally, physically, and via the course of driving on vehicles [9].

1.2 Research Motivation and Relevance

The main motivation came from a question from the Professor Behrouz H. Far (research supervisor) sparked the idea for the study: Is it possible to identify aggressive driver behaviour in self-driving cars while driving by finding the patterns in their raw GPS data? When the automobile is in auto mode, continue driving in the manner with which the driver is most comfortable. During studies and meetings, we narrowed the scope of the research. In response to the topic of what technologies are available for detecting driving behaviour in both types of cars, So, first and foremost, we attempted to review the articles on this topic. The literature review yielded a survey paper in chapter two. Scope We have specialized in reviewing publications in the technical methodologies used with the deep machine learning methodology. We discovered a lack of approach to high-risk driving diagnostics after listing all the technologies and methodologies. We next presented a model employing deep machine learning approaches on a labelled dataset. Research in the field of intelligent transport optimization conducted (or is conducting) in Professor Behrouz H. Far's laboratory falls into three general categories: optimization and intelligence before driving, while driving, and gathering information for Analysis after completing a driving course. The research that I have concentrated on, is in the category of smart driving safety optimization. It has been highlighted in the following figure.

The Optimization of the Intelligent Transportation System		
A course of transportation		
Before	During	After
(Prediction and Planning)	**(Driving Behaviour Analysis)**	(Traffic Analysis)
Vehicle Trajectory Prediction with Gaussian Process Regression in Connected Vehicle Environment [10].	**Deep Learning Approach for Aggressive Driving Behaviour Detection [11].**	Managing Urban Traffic Networks Using Data Analysis, Traffic Theory, and Deep Reinforcement Learning [12].

Table 1 Research big picture

Regarding the optimization of safety while driving, in this research, an attempt has been made to inform the driver of a possible danger. By sending a portion of the vehicle's GPS information to the model, it labels that portion of the trip into one of two aggressive or non-aggressive modes.

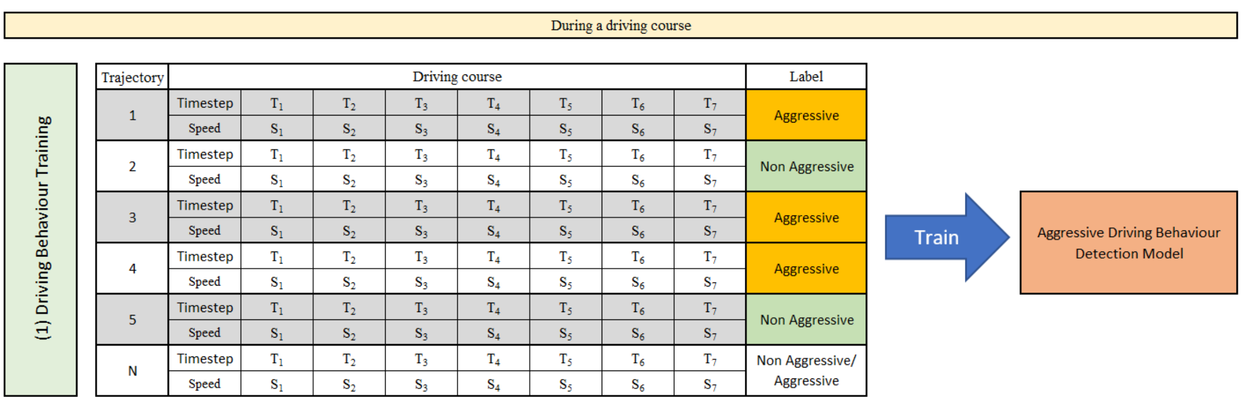


Figure 1 Model training phase

There are two main phases for model design in this research. First, model training with labeled data, and second, using the model to classify drivers' trips into two categories: aggressive and non-aggressive.

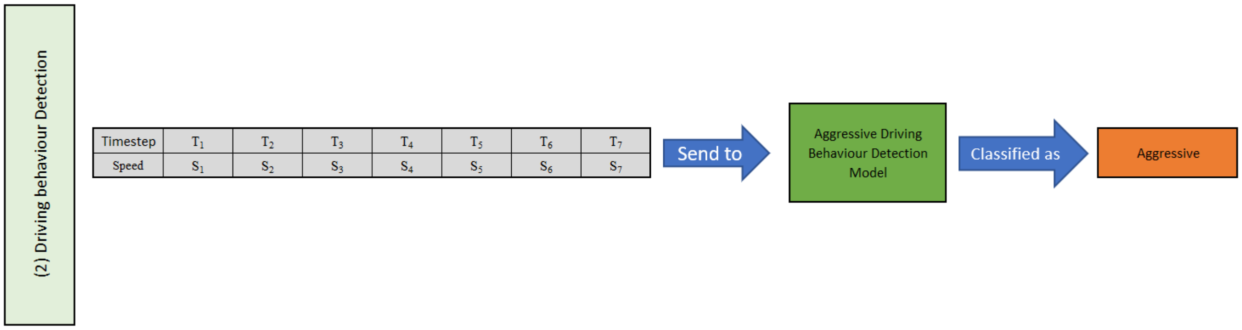


Figure 2 Classification phase

1.3 Research Objectives and Questions

There are two primary goals for conducting research, which is then broken into smaller objectives. The primary purpose is to research and examine scientific approaches for detecting high-risk driving. The dilemma here is whether the tactics used are psychological methods or the aim and the driver's current attributes. To answer it, we will not conduct behavioral research so we will do the pattern recognition methods to find aggressive driving behaviour. Is it done using traditional methods or machine learning approaches if it is a formulation method? Is it a subset of deep machine learning if machine learning methods are used?

The second purpose is to see if, after analyzing existing technologies, a new approach or method to improve on past methods can be presented. What is the new method's adequacy? To what extent does the provided approach have a discrepancy between laboratory and actual results? What approach is offered, and why is this technique presented?

1.4 Research Methodology and Scope

The first goal includes any scientific work completed between October 2015 and September 2020 with keywords containing "Driving Behaviour Analysis" and "DL algorithms," concentrating on computer-related journals and databases such as IEEE, ACM, Scopus, and Springer. We omit classical ML, psychological driving analysis, and any paper published after the dates specified. Furthermore, thanks to the "dynamic survey" technique, which means "adding papers dynamically in the future," our database will include all related papers on future dates.

The second goal comprises a proposed model that can detect aggressive driving patterns in less than 3 minutes (the choice of 180 seconds will be discussed later in this research) by gathering GPS data every second. We investigate two RNN-based approaches (GRU and LSTM) in a variety of scenarios.

The studies were evaluated in two ways: 1) by separating the dataset into training, validation, and test datasets; and 2) reserving a driver dataset for the real-world test.

1.5 Research Benefits

What makes some people more prone to road rage, and how to keep them from becoming a danger on the road. Environmental factors such as crowded roads can boost anger behind the wheel. In this study, we can alert aggressive driving behaviour and lots of casualties by detecting aggressive driving at the right time and location. The difference between the proposed model and a simple high speed detection application is described in the following. Our model deeply went through all the different experiments of aggressive driving behaviour and captured all aggressive patterns with

RNN (LSTM/GRU) methods. Sometimes a driver is not driving over speed but changing lanes in a aggressive mode.

1.6 Research Contributions

This research contains two parts: 1) A survey paper of “driving behaviour analyses” articles in the defined scope. The survey paper studies algorithm and approaches of pieces of literature on this subject that leveraged deep machine learning methods. This survey paper also presents the term “Dynamic survey” that tries to auto-update the articles' database. The methodology of the dynamic survey is a crawler that browses popular journals to find any science movements on the driving behaviour analyses. Although this is not a direct contribution of practical deep learning approach, but we designed this crawler to be sure not eliminated any research during our experiments and study.

2) A proposed model detects aggressive driving behaviour with a deep learning algorithm (Stacked LSTM) with a high confidence score. It leverages GPS-only data, extracts new data features, smartly converts input data shape, and then classifies to two classes of “Aggressive” and “Non-Aggressive.” It is evaluated with a real world-test and is reached to a high promising evaluated score.

1.7 Organization of Thesis

This thesis is organized into three chapters. The first chapter discusses the research's history and introduction of the fundamental research. The second chapter is a literature review created as a dynamic survey and submitted to the "arXiv.org" as a preprint. The third chapter includes an aggressive driving behaviour detection model submitted to the "arXiv.org" as a preprint.

Chapter 2: "Dynamic and Systematic Survey of Deep Learning Approaches for Driving Behavior Analysis," Farid Talebloo, Emad A. Mohammed, Behrouz H. Far

Chapter 3: "Deep Learning Approach for Aggressive Driving Behaviour Detection," Farid Talebloo, Emad A. Mohammed, Behrouz H. Far

Chapter Two: Dynamic and Systematic Survey of Deep Learning Approaches for Driving Behavior Analysis

2.1 Introduction

2.1.1 Abstract

Improper driving results in fatalities, damages, increased energy consumptions, and depreciation of the vehicles. Analyzing driving behaviour could lead to optimizing and avoiding mentioned issues. By identifying the driving and mapping them to the consequences of that driving, we can get a model to prevent them. In this regard, we try to create a dynamic survey paper to review and present driving behaviour survey data for future researchers in our research. By analyzing 58 articles, we attempt to classify standard methods and provide a framework for future articles to be examined and studied in different dashboards and updated about trends.

2.1.2 Keywords

driving behaviour identification, driving behaviour analysis, dynamic survey, deep learning approaches, intelligent transportation systems.

2.1.3 DBA Introduction

The lives of nearly 1.35 million people are lost every year due to road traffic accidents [13]. Between 20 and 50 million more people suffer non-fatal injuries, many of whom experience disability due to injuries [13]. More than 32,000 fatalities occurred in the US in 2013 due to drunk driving and speeding, leading to more than 19,500 deaths [14]. Even with these staggering numbers in the US, China has the most road traffic accidents globally. There were 8934 traffic accidents in 2016, causing 5947 deaths and 11,956 injuries on China's freeways. Although freeways account for just 2.8% of the overall length of public roads in China, traffic collisions, casualties and fatalities accounted for 7.7%, 9.4% and 13.7% of all traffic accidents, injuries, and deaths. Compared to other road grades, the collision rate, damage rate and death rate per 100 km of Chinese highways are 3.0 times, 3.8 times and 5.1 times higher, respectively [15].

One of the innovations developed in vehicles today to meet the need for protection and comfort in driving is Advanced Driver Assistance Systems or ADAS. ADAS are vehicle control systems that use environmental sensors (such as radar, laser, vision) to enhance driving comfort and safety by helping drivers identify and respond to potentially unsafe traffic situations. One of the primary ADAS studies relates to model driving behaviour. Driving behaviour research needs to be carried out because, based on WHO data, driver factors are among the leading causes of vehicle accidents. Examples of driver factors include over-speed speeding, drunkenness; exhaustion; dark road driving; impaired visibility; and vehicle quality factors [16]. The most vital aspect of on-road driving safety is the behaviour of drivers. The level of driving skills (e.g., professional; beginner) affect driving behaviour, and the set of decisions made at any given moment in driving may lead to one type of driving behaviour at each stage. On the other hand, driving events such as acceleration, deceleration; turning; braking lead to driving behaviour. These two separate sets are affected by the prevailing driving conditions such as traffic, weather, cars, and roads [17].

2.1.4 Scope of research

The scope of this survey paper includes all the research work performed between October 2015 to September 2020, having keywords with "Driving Behaviour Analysis" and "DL algorithms," focused on computer-related journals and databases including IEEE, ACM, Scopus, and Springer. We exclude traditional ML, psychological analysis of driving, and any paper out of the mentioned dates. Moreover, fortunately, with the algorithm of the "dynamic survey," which means "adding papers dynamically in future," our database will include all related papers on future dates.

2.1.5 Dynamic Survey Approach

It is common for "Survey papers" to usually limit the scope and study them so that the researchers will review them over a period. Consequently, after publishing the paper, any activity such as new articles or new chapters of a book related to the topic to be published after the survey paper should be considered in a new survey paper. Nevertheless, in this dynamic survey, the included articles will be updated using an algorithm in its database. (Although, this section does not have a direct relation to the main subject of the thesis, but it helped us not to miss any studies during our research. And on the other hand its an original method that can help other researchers as well.)

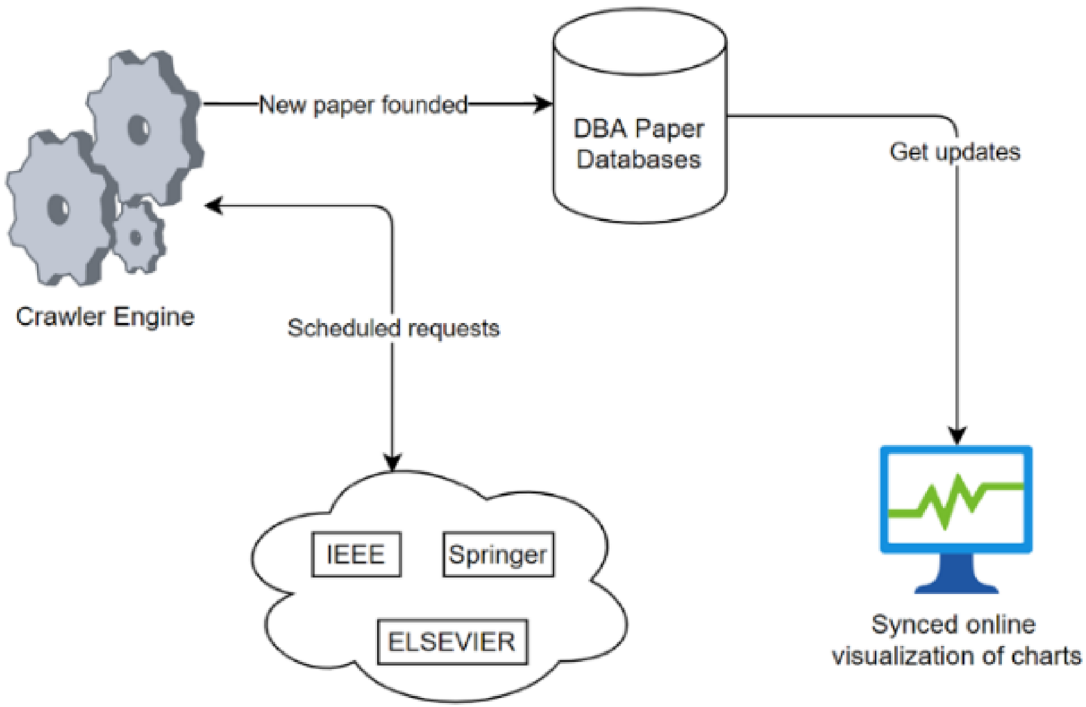


Figure 3 Dynamic survey mechanism

In the following, we explain how the algorithm works: in this mechanism, first, we adjust the recurrence period (i.e., daily, weekly, monthly) of the web requests. Then, it starts sending web requests to the APIs of defined journals (i.e., IEEE, Elsevier, Springer, …) to get the list of newly submitted articles in DBA. After receiving the list of newly published articles, it compares them with the existing list in the database to avoid duplicating an article.

Finding a new paper submitted related to DBA is not enough; we needed a space to store the data. We decided to use a relational database (i.e., MS SQL Server). Other advantages of using the relational database are avoiding redundant data, ease of inquiry, easily transferable, high security, and high efficiency. In designing a normalized database, we tried to make it article-centric. The newly found article title and core information will store in the main table, and other pieces of data will be stored and pointed to it.

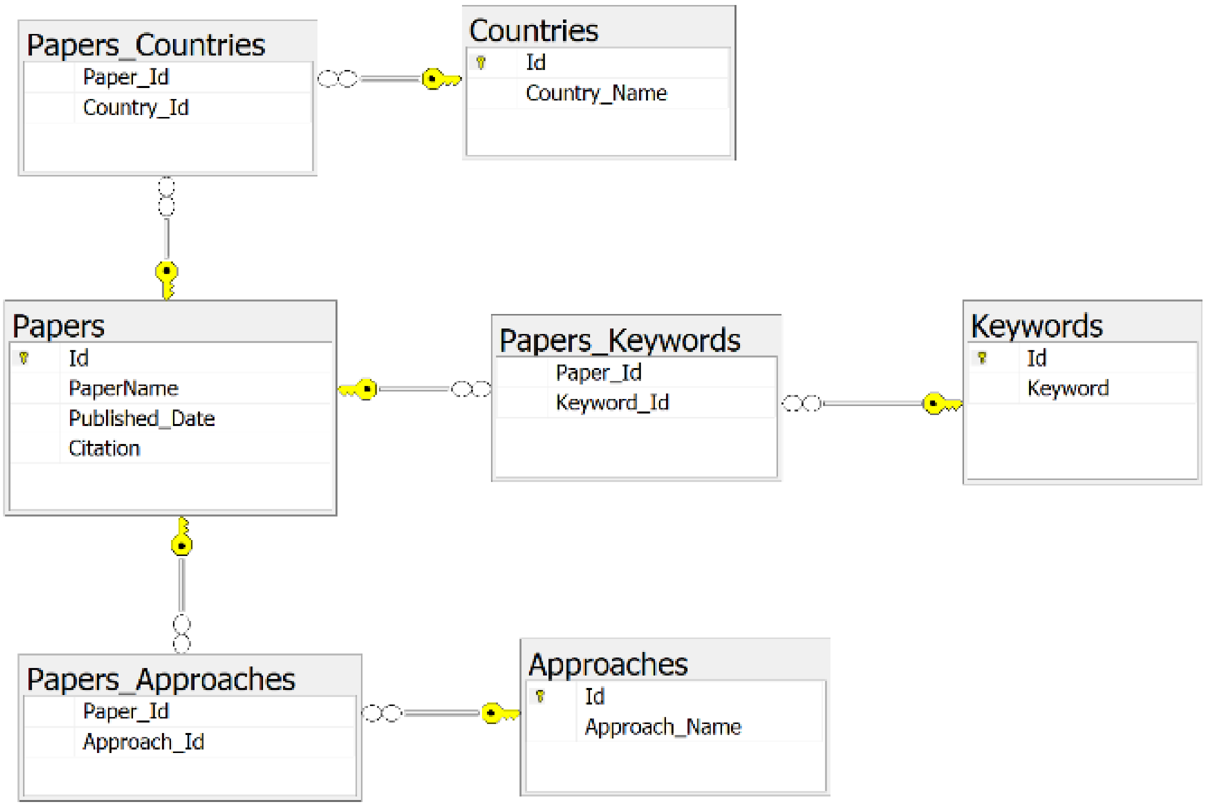


Figure 4 Papers database structure diagram

In addition, we develop a dashboard to display all articles' values as an interactive chart in Google Data Studio [18]. The researchers can use these charts to find out the trends of driving behaviour analysis in the future. They can change the dimensions, change the sorting types, zoom in and out in geographical charts to study this topic further.

	Country	Paper Count ▾
1.	China	244
2.	USA	101
3.	Japan	58
4.	Australia	24
5.	Taiwan	24
6.	Korea	16
7.	UK	15
8.	Singapore	14
	Grand total	**572**
		1 - 20 / 20

	Approach	Paper Count ▾
1.	CNN	115
2.	LSTM	107
3.	Auto Encoder	91
4.	RNN	39
5.	SOM	29
6.	DBN	21
7.	DNN	15
8.	NK-DNA	15
	Grand total	**572**
		1 - 23 / 23

	Keyword	Paper Count ▾
1.	aggressive driving behaviors	48
2.	autonomous driving	36
3.	driving assistant	30
4.	anomaly detection	21
5.	deep learning	18
6.	deep q-network (dqn)	18
7.	cybersecurity	18
8.	connected vehicle	16
	Grand total	**572**
		1 - 57 / 57

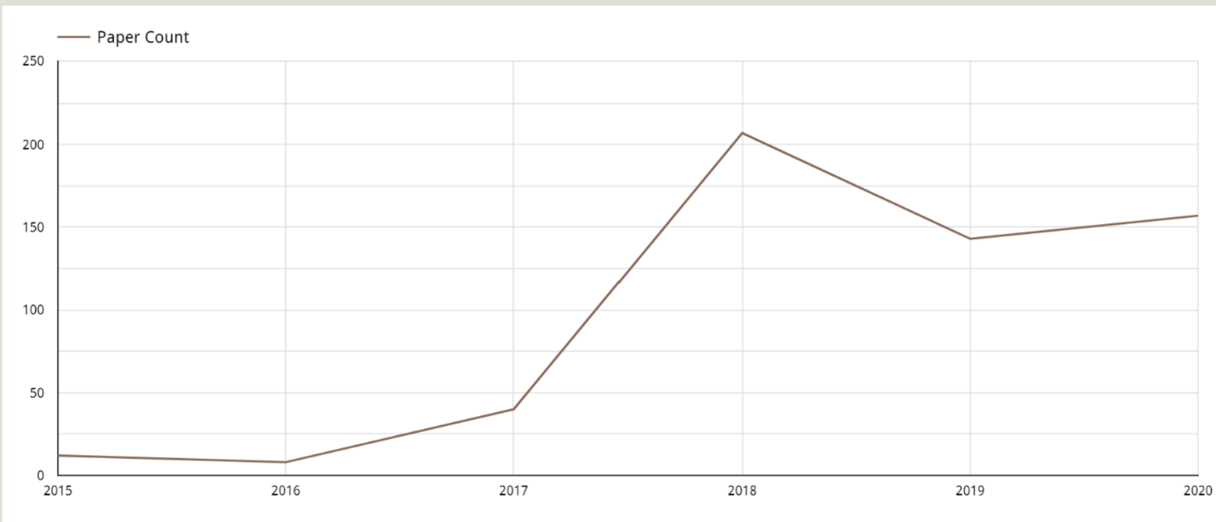
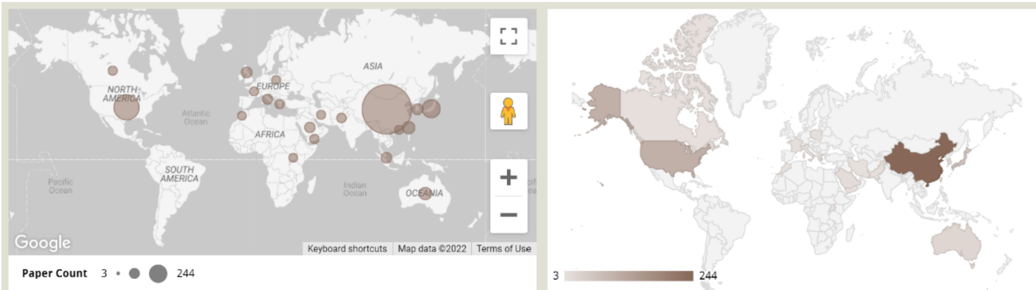


Figure 5 Dynamic sortable charts

There are four sortable charts that we will explain their functionality of in the following: 1) Sorted the countries that have more studied paper 2) Sorted the approaches that research have been used to tackle DBA studies 3) Sorted keywords of studied documents in this study 4) Showed the trend of paper counts from 2015 to 2020

[Figure 4] shows the geographical distribution diagrams of studies conducted in the field of driver behaviour analysis. The figures above present a data set in two different forms to make the study more accessible. However, in the table below, the information related to the approaches used by the researchers and the country in which the research was conducted is shown appears as a matrix.



Approach / Paper Count										
Country	CNN	LSTM	Auto Encod...	RNN	SOM	DBN	DNN	NK-DNA	null	Grand t...
China	62	58	21	27	10	17	10	5	-	244
USA	16	7	13	6	-	4	-	-	-	101
Japan	5	13	31	-	-	-	-	-	-	58
Australia	-	11	4	-	4	-	-	5	-	24
Taiwan	6	-	-	-	6	-	-	-	-	24
Korea	4	-	4	-	4	-	-	-	-	16
UK	-	6	3	6	-	-	-	-	-	15
Singapore	-	-	5	-	5	-	-	-	-	14
Saudi Arabia	6	-	-	-	-	-	-	-	7	13
Italy	6	-	5	-	-	-	-	-	-	11
Pakistan	-	-	-	-	-	-	-	-	7	8
Greece	-	-	-	-	-	-	-	-	-	6
Canada	-	5	-	-	-	-	-	-	-	6
Yemen	6	-	-	-	-	-	-	-	-	6
Grand total	**115**	**107**	**91**	**39**	**29**	**21**	**15**	**15**	**14**	**572**

Figure 6 Geographical distribution of studies on DBA

In [Figure 5], we used a treemap diagram to look at the data set from four angles. The chart on the top left of the scale shows the number of times researchers used the solutions. The chart on the top right shows the scale of the number of surveys in countries. The chart on the bottom left shows the scale of the number of times keywords are used in papers. Furthermore, the exemplary bottom diagram shows the number of attributes of each article. In [Figure 6], we develop a dynamic sortable table that includes approach and citation counts of each approach used by researchers.

Figure 7 Treemaps of different features in studied papers

All the developed files and processes are added to the GitHub repository [19]. Our database design mandates adding a newly published paper in the driving vehicle behaviour as the main object of a referable record. All the other values can be attached to the primary node (Name of the article). Moreover, concepts such as authors, affiliations; type of input and output data; and result presentation may be added.

	Approach_Name	Record Count	Citation
1.	CNN	115	12
2.	LSTM	107	13
3.	Auto Encoder	91	8
4.	RNN	39	3
5.	SOM	29	4
6.	DBN	21	3
7.	DNN	15	2
8.	NK-DNA	15	1
9.	No data	14	1
10.	GRU	13	2
11.	RL	13	2
12.	RF	12	2
13.	LINE	12	1
14.	DeepWalk	12	1
15.	GBDT	11	1
16.	K-Means	10	2
17.	SVM	9	2
18.	DT	9	1
19.	PCA	8	1
20.	GHSOM	6	1
21.	T-SNE	5	1
22.	DQN	4	1
23.	DDPG	2	1
	Grand total	**572**	**21**

1 - 23 / 23

Figure 8 Approaches, Counts, and Citation counts

2.2 Background of the Driving Behaviour Analysis

2.2.1 Declarations of Driving behaviour Analysis

It is helpful to define Driving Behaviour Analysis (DBA) by considering the term word by word. Analysis can be said to refer to *"The process of studying or examining something in an organized way to learn more about it or a particular study of something."* [20]. *Behaviour* is typically understood as" the response of an individual, group, or species to its environment" [21]. Finally, driving can be defined as" to operate the mechanism and controls and direct the course of (a vehicle)" [22]. Taken together, then, the meaning of DBA is to detect and study drivers' behaviour by leveraging the output data gathered from their vehicles. Drivers can be identified for unsafe driving behaviour such as harsh accelerating, sharp slowing; frequent braking; speeding; harsh high-speed turning; sluggish driving, frequent parking, and fatigued driving [IBM]. Driving behaviour insights can help automotive manufacturers improve design and manufacturing, assist with quality control; enhance protection, and simplify maintenance. This can help manage vehicle fleet activities, and insurance providers can get powerful insights into the vehicle use and risk evaluation of their customers. Considering the importance of DBA from another angle, we find that one of the most critical consumers of this algorithm is insurance companies that can take advantage of dynamic insurance systems by ensuring that each driver will be charged according to their driving behaviour.

2.2.2 History of Driving Behaviour Analysis

The first car built and offered for purchase occurred in the early twentieth century. Consequently, at that time, all efforts were focused on car mechanics [23]. The "Duesenburg Model A" became the first vehicle to have hydraulic four-wheel brakes in 1922; this is considered the first step in increasing car safety [24]. One of the first studies to analyze driver behaviour was the paper by Hsing-Shenq Hsieh et al. [25]. They assumed that most video systems were ineffective at unsaturated intersections due to the chaotic combinations of aggressive driver behaviour and the geometric design of curved lines. They defined their methodology using several reference points, and the Bleyl transfer method was developed as a matrix and the least-squares method (LSM).

2.2.3 Deep Learning Methods used in aggressive driving behaviour analysis

AI aims to give computers the mental power to program them to learn and solve problems. Its purpose is to simulate computers with human intelligence [26]. In recent years, various algorithms in the analysis and understanding of driving behaviour have been used. To the best of our knowledge, we explore the papers scoped in the "scope of research"; related to the DBA concept. Furthermore, we explore the DL approaches those researchers used to prepare results. In the next step, we have investigated the citation number of each paper and tried to find out the best of them regarding their method and approach popularity.

Our paper focuses on studies that used DL for this research. Instead of defining the hierarchy and layering of existing algorithms classically, we address the popularity of algorithms to provide a background for analyzing and categorizing existing articles in this field. The following section lists the most popular methods to detect driving behaviour patterns in the researcher's papers.

2.2.3.1 Convolutional Neural Network

The term CNN means that a statistical operation called Convolution (a specialized sort of linear reaction) is used for the network [27]. Convolution is a function derived from two functions by integration (in strictly mathematical words), which describes how one's form is changed by another [28]. The most significant benefit of CNN relative to its contemporaries is that it automatically identifies the vital features without any human supervision [29]. CNN has several critical drawbacks: many training samples are needed for learning weight parameters, and a strong GPU is needed to speed up the learning process. Also, the strong CNN is often not taken advantage of by researchers who do not have such computing resources, time, and large-scale training data [30]. In the reviewed literature, the most popular methodology is the CNN algorithm.

2.2.3.2 Recurrent Neural Network – Long Short-Term Memory

A subset of neural networks used to analyze sequential data input or output are RNN. RNNs have a temporal relationship between input/output sequences [31]. RNNs use the previous outputs as inputs that have hidden states. The advantages of RNNs are 1) the possibility to process the input of various lengths, 2) the fact that the size of the model does not increase with the input size; and 3) the reality that the history of the previous information is included in the calculation, and that the weights are shared over time. However, RNN has several disadvantages, including 1) slow calculation, 2) difficulty accessing information from long-term history, and 3) that future inputs cannot be considered for the current situation [32].

2.2.3.3 Auto Encoders

AEs are practical learning approaches that aim to transform input to output with the least possible error [33]. An AE finds a representation or code to classify different inputs to perform valuable transformations on the input data. For instance, a neural network finds a code that can turn noisy data into clean data by denoising AEs. Noisy data can be transformed into coherent sound in an audio recording of static noise [34].

AEs require considerable computational resources and data. The functionality we attempt to retrieve can often be blurred by a loosely organized testing dataset used in AE training. AEs can be coupled with various neural network architectures, such as feedforward NNs, CNNs, and RNNs, in semi-supervised learning activities. The combinations listed previously can provide good results in multi-task ML problems by simplifying the inputs to a representative code. Nevertheless, it can also harm the model's interpretability even more as it is a trade-off for researchers to select between the simplicity of network or complexity of interpretation. AEs can collaborate with other neural networks independently in unsupervised and semi-supervised learning activities, considering their drawbacks [35].

2.2.3.4 Self-Organizing Map

The Self-Organizing Map (SOM) projects a high dimensional distribution on a primary grid that is in order. SOM converts complicated nonlinear relationships between high-dimensional data objects to more straightforward geometric relationships. Compressing the most important topological and metric relationships while preserving specifics will result in complex abstractions. SOM process analysis, perceptions, and communications in complex activities [36].

2.3 Key-Papers Review

In this section, we review the most cited papers related to our review. A more detailed summary is illustrated in Appendix A. Recent work by Weishan Dong et al. [37] examined and identified driving behaviour, extracted them, and added five new statistical features using only latitude and longitude characteristics; it was essential for them to help the model interpretation. The authors used GPS data only and claimed that in the future, with complete information, such as On-Board Diagnostics (OBD) data and other sensors, the results will be more accurate. They then split the data into specific frames. Each frame was labelled "Driver Id," and the method was "supervised."

First, the researchers used the method of Yang et al. [38], followed by the use of the Integrated Recurrent Neural Network (IRNN) method, plus the "two stacked recurrent layer." In addition to these two methods, Dong et al. utilized "non-deep learning" methods. Gradient Boosted Decision Tree (GBDT) and "TripGBDT" methods employed the Kaggle site dataset for implementation; In this method, statistical data is used along with the available features (57 in total). Several studies investigated whether the deep learning methods (i.e., hidden global travel information) perform better than the GBDT method (i.e., information is shared as a feature). One result showed that if the sampling rate were less than 0.1 Hz (a record in 10 seconds), the results would be severely low. The Kaggle 2015 competition on driver telematics analysis data [39] was used to test the proposed researches. Dong and colleagues found that the derived traits were not as strong as those learned by DL.

Furthermore, the "Stacked-IRNN" method was seen to perform better than the others. However, it naturally costs a lot to converge over time. The researchers noted the operational issues that DL methods for online prediction are much more helpful than "TripGBDT." Privacy is one of the critical issues in the use of telematics data. Furthermore, road shape, traffic, and weather can affect driving behaviour. Also, vehicle sensor data such as OBD can be added to the model as a feature.

Pengyang Wang et al. [40] assumed that driving activity is a dynamic task that involves professional multi-level movements, such as acceleration, deceleration, constant speeding, left turning, right turning, and straight movement that would be complex interpretation for an AI model. Wang et al. claimed that studying driving behaviour will help to analyze driver performance, improve traffic safety, and eventually facilitate the development of intelligent and resilient transport systems to allow many critical applications, such as tracking drivers, automobiles, and highways; providing early warning and driving assistance; improving driving comfort; and saving energy. Three distinct types of DBAs exist: 1) Descriptive analysis is the first type, in which transport experts identify metrics (e.g. harsh or repeated acceleration/braking, sharp turn, or pre-turn acceleration) based on a transport theory that explains driving behaviour [41]. 2) In the second type, predictive analysis, researchers utilize driving data patterns and ML methods (e.g. SVM; Naïve Bayesian) to forecast vulnerable scores [42]. 3) Casual analysis describes the causal factors in driving behaviour and demonstrates how these factors affect road safety [43].

Wang et al. developed a peer and temporal-conscious representation learning-based analytical framework for DBA using GPS tracks. Firstly, a series of Multiview driving state change graphs from GPS tracks were created to describe each vehicle's complex driving activity. Secondly, graph-graph peer and current-past time-dependent driving behaviour patterns were defined, and peer and time-dependent modelling were integrated into a single auto-encoder-based optimization system. Driving behaviour representations for estimation and historical evaluation were studied, with risky zone identification as implementations. Finally, detailed tests were performed to demonstrate the proposed system's improved efficiency with GPS tracks in real-world cars. The researchers described two phrasal terminologies that allowed them to incorporate their method. *Driving Operations* are defined as a collection of actions and measures that a driver operates while driving a car, according to the driver's judgement, expertise, and skills. *Driving State* is concerned with how vehicles travel at a certain time point or in a short time window. In other words, a driving condition of a car varies with time, which involves the speed status (i.e., acceleration, deceleration, steady speed), and the path status (i.e., turning left, turning right, going straight). A series of driving states may be: [<acceleration, moving straight>, <constant speed, moving straight>, <deceleration, turning right>]. The suggested approach took advantage of Multiview driving state transfer graphs.

Different observers interpret the transition from two different perspectives: the likelihood of transition and how long the transfer continues.

Three objectives were followed in the model design. First, structural consideration: by designing the desired graphs, they were transformed into vector data. A second objective was peer dependency: Drivers who mimic each other's actions, patterns, and attitudes. The model should reflect them according to the graph-graph peer dependency model. The third objective was temporal dependency: The current time slot's driving operations demonstrate clear autocorrelation connected with the previous driving states.

Wang et al. [40] analyzed driving habits from the context of representation learning. They considered how fast and how long people travelled by building driving state transition graphs. They investigated how one specific driving behaviour relies on another driving behaviour. The framework was generated by empirical modelling of the interconnections between the peer and temporal dependencies. They first defined driving behaviour using Multiview driving state graphs. They developed the idea of graph-graph (definition = trajectories with similar driving behaviour in the graph-graph peer dependency should have near representations in the learnt representation feature space [40])peer penalties to capture the temporal dependency of a single G-G peer by contrasting a graph-graph peer's present value with its initial value. They also applied the device to detect hazardous routes and rank drivers according to driving behaviour automatically. Test runs on real-world data have shown that Spatiotemporal Representation Learning is efficient for driving.

Jun Zhang et al. [44] recommend a DL system for behaviour identification by fusing convolutional and recurrent neural networks, called attention-based DeepConvGRU (Convolutional, Gated Recurrent Unit) DeepConvLSTM. First, in-vehicle sensor data via CAN-BUS is gathered to classify drivers' driving habits. The data was separated into parts for the method of normalization and sliding window study. Finally, the derived driver action patterns were used in a "deep learning" algorithm for recognition. Their key contributions are described as follows: their architecture conducted automated behaviour detection on real-time multi-dimensional in-vehicle "CAN-BUS" sensor data, capturing local dependence among the temporal component (i.e., velocity, acceleration) data and across spatial locations. By incorporating the attention function, their model may catch salient structures of high-dimensional sensor data and explore the correlations among multiple sensor data channels for rich feature representations, enhancing the model's learning efficiency. Their architecture can be used to train end-to-end with no function engineering (which means, instead of adding statistical functions to add more value to the dataset), utilizing raw sensor data without preprocessing relevant to any sort of sensor.

The GRU/LSTM cells distinguish driving habits by adding historical habit values to secular values. The "Deep Convoluted GRU" model used DL to exploit temporal dynamics. The proposed approach outperformed the conventional system on the "Ocslab driving dataset[45]". The proposed methodology learnt features from the original signals and fused the learned features without any special preprocessing. Surprisingly, the DeepConvGRU obtained competitive "F1 ratings" (0.984 and 0.970, respectively) using at least 51 raw sensor input channels.

Jooyoung Lee et al. [46] established a method to analyze in-vehicle driving data and demonstrate possible violent driving signs. The mentioned system for detecting sudden shifts was based on a two-tier clustering strategy. Some researchers have utilized these methods to detect sudden shifts in driving and cluster driving incidents. With this process, actual in-vehicle driving records of taxis in Korean metropolitan cities were examined. The clusters were used to assess whether another driver's driving record is a possible risk of violent driving and include statistics on potentially aggressive driving.

The research of Jooyoung Lee et al. [46] was performed sequentially to recognize violent driving habits. The technique comprised a three-stage advancement of a mission, detecting a transition, and extracting functions. An in-vehicle recorder was developed to document driving conditions over time. As the data on RPM (revolutions per minute), acceleration and yaw rate are used, the model's precision improves as the three time-series data display significant improvements. When the change point is observed, they decide it has passed the 5th percentile of the results. Once a rapid shift in direction, acceleration, and yaw rate are observed, they can identify the phenomenon as a driving event. The researchers used unsupervised learning to gather sudden shift events (unexpected shifts) and categorize instances (driving incidents). The framework can evaluate driver behaviour and give recommendations to drivers on their driving style. They think it can be a helpful tool for driver education because driving records may include driving behaviour in actual road conditions, unobservable in controlled environments. Although the driver's self-reported aggressive driving incidents could be related to collisions, it is not yet confirmed if aggressive driving events or accidents are connected. The authors suggested they might have potentially affected their study's findings through driver characteristics, but driving reports have already collected these factors. Researchers could not analyze the effect of other variables on driving activity because personal data and sensor limitations hindered precise estimates of the other factors.

2.4 Reviewing the datasets

The "Kaggle. Driver Telematics Analysis" [39] dataset has a directory containing multiple files. There are 200 CSV files found inside each folder. Each file defines a driving trip. The trips are recordings of the location of the vehicle per second (in meters). The trips were based on starting at the origin (0,0), arbitrarily rotated, and short lengths of trip data were omitted from the start/end of the trip to safeguard the privacy of the drivers' locations. A small and random number of false trips (trips that the driver of interest did not drive) are put in each driver's folder. The number of false trips or a labelled training set of authentic festive trips is not given (it varies). In any given folder, most of the trips belong to the same driver [39].

Driver ID, order ID, time, latitude, and longitude are included in the "Didi Chuxing GAIA Initiative to the research community" dataset. The GPS trajectory's precision is 3 s, and the tying lane processes it. With picking the one-month drip taxi data for October 2016 in Xi'an, China; A more straightforward scoring system was used to mark this dataset [38].

The "UAH-DriveSet" is a public data array captured in multiple settings by the driving tracking software "DriveSafe," by separate testers, supplying a vast number of recorded and processed variables across all smartphone sensors and capabilities during independent driving experiments. The application was tested on six different drivers and cars, with three different behaviours (normal, drowsy, and aggressive) performed on two types of roads (motorway and secondary roads), resulting in more than 500 minutes of naturalistic driving with its related raw data and additional semantic knowledge, along with video records of the trips [47].

It was legislated in Korea in 2011 that all commercial vehicles (e.g., cars, buses, and taxis) must have a digital tachograph (DTG) fitted, a kind of in-vehicle driving recorder for safety monitoring, to capture the "DTG database" dataset (Traffic Safety Act Article 55 in Korea). The DTG device imports the driving documentation from the On-Board Diagnostic Systems (OBD-II) terminal and stores them on the Secure Digital memory card (SD). Data stored in the memory is periodically extracted and transmitted to the Korea Transport Protection Authority (TS) server via the internet [46].

"OSeven Telematics, London, United Kingdom": Data is obtained from an already established mobile program on both iPhone and Android smartphones. The program is still running in the mobile operating system such that no user intervention is taken when commuting. The program gathers raw data from smartphones using multiple parameters using accelerometers, gyroscopes, and GPS cameras. In m/s2, the accelerometer will record the acceleration of a smartphone in terms of gravity acceleration, while the gyroscope measures the angular velocity of the smartphone in rad/sec. Finally, GPS data is obtained to monitor the speed of the vehicle and the vehicle's coordinates. Because the program uses cloud-based services, data is transmitted to the server for storage anonymously for further analysis after automated identification at the end of the ride [48].

The "KITTI" Data Collection includes the specifics of raw gray stereo squares; natural colour stereos and colour squares; 3D Velodyne point clouds; 3D GPS/IMU data; calibrations, and 3D entity track-list marks, which can then be processed and registered at 10 Hz. Directories and directories with dates of formation are presented. Most consumers need to transform and cleanse the data after processing it [14]. KITTI dataset indicates a one-week route of 10.357 taxis in the "T-Drive trajectory dataset." This dataset comprises approximately 15 million points and a cumulative distance of nine million kilometres [49].

The HCRL dataset comprises a ride from Korea University to the SANGAM World Cup Stadium of ten drivers, a cumulative driving period of around 23 hours, and a route that involves riding via Seoul and the surrounding areas for about 46km [45].

The "Warrigal" dataset is a broad, rich dataset extracted in an industrial environment from the experiences of large trucks and smaller 4WD vehicles. A fleet of 13 vehicles working in a surface mine for three years collected the results. Information about the vehicles' status (e.g., location, speed, and heading) and their peer-to-peer radio contact descriptions are contained in the dataset. With a resolution of 1 Hertz, the data extends three years. To the best of our knowledge, no other publicly accessible data collection comes near this degree of information over such a significant period. There is no precedent for the research possibilities and applications that these data allow. This dataset has already been used to analyze map formation, protection analysis, driver purpose inference and wireless network antenna failure [50].

2.5 Survey Dimensions

After reviewing the articles published in this field, we categorized them by the method used for DL, concluding that CNN, LSTM and AEs were the most common methods [Figure 7].

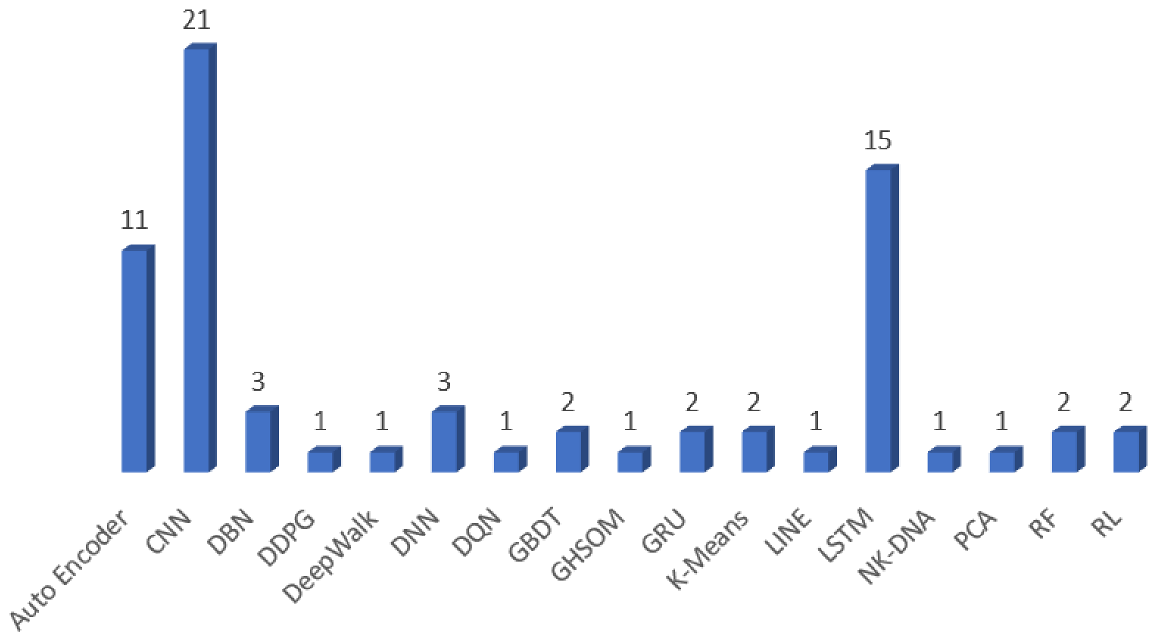


Figure 9 Approaches used counts

In terms of publications, we have categorized and sorted the articles. The largest share of article publishing was found to be in Scopus, IEEE, and ACM, respectively [Figure 8].

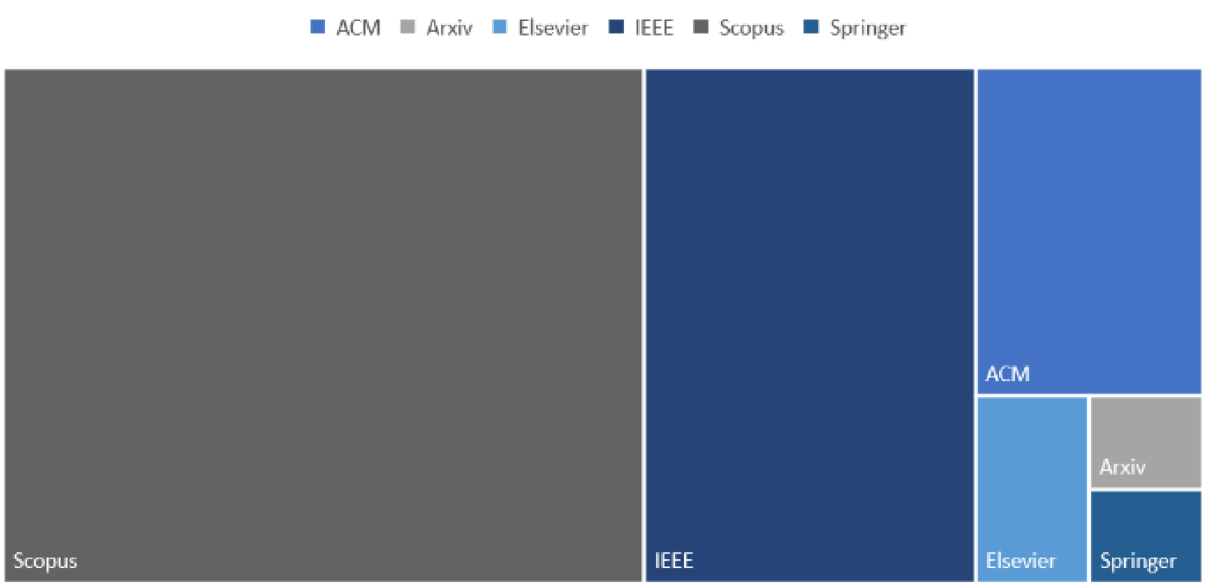


Figure 10 Database's paper counts in the DBA field

We have found that some researchers do not make available their research data, which is typically owned by a specific organization and only report the results of their research. At the same time, some other researchers made their data available to the public. The proportion of these two types in the total number of articles we considered is 37 to 19, respectively [Figure 9].

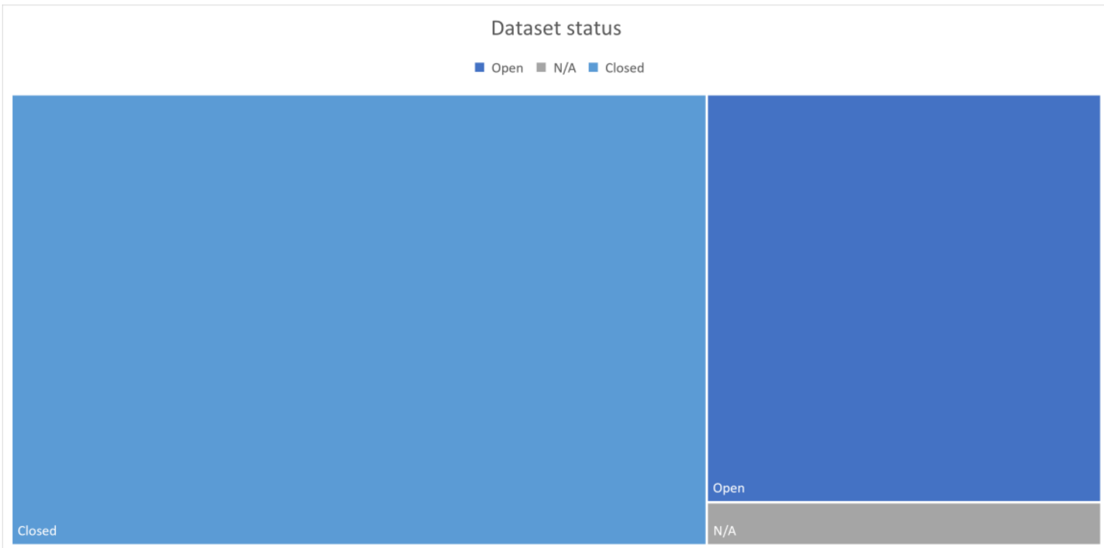


Figure 11 Dataset statuses of reviewed papers

There are times in the research process when a researcher uses several datasets to prove a proposed theory or algorithm. Examining the available articles, we found that the number using more than one dataset is seven, versus 33, which used one input database.

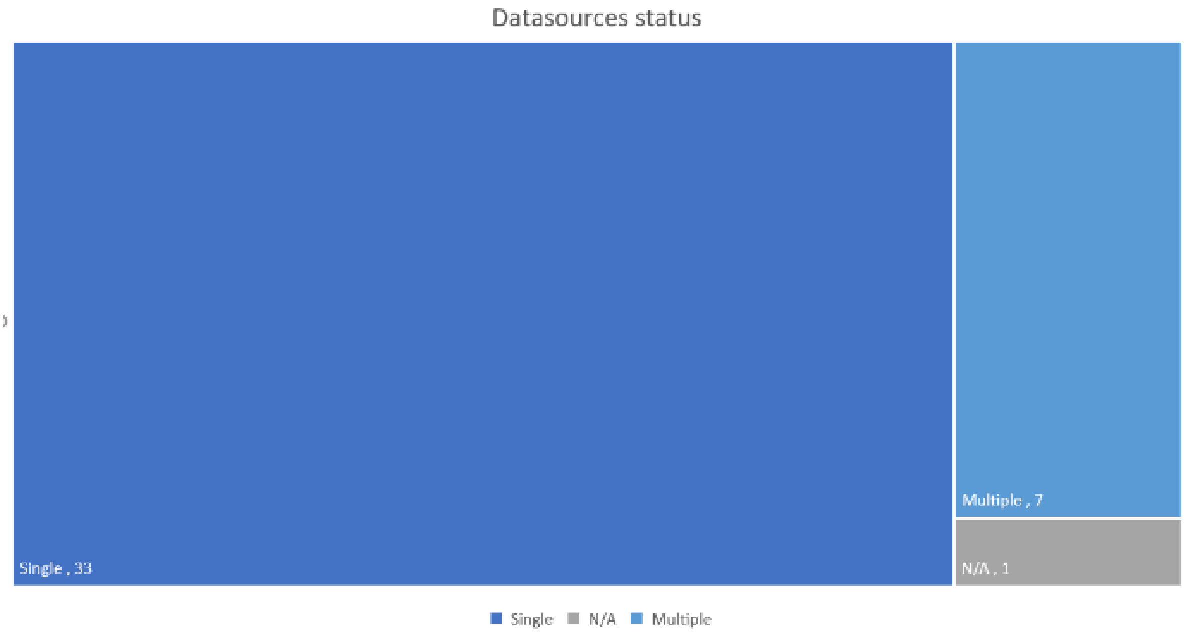


Figure 12 Sources of data status

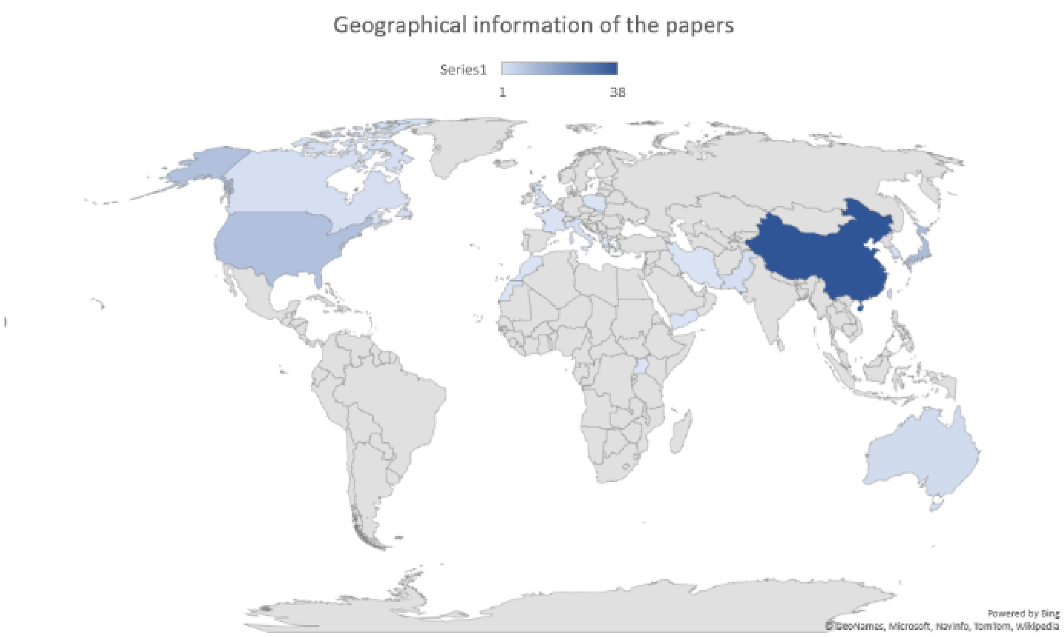


Figure 13 Geographical distribution of publications

2.6 Future Direction and Outlook

Following the publication of this paper, we decided to enhance the accuracy of driving behaviour identification using deep learning neural networks and the "LSTM" technique under the "RNN" branch. Using one of the available datasets, we attempt to build, test, and assess the required modelling.

Following that, we will expand on the technique we presented to implement survey papers so that researchers may use it as a general open-source library for any research publications, independent of the subject covered in this study.

2.7 Challenges and Opportunities

We report the challenges of researchers in this field and then address our challenges in this review. One of the most critical challenges facing researchers in this field is finding suitable datasets to perform various calculations to improve their algorithms. Usually, data heterogeneity presents another challenge once data sets are found, meaning that the measurements made during the data collection process may not have been carried out at the same time interval. Researchers need to homogenize their data at this stage. Next, researchers must decide what features to accept in their proposed model.

Furthermore, because the scope of our review lies in the field of DL algorithms, researchers have tried to use all the features and sometimes even add the calculated features to them. For example, instantaneous velocity was calculated and sent to the model using different points in the associated times. Some researchers question these calculated features and believe that the deep ML model extracts them.

A challenge related to our review is the number of papers to be surveyed and the adoption of inclusion and exclusion criteria. Several publications took place over different periods and in separate databases. The lack of a centralized database update motivates us to redesign our survey methodology to be dynamic to cover future work in this field. We further implement a dynamic relational database management system that periodically crawls several pre-set databases. Moreover, the dynamic database design allows other databases under user control with different inclusion/exclusion keywords. Another challenge to our survey methodology is the means of actively representing extracted information from reviewed papers. Most of the previous work provides static views of this information that may not reflect the future directions in this field. We propose actively demonstrating the extracted information using an interactive platform (i.e., Google Data Studio). In addition to the challenges mentioned above, we encounter another issue when developing this dynamic database: communicating with different interfaces in different database search engines. We further address the inconsistency in the database interface by implementing an adaptable interface in dynamic database design that can easily connect to several interfaces.

2.8 Conclusion

Accidents impose severe socio-economic complications for the community, and thus safe driving behaviour is a critical component in saving lives on the roads. Considerable research efforts were conducted to understand the fundamental factor that affects driving behaviour in different settings. In this survey, we began by discussing the primary methodologies used to analyze driving behaviour patterns. Considering the analysis of different publications in this area, we find that the field of driving behaviour analysis is increasing due to the interests of different stakeholders in studying driving behaviours for a safer transportation environment.

We have presented a dynamic methodology for the previous review in analyzing driving patterns to identify driving behaviour. We collected several previous studies and categorized them according to the methodologies used in data analysis. We compared the advantages and limitations of the major papers in this field. We realized the importance of a dynamic survey mechanism that enables research to add new research efforts to existing ones. Fortunately, our dynamic survey methodology will assist researchers in this field in the future to better understand the current contributions to driving behaviour analysis. If an article on driving behaviour is published, the dynamic database automatically adds it to our database data warehouse and makes it available for further analysis. The availability of data on this field is crucial to the success of driving behaviour analyses. We discuss several publicly available data sources that can be used to analyze driving behaviour.

Another important point we wish to highlight is that, after analysis of different models and algorithms proposed by previous researchers, we conclude that the precision of algorithms which in some way implemented the subject of time series in their models is higher than those models that deal only deals with data changes regardless of time. The number of articles that considered this field from a graph perspective has so far been minimal. In this way, the vehicle movement sequences to extract driving behaviour are considered consecutive graphs; the existing pattern in modifying these graphs is classified. The most up-to-date articles in this field show the high accuracy of this way of thinking. Fortunately, in the future, our framework will assist researchers in this field in following and analyzing the existing trend in this field from other angles.

Chapter Three: Deep Learning Approach for Aggressive Driving Behaviour Detection

3.1. Introduction

3.1.1 Abstract

Driving behaviour is one of the primary causes of road crashes and accidents, and these can be decreased by identifying and minimizing aggressive driving behaviour. This study identifies the timesteps when a driver in different circumstances (rush, mental conflicts, reprisal) begins to drive aggressively. An observer (real or virtual) is needed to examine driving behaviour to discover aggressive driving occasions; we overcome this problem by using a smartphone's GPS sensor to detect locations and classify drivers' driving behaviour every three minutes. To detect timeseries patterns in our dataset, we employ RNN (GRU, LSTM) algorithms to identify patterns during the driving course. The algorithm is independent of road, vehicle, position, or driver characteristics. We conclude that three minutes (or more) of driving (120 seconds of GPS data) is sufficient to identify driver behaviour. The results show high accuracy and a high F1 score.

3.1.2 Keywords:

Driving behaviour detection, driving behaviour analysis, Aggressive driving detection, Supervised deep learning classifier

3.1.3 DBC Introduction

With the number of automobile accidents, fuel economy, and determining the level of driving talent, the DBA (Driving Behaviour Analysis) becomes a critical subject to be calculated. Depending on the types of car sensors, the inputs and outputs can then be examined to establish if the DBC (Driving Behaviour Classification) is normal or deviant. According to World Health Organization (WHO) publications, studying driving behaviour is necessary. Because it is one of the primary factors contributing to catastrophe, driver factors include altitude, intoxication, fatigue, poor road conditions, eyesight impairment, and vehicle performance considerations [16]. Thus, considering the amount of damage in a car accident, in this study, we examine the problem of detecting violent driving using GPS data with a few minutes of driving per person.

There are many types of sensors connected to a control area network to monitor driving behaviour. Driving behaviour data is multidimensional, time-series data that has been calculated. In some cases, the dimensions of time series data are not statistically independent [51]. A proper depiction of driving characteristics might be critical in applications such as autonomous driving, auto insurance, and others. On the other hand, traditional methods rely significantly on handcrafted features, impeding ML algorithms' potential to reach superior efficiency [37]. Driving is a dynamic endeavour requiring various ability levels (e.g., acceleration, braking, turning); this dynamicity can distinguish drivers' driving behaviour. Compared to a fingerprint, everyone has distinct driving patterns, such as a set speed, acceleration, and braking patterns [52]. However, there are different ways to find patterns and classify them in particular [53], [54].

Driving behaviour analysis will assist us in determining driver efficiency, enhancing traffic safety, and eventually encouraging the development of intelligent and resilient transportation systems. Although various attempts have been made to evaluate driving behaviour, representation learning can improve current methodologies by exploring peer and temporal connections in driving behaviour [40].

Numerous reports on road safety have focused mainly on the elements that contribute to severe and fatal accidents. As a result, less emphasis has been placed on minor injuries or events before a crash [55]. This reality may lead to inaccurate beliefs about injury prevention and management. While the DBC received considerable attention in the past, much remains to be learned about it, including the dimensions of driving patterns and their potential impact on road safety [56].

3.1.4 Scope of research

This study proposes a model that can discover the aggressive driving pattern in less than 3 minutes (the selection of 180 seconds will be described later in this research) by capturing GPS records every second. We examine two different RNN-based methods (GRU, LSTM) in various circumstances. The experiments have been evaluated in two approaches: 1) Splitting the dataset into training, validation, and test datasets; and 2) reserving a driver dataset to have the real-world test.

3.2. Driving Behaviour

Because of different driving factors (fatigue, intoxication, drowsiness, distraction), drivers' Behaviour may vary; road adhesion, traffic, and weather conditions also influence driving traits [57]. The choice of driving speed is one element of driving style that has emerged as a significant predictor of differential accident participation in recent years [58]. Unsafe driving habits may develop because of two main factors. First and foremost, drivers may have varying attitudes about driving, including varying anxiety levels about the potential of a collision. Second, drivers may have differing perspectives on what constitutes good and poor driving and their level of competence and safety on the road [53]. Although there is a link between some demographic characteristics and accident risk, this link is mediated by several other variables that should be considered. Despite this, age and gender are related to accident risk even after considering these driving style variables [59]. In this study, we want to find the correlation between changes in vehicle states and driving behaviours. The following section will discuss different sensors that may be utilized to find the relation above.

3.2.1 Sensors

An observer (online = human, fleet tracker / offline = sensors, camera records) must evaluate their driving conduct in a driving course. There are proposed models that try to monitor the drivers by utilizing various sensors and detecting driving Behaviour by changing drivers' different conditions [60] [61]. There are two types of sensors in autonomous and non-automated vehicles: "Environmental" and "Vehicle State" [62]. In this study, we are using the vehicle states (position and changes) sensors. The most applicable vehicle states sensors are: IMU, CAN J1939, Magnetic Compass and GPS. Regarding the dataset used in this study, we will study GPS deeper in the section that follows.

3.2.2 GPS

The GPS does not require data transmission from the user; it functions independently of any cellphone or internet reception [63]. GPS is crucial for military, civil, and commercial purposes worldwide [63]. The US government developed, maintains, and makes the system openly available to anybody with a GPS device [63].

The GPS receiver determines its position and time using data from many GPS satellites. This data is sent to the receiver by each satellite. A very stable atomic clock, synced with ground clocks, is carried by each satellite. Day-to-day corrections are made for time differences. Similarly, the satellite placements are precise[64]. GPS receivers also contain clocks, but they are less accurate and steady. Radiation delays are proportionate to distance since radio waves have a fixed speed regardless of satellite speed. Because the receiver must compute four unknown values, four satellites are required at minimum (three position coordinates and a clock deviation from satellite time)[64].

The raw GPS record captured from the mobile devices has at least these attributes: Speed (Km/h), Latitude, Longitude, Altitude, Vertical accuracy, and Horizontal accuracy. This article attempts to classify driving behaviour using most of these parameters first and subsequently only using speed variations and their correlation with latitude and longitude variations.

3.3. Classification approaches

This step uses GPS (Latitude, Longitude, Altitude) data to classify aggressive or non-aggressive driving behaviour. As the trajectory data of a driver is a sequential dataset (time series), we use RNN approaches in this study [65]. RNN is a subtype of supervised DL in which the previous step's output is used as input for the next phase. For sequential data, the RNN deep learning method is optimal [65]. The hidden state, which memorizes certain information about a sequence, is the most crucial aspect of RNN. RNN transforms independent activations into dependent activations, decreasing the complexity of increasing parameters and remembering each previous output by sending each output to the next hidden layer as input. In this study, we go through LSTM and GRU methods to experiment with the accuracy of the proposed model in different circumstances. In the following section, the differences between GRU and LSTM are described.

3.1 GRU vs. LSTM

RNNs are designed to work with time series; they use previous sequence information to produce current output. Memory problems arise in RNNs because of a vanishing gradient. RNN suffers from vanishing gradients more than other neural networks as the number of steps increases[26]. To explain vanishing gradients, consider the following procedure: to train an RNN, we backpropagate through time, computing the gradient at each step. The gradient is used to update the weights of the network. The gradient value will be below if the previous layer's effect on the current layer is modest. If the gradient of the previous layer is slight, the gradient of the following layer will be as well. Gradients grow smaller as we backpropagate. A smaller gradient indicates that there will be no weight update. Consequently, the network fails to learn prior inputs, causing short-term memory problems [31].

Two customized variants of RNN were developed to solve the vanishing gradients issue. They are as follows: 1) GRU and 2) LSTM. LSTMs and GRUs use memory cells to store the activation value of preceding steps in a long sequence. Gates are used in networks to regulate the flow of information. Gates can learn which inputs in a sequence are significant and store their knowledge in a memory unit. They may provide data in lengthy sequences and utilize it to generate predictions [32].

The workflow of GRU is the same as RNN, but the difference is in the operations inside the GRU unit. Inside GRU is two gates: 1) reset gate and 2) update gate. Gates are nothing but neural networks; each gate has its weights and biases. The update gate decides if the cell state should be updated with the candidate state (current activation value) or not. The reset gate is used to decide whether the previous cell state is essential or not. The candidate cell is simply the same as the hidden state (activation) of RNN. The final cell state is dependent on the update gate. It may or may not be updated with the candidate state. The final cell Removes some content from the last cell state and writes some new cell content [31].

Long short-term memory (LSTM) is like GRU in that they are designed to address the vanishing gradient issue. In addition to GRU, there are two additional gates here: 1) the forget gate 2) the output gate. Because all three gates use the sigmoid activation function, they are between 0 and 1. The forget gate determines what is retained and forgotten from the previous cell state; it determines how much information from the previous state should be kept and how much should be lost. The output gate determines which portions of the cell are sent to the concealed state [31].

3.4. Dataset and challenges

The "UAH-DriveSet" [66] is a public repository of data collected from various testers in various conditions by the driving monitoring program "DriveSafe." This dataset intends to speed progress in driving analysis by providing many characteristics collected and analyzed during independent driving tests using all smartphones' sensors and capabilities. The application was run on six distinct drivers and vehicles. At the same time, they engaged in three distinct behaviours (normal, drowsy, and aggressive) on two distinct types of roads (highway and secondary road), yielding over 500 minutes of naturalistic driving with associated raw data and additional semantic information, as well as video recordings of the trips [66]. This dataset contains six distinct drivers; each driver drove two roads - one of which was 25 kilometres long and with a maximum speed limit of 120 kilometres per hour, and the other of which was 16 kilometres long and had a maximum speed limit of 90 kilometres per hour - while exhibiting three distinct driving behaviours: normal, drowsy, and aggressive. Because the "RAW GPS.txt" file contains nearly all the information we want, including speed, latitude, longitude, altitude, vertical and horizontal precision, and sample timestamp. We use it to categorize the drivers' Behaviour. While this is the ideal dataset for our situation, it does have some limitations. The drivers are comprised of five men and one female. The minimum and maximum age ranges are 20-30 and 40-50. Except for one car, they are all made in Europe. Additionally, one of the cars is a battery-electric vehicle. In the next section, we examine the limitations and the solutions that we propose to mitigate them.

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

Table 2 List of drivers and vehicles that performed the tests

3.4.1 Dataset limitations and solutions

1. Each driver's Behaviour differs from the others; for example, one driver's normal Behaviour may differ from others. As a solution, we have all the drivers' training data by splitting a trip into smaller batches and giving some to the system for learning and the rest for validation and testing.
2. The most challenging aspect of the dataset is labelling an entire route with a single style of driving. However, there have been instances when the driver drove contrary to the label. We choose to ignore it as noise; given the nature of human beings, it is quite natural for an individual's Behaviour to vary throughout a driving course.
3. Because each driver's driving speed varies, the quantity of data points in each dataset file varies. The solution is to divide our dataset into smaller groups, work on them individually, and make the frequency of the events the same.
4. The batches must have the exact dimensions to feed our data to the model. For example, we cannot provide 20 kilometres of one route for learning in one batch and the remaining 5 kilometres (3 kilometres for testing and 2 kilometres for validation) in two separate batches. The solution is to divide our dataset into smaller batches, the same size as the data points, and work on them individually.
5. The low volume dataset for deep learning is an issue, as the dataset content described previously. Obviously, for deep learning pattern recognition, we need to have more volume of the dataset. So, we proposed overlapped time series sequences to provide more training, validation, and test dataset as input for the designed model.

6. Model sensitivity occurs during the model training because of imbalanced weights of classes. The nature of aggressive or non-aggressive driving made this an issue. It means that when we drive, the potential of aggressive driving is far less than normal driving. We oversampled aggressive driving during the training and validation phase and used weighted classes in our RNN models to address this phenomenon.

3.5. Methodology

Our proposed model is a labelled (supervised) data-based deep learning pattern recognition model. The best outcome is then reached in the evaluation (real-world test) process by adjusting the topology and hyperparameters. The time-series data of speed changes in a driving trajectory is shown in the figure-1. In addition to speed, our dataset also includes geographic position information, which leads to a better outcome in the deep learning process.

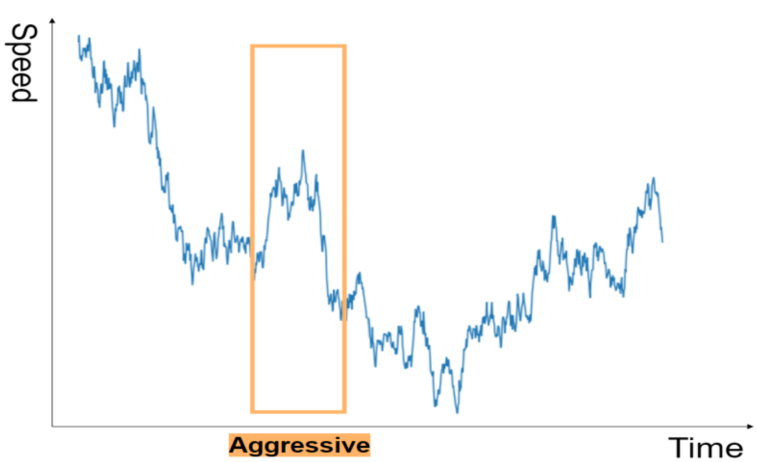


Figure 14 Speed changes of a trajectory

We construct various LSTM and GRU architectures with varying parameter values and evaluate their output to determine which design best fits our situation. The original dataset is divided into three sections: training, validation, and test. Two types of normalization (Min-Max and Standardization) approach are used first, followed by a seven-layer LSTM/GRU model with drop-out, batch normalization, delta, and shuffled training datasets before splitting.

Figure 2 shows that in the first layer, we are preparing a trajectory value of a driver with 120 seconds of their driving that each moment has eight features (speed, longitude, latitude, altitude, and differentials). Then, the following seven neural networks are LSTM/GRU (different experiments), drop out (make it more complex for the model to find patterns easier), and a batch normalizer that helps to the consistency of values sent to the next layer. After seven layers of LSTM/GRU layers, a dense layer with activation of sigmoid classify the pattern of the trajectory to one of the classes of aggressive or non-aggressive.

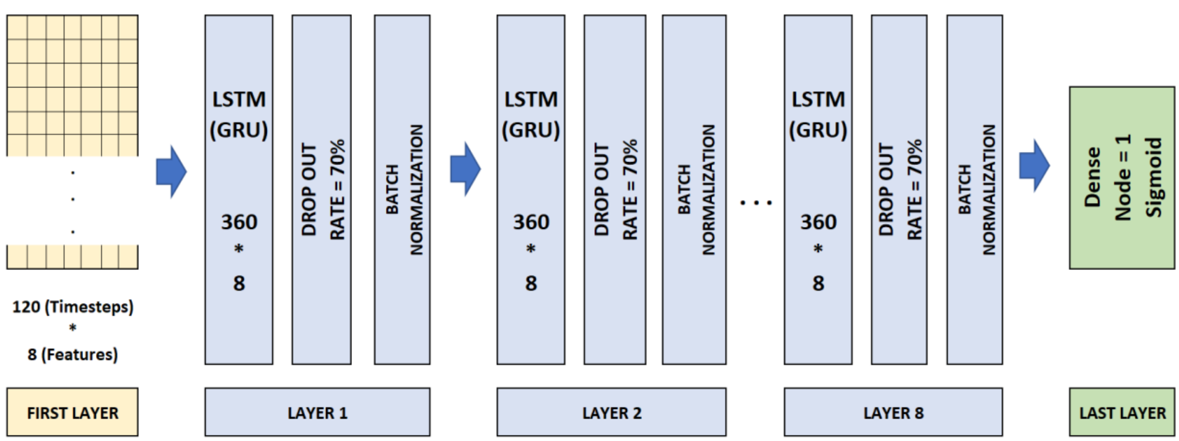


Figure 15 Neural Network Diagram

We implement 24 different models based on the parameters below:

1. **Input shape:** The input shape went from 60 seconds to 120 and then to 180, which improved the accuracy; the trend shows that we will get better accuracy than driving GPS records to be sent for the input layer. Nevertheless, as we want to implement a real-world model to be deployable on an embedded device, the accuracy (98% on test evaluation) of the model that works with 2 minutes of driving would be sufficient.
2. **Normalization type:** Normalization is used to reduce the amount of duplication in a connection or collection of relationships. In the experiments, the "Standardization" was shown to be superior to "Min-Max" normalization.
3. **The number of Hidden Layers:** To obtain the optimal decision boundary, we must use hidden layers; thus, we gradually increase the number of hidden layers from one to seven, with seven providing the best results. We make the model complex enough to capture all the patterns and map them to the correct target class.
4. **Drop-out:** Drop-out is a technique for preventing a model from overfitting, and so introducing drop-out after each GRU/LSTM layer helped our model avoid overfitting. We use a 70% drop-out value to let the model find all its nodes, relations, and weights.
5. **Batch normalization:** Batch normalization is a technique for standardizing the inputs to a network that can be applied to either the activations of a preceding layer of inputs or to the activations of a subsequent layer of inputs directly. Batch normalization accelerates training in some situations by halving or bettering the number of epochs and provides some regularization, hence lowering generalization error. Batch normalization undoubtedly aids our model.
6. **Shuffling the training Dataset:** After several tests, we discovered that one of the issues with model training is that the last segment of each trajectory is always given to the model for validation. However, the model picked up on 70% of drivers' first Behaviour. Nevertheless,

the model will encounter all drivers' Behaviour using this new method, which involves shuffling the training dataset before dividing it.

7. **Adding differentials:** The delta rule is a gradient descent learning rule for updating the weights of the inputs to a neural network. It is a particular case of the more general backpropagation algorithm and helps in slightly improving the accuracy.

3.6. Data preprocessing

1. Single row as a data point vs time-series: If we treat each row as a data point in the primary technique and pass them to our model, we notice that this strategy is invalid for our problem because the data points are related in time. It is illogical to classify a driver's Behaviour based on a single geographical data point. For example, if only an individual driver is in a specific location, we cannot judge that they are driving aggressively.

2. Window size of data points, time-correlation: We know our dataset is a time series dataset since each row corresponds with the preceding and next rows. Additionally, we understand that the driver's current location is irrelevant at any given time, but the location changes and how they occur are critical to us. As a result, we chose to employ the window size notion, treat a batch of rows as a single data point, and send them to the model to verify that it is discovering relationships between distinct data points.

3. Variation and road-type features: We enhance our model by including variations and road-type variables. Variations may be a more helpful feature for our model because they connect two distinct data points and aid the model in determining their correlation. Additionally, given that we have two distinct roads, understanding the road type can aid the model. Nevertheless, we try to

add those variations to make the dependency of the model to the specific location of the road that the dataset gathering occurs, and it drastically helps the proposed model.

4. Shuffling: We choose various segments of each road as a test and validation dataset to demonstrate the route's whole course to our model. For instance, rather than utilizing the first 20 kilometres of our road for training and the remaining five kilometres for validation and testing (on a 25-kilometre road), we split our dataset into the specified window size first, then mixed the data and utilized a percentage of batches for testing.

5. Overlapping the datapoints: When we utilized a larger window size, for example, 180 sequences of GPS records, the number of data points decreased substantially. Thus, we applied the overlapping idea. In this study, we use the sliding window concept to choose the batches.

6. The "speed limit" as a feature: We included a speed difference with the road's maximum speed to the dataset because we have two roads with varying maximum speeds in our dataset. It enables the model to link the top speed with driving behaviour.

7. Evaluation based on "not seen driver" (real-world evaluation): Since our dataset has six distinct drivers, we partition it to make our model more generic. Five drivers are chosen for training and validation, and one is separated and never shown to the model to reserve for the testing phase. This practice simulates real-world tests conducted in our model evaluation section.

By more understanding of the data, it is possible to enhance the subsequent stages of DL activities. Comprehending data implies the completeness of the data, its purpose and application[26]. Then comes the data cleaning phase, which entails completing gaps in data, smoothing out noise, identifying and removing outliers, and addressing discrepancies. Following that, data integration is required, which is often necessary when combining different databases or files. Each driver's dataset occupies a separate folder, and each folder contains different types of driving on different roads. So, in this step, we code a function to walk between folders and combine all the files into one integrated file with the tags of driver label, type of driving and name of the trajectory. In the following data conversion, we are confronted with data normalization, modification, and aggregation procedures at this data preprocessing step. We use both Min-Max scaling and standardization in preprocessing of feature scaling of data for the model. A critical finding of Min-Max Scaling is that it is strongly affected by our data's highest and lowest values, which means it will be skewed if our data includes outliers. So, all experiments that utilize standardization have better results. In the following, there are two examples and charts of the feature scaling concept.

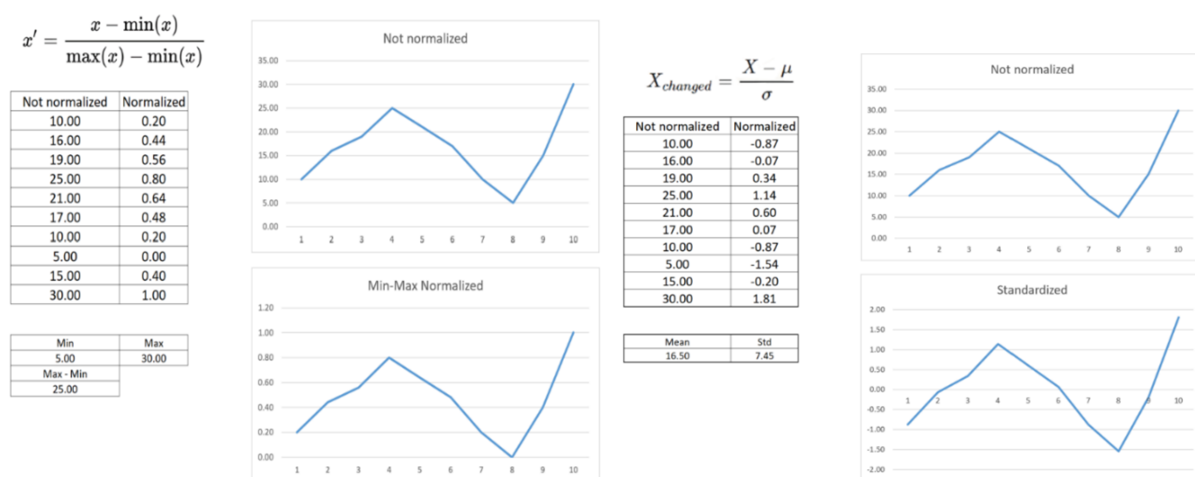


Figure 16 Min-Max and Standardization normalization formula and examples

3.6.1 Split dataset preparation

Dataset Split is a technique to evaluate the performance of the ML classification model. We take a given dataset and divide it into three subsets. The training dataset is a set of data used for learning (by the model), that is, to fit the parameters of the ML model [67]. The validation dataset is a set of data used to provide an unbiased evaluation of a model fitted on the training dataset while tuning model hyperparameters. It also plays a role in other forms of model preparation, such as feature selection and threshold cut-off selection. The testing dataset is a set of data used to provide an unbiased evaluation of a final model fitted on the training dataset [26].

Our proposed model for the learning phase experiences two different methods. In the first method, shown in Figure 2, all the information is first merged. Then the training, validation and test dataset are split. In this experiment, the model has a chance to see at least part of the trajectory of all drivers. However, in the second method, the D5 driver is wholly excluded from the training and validation process and is only evaluated during the model testing. The advantage of the first method is that the model faces more occurrences of different datasets. Hence the disadvantage is that the model may have poorer performance in the real world. The benefit of the second method is that the simulation model has practically passed the real-world test. However, at the same time, it loses the chance of encountering a more significant data set during training, which will be solved during deployment. The way to solve the last problem is that the model is simultaneously in classifier and learning mode in the production environment, which also classifies driving behaviour. Moreover, it learns new scenes.

<table>
<tr><th>Dataset name</th><th>Percentage
(of selected datasets)</th><th colspan="5">Data of Drivers (shuffled)</th></tr>
<tr><td>Training</td><td>80%</td><td rowspan="2">D1</td><td rowspan="2">D2</td><td rowspan="2">D3</td><td rowspan="2">D4</td><td rowspan="2">D6</td></tr>
<tr><td>Validation</td><td>20%</td></tr>
<tr><td>Testing</td><td>100%</td><td colspan="5">D5</td></tr>
</table>

Table 3 Unseen driver for the test phase

Dataset name	Percentage (of selected datasets)	Data of Drivers (shuffled)					
Training	70%	D1	D2	D3	D4	D5	D6
Validation	15%						
Testing	15%						

Table 4 Normal approach of dataset split

3.6.2 Changes of the values

One of our primary responsibilities as model designers is to minimize the model's reliance on the dataset. As a result, we added modifications to each dataset record's GPS values, such as latitude, longitude, and altitude, in this phase. Thus, the first record of each route is treated as 0. Furthermore, each timestep tracks changes. For example, in Figure 3, it is shown that the latitude value changes from 23.45 to 29.45. Thus, in the "latitude delta" cell, positive six changes of values are logged.

Timestep	Latitude	Longitude	Altitude
1	23.45	56.78	12.56
2	29.45	59.78	11.50
...	...	...	...

Timestep	Latitude	Longitude	Altitude	**Latitude Delta**	**Longitude Delta**	**Altitude Delta**
1	23.45	56.78	12.56	**0**	**0**	**0**
2	29.45	59.78	11.50	**+6**	**+3**	**-1.06**
...	...	...	...	**...**	**...**	**...**

Figure 17 Changes of values

3.6.3 The overlapped divided method

The UAH database contains various trajectories of six drivers on two distinct roads while exhibiting various driving behaviours. If we utilize basic cuts to identify driving patterns, our data volume will significantly decrease. If we create trajectories using the overlapping split method, our data volume will grow by up to tenfold. In another way, since our suggested model is based on deep machine learning techniques, it needs a more significant amount of data. In Figure 4, it is evident that with 6 points of timesteps instead of two trajectories, we use them in 6 trajectories.

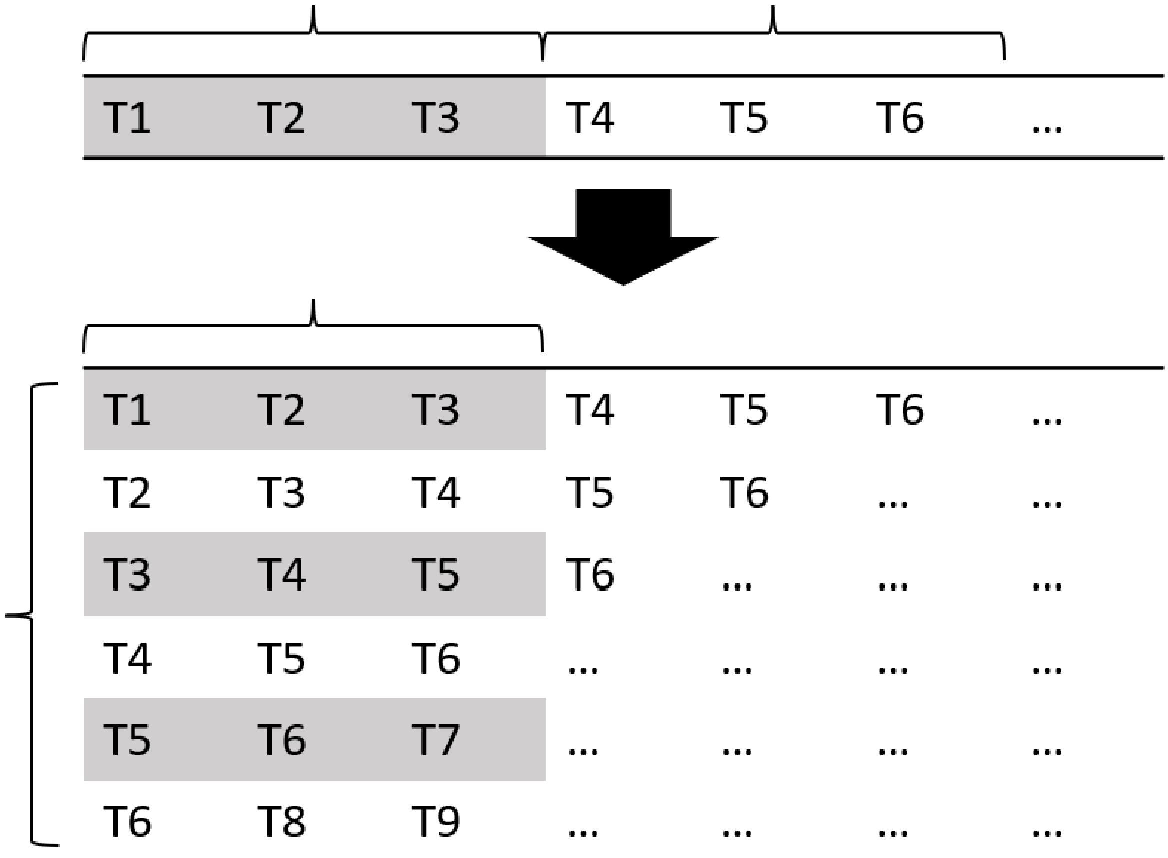


Figure 18 Overlapping of trajectories timeseries

3.7. Evaluation

Once we fit a deep learning neural network model, we must assess its performance on a test dataset [67]. Evaluation of the Test dataset is crucial since the reported performance lets us pick between candidate models and educates us about how optimum the model is at handling the problem. We employ a conventional binary classification issue in this work. We investigated two distinct techniques to analyzing the data in this investigation. To assess model outcomes, one utilizes cross-validation, while the other uses external evaluation. We used cross-validation as a technique for determining how well a statistical study generalizes to a different data set. This approach evaluates deep learning models by training them on existing input datasets and then testing them on complementary datasets. We were able to obtain excellent outcomes in this manner. However, to boost confidence in the outcomes. We also employed the process of external evaluation. In this manner, we repeated the tests on the designed model, but with alterations in the sort of way in which the training dataset, validation, and testing were separated. Before separating the data, we alternatively put aside one of the drivers to operate as if it were the actual world. As a result, the model does not observe the driver, and we only used all of that data while testing and assessing the model.

Another distinction between khodairy et al.'s [68] research and ours is that they employ the fixed split approach to divide driving trajectories into equal sections. In our technique, we employ the dynamic method. As indicated in Section 3.6.3, we attempted to prepare as many trajectory pieces as feasible to find more patterns.

3.7.1 Accuracy

The difficulty with accuracy as our primary performance metric is that it does not fare well with a significant class imbalance. Let us explain our model parameters in our target vector, 0 signifies normal, and 1 means aggressive driving. If we utilize the accuracy statistic, it says that 99 percent of the time, the model characterizes the "normal" driving accurately. However, when it comes to identifying aggressive driving, it can categorize 70 percent of inputs. So, the accuracy cannot reflect an acceptable metric for our model. In the following section, we will explain the "F1 Score".

3.7.2 F1 Score

The F1 measurement is an overall assessment of a model's correctness that combines precision and recalls in that addition and multiplication blend two compositions to form a different notion entirely [69]. An excellent F1 score indicates we have low false positives and low false negatives, so we properly detect genuine threats and are not bothered by false alarms. An F1 score is ideal for 1, whereas the model is a dismal failure with 0.

All models will create some false negatives, some false positives, and maybe both. While we may tweak a model to reduce one or the other, we typically confront a trade-off, where a decrease in false negatives increases false positives or vice versa. We will need to optimize for the performance measures that are most beneficial for our unique situation.

3.8. Experimental results

The findings (Figure 5) indicated that with the LSTM algorithm, we had an accuracy of 99.6 percent in three minutes of driving and 98.4 percent in two minutes of driving. Due to the near distance between three minutes and two minutes, we might offer the model based on two minutes between two to three minutes.

The characteristics and settings of the model are detailed below. The number of input ports is 120 nodes, and the number of intermediate levels is eight, with each layer containing 360 nodes. In the last layer, we employed a layer with a Sigmoid activation function to conduct the categorizing. In the last layer, we utilized the output bias initializer to alter the weight between classes.

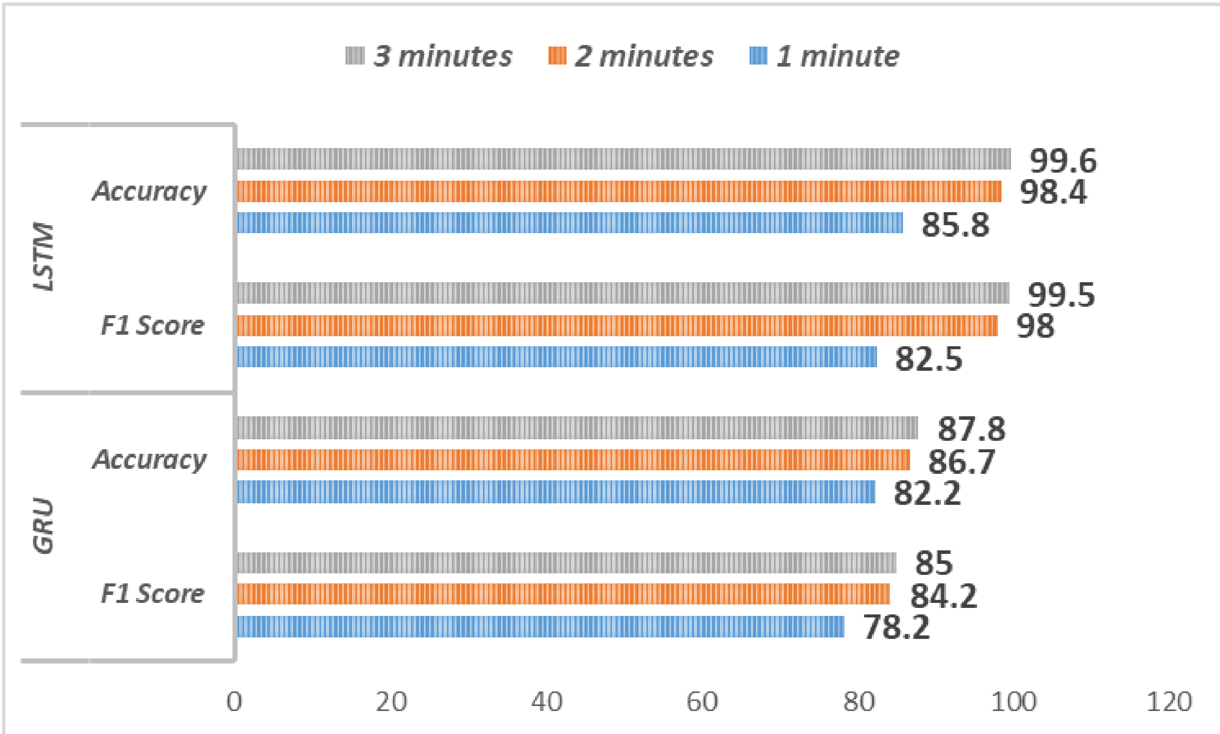


Figure 19 Models Evaluations

In Figure 6, we can see the accuracy and F1 score values. These tests are generated by entirely reserving the dataset of a driver (Driver 5) for the validation phase. Our suggested model achieves 93 percent accuracy in real-world testing with three minutes of driving. In prior investigations, this approach has not been employed for validation and is essential in its type.

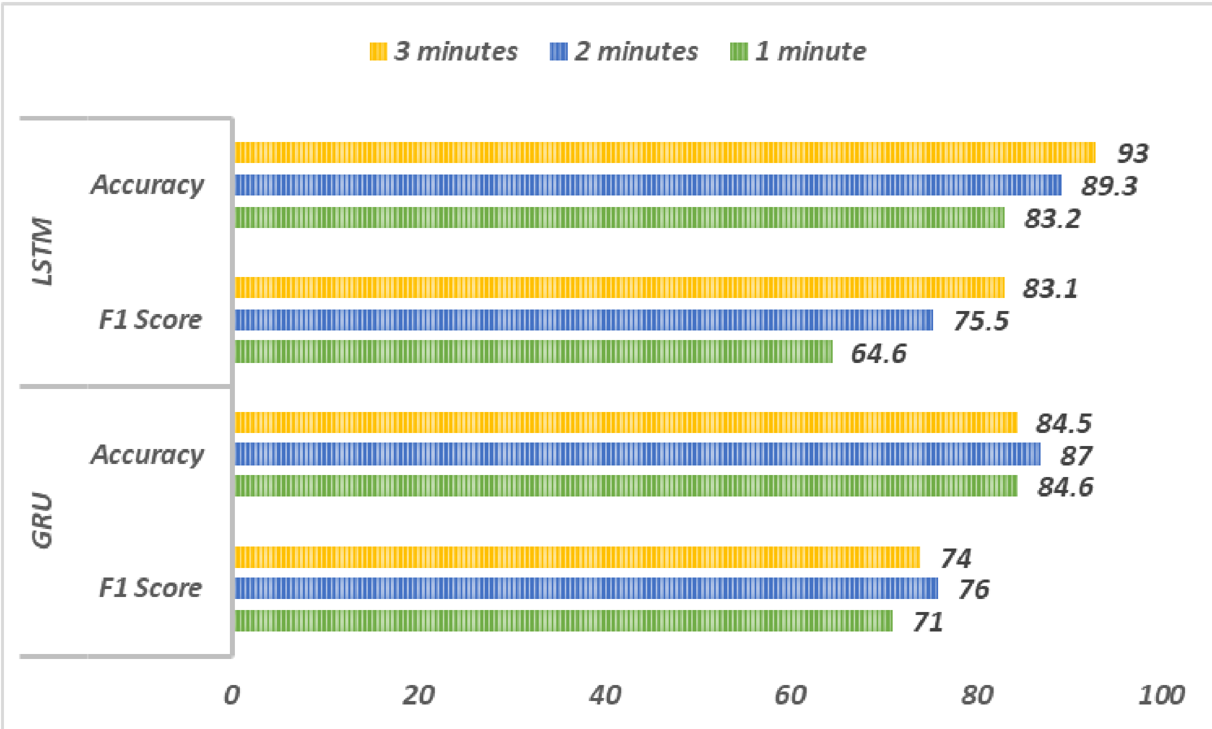


Figure 20 Real-world Evaluations

3.9. Conclusion

Our dataset comprises time-series data, and algorithms that can detect the relationship between time and feature changes produce excellent results in our study, as shown in table 6. Regardless of whether the model is evaluated using reserved validation data or real-world tests. The real-world results also show that their driving behaviour can be characterized (aggressive or non-aggressive) by having GPS recordings of around three minutes of the driving trajectory.

Table 6 categorizes the studies we conducted into two broad groups. For experiments, we employed the GRU approach initially, followed by the LSTM method. This approach is substantially quicker and more efficient than previous RNN methods in performing computations.

We began with little outings (one minute). The time was then raised to three minutes. We tried with multiple normalizing approaches for each trip size, utilizing two MIN-MAX methods and ultimately the Standardization method.

Normalization outperformed standardization in both types of algorithms. To eliminate bias in studies, we attempted to employ two alternative methods of assessment (cross-validation and external). And we displayed all of the experiments and results in a table. I attempted to utilize several criteria such as loss, accuracy, precision, and F1 to ensure that, despite the fact that our data is of the unbalanced weight class type, there are no measurement mistakes in assessing the findings.

3.10. Future works

This model will be embedded in a program run on multiple smartphone operating systems in the following phases. Because the suggested AI model can identify the driver's behavioural driving behaviour every three minutes, the information is synced every three minutes with the server system situated in the cloud. This device will function with any cellphone that permits access to GPS, regardless of the type of vehicle and whether the vehicle is a self-driving or conventional type.

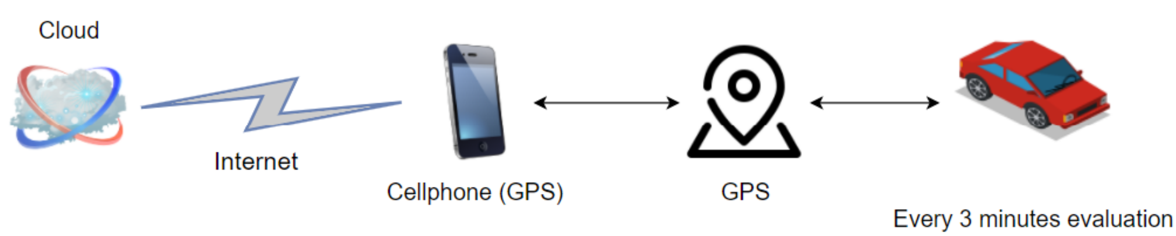


Figure 21 Embedded AI Model in the smartphone

In the proposed approach, which deals with the aggressive driving detection model, good things can be done in the future. Psychological research, for example, can be incorporated into this paradigm. A future proposal would be to give the driver a questionnaire before and after driving or to include personal medical information such as heart rate or blood pressure as input to the model before, during, and after driving. One of the benefits of the model we provided is that a new feature may be added to it forever, and it detects an aggressive driving style using deep learning approaches.

Chapter Four: Conclusion

4.1 Summary and conclusion

Supervised behavioural pattern detection is an interesting deep learning technique that can allow for an interpretable output. The system proposed in this work (Chapter 3) takes this a step further by ensuring that each section of the process, data preprocessing, trajectory preparation, overlapped time-series input, stacked RNN customized model strike a good balance between simplicity and performance. Specifically, this work uses a customized value changes calculation stage (Section 3.6.2) that adds the number of features without losing the model's performance, improving pattern detection. The ability to add the unlimited features as input of the proposed model (Section 3.5) that utilizes the algorithm adapted for aggressive driving behaviour detection is essentially a new way of improving supervised deep learning algorithms.

The proposed Stacked layer LSTM model adds a layer on top of the classification algorithm that enables monitoring systems to identify aggressive drivers within a much shorter time scale and can be applied on an embedded system independent of any vehicle type. This work was evaluated with two different approaches: 1. Cross-Evaluation 2. The external dataset (Section 3.8) was as performant as previous research with simpler and faster calculations (Section 3.7.2).

Overall, this approach shows promise and has the potential to be used in regulatory organizations and other settings where non-technical people require insight into deep learning models.

4.2 Thesis contribution summary

A summary of the list of contributions to this thesis:

- Survey paper:

  Our research attempted to construct a complete survey paper to examine and offer driving behaviour analysis survey data to future scholars. We sought to identify conventional approaches by examining 58 publications and create a framework for future articles to be analyzed and explored in various charts and datasets.

- Dynamic survey approach:

  In contrast to traditional "survey papers," which typically limit the breadth of the study, we attempted to present a new model called "Dynamic Survey," which aids in the study's implementation. In a typical "survey paper," any action connected to the topic published after the survey paper, such as new articles or chapters of a book, should be considered a new survey paper. Nonetheless, the included articles in this dynamic survey will be updated using an algorithm in its database and a crawler that finds and submits linked published papers to the database. As a result, all dashboards and trends are still active and ready for analysis by the next researchers.

- New approach of overlapped data preparation:

  Our study dataset included a variety of trajectories from different drivers on two separate routes while demonstrating a variety of driving behaviours. If we had used basic cuts to identify driving patterns, our data amount would have been massively diminished. As a result of applying the overlapping split approach to build trajectories, our data amount increased tenfold. In another sense, because our proposed model is based on deep machine learning techniques, it required a larger amount of data.

- Stacked deep learning model:

  We built various LSTM and GRU architectures with variable parameter values and assessed their output to decide which design best suits our needs. Before splitting, a seven-layer LSTM/GRU model with drop-out, batch normalization, delta, and shuffled training datasets is utilized, followed by two types of normalizing procedures. We created a trajectory value for a driver based on 60/120/180 seconds of driving, with each instant including eight characteristics. The next seven neural networks include LSTM/GRU, drop out, and a batch normalizer, which improves the consistency of values delivered to the next layer. After seven LSTM/GRU layers, a thick layer with sigmoid activation classifies the trajectory pattern as aggressive or non-aggressive.

- Multiple way of evaluation:

  In this study, we looked into two different approaches for assessing data. We performed cross-validation to see how statistical research generalizes to a different data set. This method assesses them by first training them on current input datasets and then testing them on complementary datasets. We were able to get good results in this method. However, in order to increase trust in the outcomes. We also used the external evaluation technique. As a result, we repeated the tests on the planned model; alternatively, we set apart one of the drivers to work as if it were the real world. As a result, the model does not watch the driver, and we only used all of that data during testing and evaluation.

4.3 Suggestions for future works

The dynamic survey study extends this research path by allowing keywords to be tracked and current dashboards to be re-examined. When new inputs are received, these dashboards are intended to highlight new patterns. What if, for example, the most recent research approach documented with "aggressive driving detection" has moved from CNN to RNN? or is the RNN still the best approach to identify time-related datasets?

Adding psychological information to the suggested technique, which deals with the aggressive driving detection model, would be a smart thing to undertake in the future. This paradigm can integrate, for example, psychological studies. A future idea would be to provide a questionnaire to the driver before and after the drive, or to integrate personal medical information such as heart rate or blood pressure as input to the model before, during, and after the trip. One advantage of the model we supplied is that new features may be added to it indefinitely, and it detects aggressive driving behavior using deep learning methodologies.

In the future phases, this concept might be included in a software that runs on several smartphone operating systems. Because the proposed AI model can recognize the driver's aggressive driving behavior every three minutes, the data is synchronized with the cloud server system. This gadget will work with any cellphone that has GPS access, regardless of the type of automobile or whether it is self-driving or conventional.

Appendix:

Article	Proposed approaches	Citation	Dataset	Summary
[37]	CNN; Pooling; RNN;	77	Kaggle. Driver Telematics Analysis. [39]	For DL-based driving behaviour analysis, GPS data was utilized; extracting important attributes explains behaviour patterns. Human effort and effort both suffered.
[38]	CNN	0	The Didi Chuxing GAIA Initiative to the research community; [70]	The paper proposes dividing drivers into four types: risky, dangerous, safe, and low risk. This paper's main contribution is using CNNs (Convolutional Neural Networks) to process raw trajectories into inputs for the CNNs. After training the CNN network, 77.3% accuracy was achieved.
[71]	RuLSIF; SOM; Clustering; Deep auto-encoder;	1	Kaggle. Driver Telematics Analysis. [39]	The vehicle data recorder was replaced with an internal smartphone sensor. However, unlabeled telematics data limits their application in analyzing driving patterns. Unsupervised learning was used to obtain mobile telematics data. Three significant components included a self-organizing map, a nine-layer deep auto-encoder, and partitive clustering algorithms.
[72]	Resampling; Normalization; Stacked-LSTM;	47	U-AH Dataset [47]	Recent Stack LSTM Recurrent Neural Networks for classifying driving behaviour; time-series classification was applied using smartphone sensors. The Stacked-LSTM model was validated using the dataset known as UAH-DriveSet. An LSTM stack excelled on the UAH-DriveSet.
[46]	Abrupt change detection; Sparse auto-encoder; Two-level clustering (SOM; K-means)	16	DTG database maintained by the TS (Traffic Safety)	The findings find habits in driving. Three different data analytic analysis methods were used, including abrupt change detection. This model was developed on data from 43 Korean city taxis. The framework can find aggressive driving clusters in large-scale driving records.
[48]	Two-level K-Means	8	OSeven Telematics, London, United Kingdom	Information about harsh events occurrence, acceleration profile, mobile usage, and speeding was used in this study to detect unsafe driving behaviour. To separate aggressive from non-aggressive trips, they conducted an initial clustering. A second-level clustering was done to delineate "normal" trips from unsafe ones.

[73]	Multi-CNN; GBDT predictor	1	KITTI dataset [14]	Feature integration is critical, which is why they propose the multi-CNN architecture. A dynamic fixed point compression method is applied in our system; smaller model size and faster speed can be achieved while the accuracy is high; prediction results are a driving score that reflects driver behaviour.
[74]	maximum entropy inverse reinforcement learning (MEIRL) with automatic feature correction	22	N/A	The building block for many LBS applications is trajectory outlier detection. The paper focuses on accurately detecting outliers in-vehicle trajectories. The proposed solution uses a late-stage alarm for a missed outlier trajectory (i.e., the trajectory has not yet reached the destination).
[40]	Auto-Encoder; Deep Walk; CNN; LINE	32	T-Drive trajectory dataset [49]	A GPS trajectory analysis framework (PTARL) was developed. GPS traces were used to track driving operations and driver states. When determining a driver's behaviour, multiview driving state transition graphs were used. A representation learning method for sequence learning from time-varying, yet relational state transition graphs were produced. According to the method, graph-graph dependency and temporal dependency can be handled using a unified optimization framework.
[75]	Pattern recognition; GHSOM;	3	N/A	A pattern recognition process was used to model the driving pattern based on one driver and a fleet's energy consumption. The GHSOM shows that learned driving behaviours can be recognized as the number of driving cycles increases. Additionally, the proposed framework would enhance driver behaviours and make it easier to design an ADAS.
[76]	SFG; GRU (an enhancement of LSTM) combine with FCN;	1	HACKING AND COUNTERMEASURE RESEARCH LAB. [45]	This paper presents a new technique, LiveDI, which uses driving behaviour to identify drivers. The model uses GRU and FCN to learn long-short term patterns of driving behaviours from drivers. Additionally, training time was increased by implementing the SFG algorithm to identify a time window for analysis.
[77]	GHSOM (Unsupervised) + SVM (Supervised)	5	N/A	A pattern recognition approach is proposed to model the driving pattern, given the consumption of an EV. Gradual drivers' behaviour change is implemented through the

				GHSOM, and classifiers are implemented with clustered neurons for an online process using SVM.
[78]	CGARNN-Edge	9	N/A	A "pBEAM" platform for personalized driving behaviour modelling is promoted. The driving behaviour model is built on top of "GARNN," which follows dynamic changes in everyday driving. Moving models to the edge improves model performance and robustness. "CGARNN-Edge" is a model tailored to drivers' personal information and preferences as additional conditions.
[79]	SVM; RF; NN	4	N/A	This paper uses ML methods to analyze and predict driving routes, establishing a solid foundation for improving driver behaviour.
[80]	DNN; LSTM	12	Kaggle. Driver Telematics Analysis. [39]	This study analyzes sensor data to identify sematic-level driving behaviour. A large dataset was utilized layer-by-layer for driving maneuvers. The specific maneuver driver ID is helpful in supervised learning of higher-level feature abstraction. This paper proposes a joint histogram feature map to normalize the "Shallow features" for DL. The results show that DNN is suitable for classifying driving maneuvers, with 94% accuracy, whereas LSTM NN has the accuracy of 92% when identifying a specific driver.
[81]	LSTM;	9	N/A	The perceived risk by drivers in different groups on a two-lane road is tested, using a DNN method to summarize environmental features. These training and testing data are for the learning network. Using an LSTM model, risk perception is modelled as a function of traffic conditions and vehicle data.
[51]	PCA; Fast ICA; KPCA	89	N/A	The DSAE method is used to uncover previously hidden driving features for visualization. The DSAE has a method of producing a driving colour map using 3-D hidden feature extraction to RGB colour space. For a driving map, colours are placed in the corresponding map locations.
[82]	Rep-DRQN; LSTM;	1	Simulated data (SUMO)	Traffic flow can be improved by applying reinforcement learning techniques to a traffic control system. First, a microcosmic state representation, which integrates vehicle dynamics, such as lane changing, car-following, and previous phases of a traffic light, is proposed. The red light flooding the system is also incorporated into the action space. A partially LSTM network is used to

				improve travel experience and efficiency. In practice, parallel sampling is used to speed up training convergence.
[83]	LSTM;	3	HACKING AND COUNTERMEASURE RESEARCH LAB. [45]	The uniqueness of a driver's driving behaviour helps driver profiling and vehicle security (anti-theft systems). This paper analyzes data-driven end-to-end models intended for behaviour identification and examines the principles that underlie the model designs. The real-world driving dataset is employed in cross-validation to test various data-driven DL and machine, learning models.
[84]	CNN; LSTM	4	Gathered by themselves	This promising research employs a two-stream CNN approach for video-based driving behaviour recognition. CNN collects motion information by computing optical flow displacement over a few adjacent frames. A spatial-temporal fusion study was conducted to determine behaviour recognition, constructing a 1237-video dataset simulating different driving behaviours to test the model's efficacy.
[85]	Deep RL	10	Simulated data	A decision-making method based on deep reinforcement learning is proposed for connected vehicles in complex traffic scenarios. The model has three primary components: a data preprocessor that transforms hybrid data into a grid matrix data format; a two-stream deep neural network that extracts the hidden features; and a deep reinforcement learning network that learns the optimal policy. Additionally, a simulation environment is built to train and test the proposed method. The results show that the model can learn the best overall driving policy, such as driving fast through diverse traffic without unnecessary lane changes.
[60]	Dedistracted Net; CNN;	4	Gathered by themselves	DedistractedNet was built to identify distracted driving behaviours from an image. DedistractedNet uses neural networks to identify driving behaviour features without onboard diagnostics or sensors. The experiments show that the DedistractedNet performs better than the other baseline CNN methods.
[61]	MV-CNN + Data Augmentation	14	Gathered by themselves	This paper introduces a driver behaviour recognition system utilizing a six-axis motion processor. DL learns from onboard sensor data. A new algorithm is proposed (called MV-CNN) that includes the multi-axis

				weighted fusion algorithm, background noise fusion algorithm, and random cropping algorithm. Following the CNN model, a new model, called MV-CNN, was developed.
[86]	Stacked Auto-Encoders;	0	Simulated data	DL is the proposed method of classifying individual drivers (stacked autoencoders). Sensor signals from a driving simulator were used to assess drivers' driving skills. The maximum driving skill recognition rate was 98.1 percent, and the recognition rate was also increased in this research.
[87]	DBN	6	Gathered by themselves	A deep belief network (DBN) was used to build the learning model, and training data was collected from real-world road drivers. Using the model, they predicted the front wheel's steering angle and the vehicle's speed. Prediction results show that DBN has higher accuracy and adapts to different driving scenarios with fewer modifications.
[88]	Reviewing all approaches;	4	N/A	"HIDB" is categorized into two major categories: Driver Distraction (DD), Driver Fatigue (DF), or Drowsiness (DFD). Aggressive Driving (ADB) is also discussed. ADB is a wide range of driving styles that have significant consequences. DD, DFD, and ADB are affected by the experience, age, and gender or illness.
[89]	Deep Auto Encoders;	4	Gathered by themselves	A new approach to proactive driving using human experts and autonomous agents is introduced. DL methods extracted latent features. Velocity profiles were created to provide an autonomous driving agent with human-like driving skills. Being proactive was shown to help avoid unnecessary jerkiness.
[90]	Spectral Clustering Algorithm; LSTM;	19	Gathered by themselves	Using unsupervised spectral clustering, researchers identified a macroscopic relationship between driving behaviour and fuel consumption in the natural driving process. Additionally, dynamic information was acquired from the driving environment and driving data to link different driving behaviours to fuel consumption features to give computers the ability to recognize environments. The vehicle's operating signal data was used to provide the training data for the DL network. Fuel consumption feature distribution was based on roadway data and historical driving data.

[91]	LSTM;	0	The Warrigal dataset [50]	The researchers have developed (1) a novel feature extraction method for raw CAN bus data;(2) a novel boosting method for driving behaviour classification (safe or unsafe) that combines advantages of DL and shallow learning methods; and (3) a first-of-its-kind public transportation industry evaluation using real-world data to ensure accurate labels from industry experts.
[92]	Deep Q-Network	3	Gathered by themselves	This L-HMC combines deep reinforcement learning with collision avoidance capacity. An improved DQN method is used to learn the best driving policy for pedestrian collision avoidance. The findings demonstrate that the deep reinforcement learning-based method can rapidly learn an effective pedestrian collision avoidance driving policy. Meanwhile, L-HMC uses flexible policies to avoid pedestrian collisions in typical scenarios, improving overall driving safety.
[93]	Stacked Auto-Encoders;	3	Gathered by themselves	This novel DL-based model is built for abnormal driving detection. A stacked sparse autoencoder enables learning driving behaviour features. Training is layer-wise, greedy. This study is the first time researchers have used DL to build representations of driving features using autoencoders. The algorithm is also denoised with an algorithm, making it more stable. Dropout is commonly used in training to reduce overfitting. The proposed system has better performance for finding abnormal driving.
[94]	LSVDNN	0	Gathered by themselves	By using the designed model, the output used for controlling the vehicle is obtained. The learning and validation approach for self-driving vehicles (LSV-DNN) is outlined, and a convolutional network based on vehicle cameras and computer data is developed. Obstacle detection is carried out with the best accuracy and speed using the Yolo algorithm version 3.
[95]	DCNN	2	https://github.com/abdugumaei/ADBs-Dataset	A real-time detection system is proposed, utilizing bio-signals and a deep CNN model, incorporating edge and cloud technologies. The system contains vehicle edge devices, cloud platforms, and monitoring environments linked via a telecommunication network. Processed bio-signal datasets are employed to test the proposed DCNN model. The dataset was collected using a different

				time window and time step than the bio-signal datasets.
[96]	Denoising Stacked Autoencoder (SDAE)	4	Gathered by themselves	An improved DL model is proposed in this study to develop a graphical representation of driver behaviour and the road environment. A Denoising Stacked Autoencoder (SDAE) is proposed to provide output layers in RGB colours. The dataset was collected from an in-vehicle GPS tracking device on an experimental driving test. By using graphics, the method efficiently identifies simple driving behaviours and other events encountered along the path.
[97]	Deep Deterministic Policy Gradient (DDPG);	0	Simulated data (TORCS)	Adaptive driving behaviour for simulated cars is proposed using continuous control deep reinforcement learning. The DDPG delivers smooth driving maneuvers in simulated environments. Recurrent Deterministic Policy Gradients were used to encode time (or Recurrent DDAGs). A trained agent adapts to traffic velocity.
[98]	DBN; LSTM;	42	Simulated data (NGSIM, 2006)	This paper uses data-driven LC modelling using DL. To better model the LC process, Deep Belief Network (DBN) and Long Short-Term Memory (LSTM) neural networks are employed (LCI). The "NGSIM" project's empirical LC data is used for training and testing the proposed DBN-based and LSTM-based LCI models.
[99]	DBN-FS (Fuzzy sets)	1	Gathered by themselves	The feature matrix contains data on nearly 2,000 lane-change videos. Also, vehicle information is obtained based on license plates. A state-of-the-art DBN DL algorithm creates a lane-change behaviour model incorporating relevant vehicle, driver, and driving variables. The model's superior accuracy, feasibility, and concreteness are verified by comparison with other standard models.
[100]	CNN	0	Simulated data (OpenAI)	DL-based learning techniques are proposed in this paper, which can be applied in various driving scenarios. The proposed method is tested for effectiveness and efficiency, and the proposed methods are shown to outperform other ML methods.
[101]	LTSM-FCN	5	U-AH Dataset [47]	The solution proposed in this paper is based on a Long Short-Term Memory Fully Convolutional Network (LTSM-FCN) to identify driving sessions that include aggressive behaviour. The problem is

				formulated as a time series classification, and the validity of the approach is tested on the UAH-DriveSet, a dataset that provides naturalistic driving data collected from smartphones via a driving monitoring application.
[102]	CNN	18	SEU-DRIVING / KAGGLE-DRIVING	A DL method for classifying driving behaviour in a single image is investigated in this paper. The classification of driving behaviour is a multi-class problem. The research team discovered a solution to this problem in two ways: Extract multi-scale features using multi-stream CNN was extracted and then combined into a final decision for driving behaviour recognition.
[103]	gradient boosted model with grid search;	1	https://insight.shrp2nds.us	Given road conditions and driver behaviour, the study included multiple factors to produce an interpretable model for accident occurrence. Seven thousand seven hundred trips were studied using four ML and DL techniques. Accident prediction was achieved by a gradient boosted model. Predictive factors were shown to be primary behaviour, pre-incident maneuvers, and secondary task duration.
[104]	Feature selection with NN	1	Gathered by themselves	Feature extraction and a DL model are suggested to detect abnormal driving behaviour. This method was developed based on bin variation calculation and subsequent feature generation. Variance similarity was used to expand the subset. Variance data from data segments with specific driving behaviour class definitions revealed the connection. Driving behaviours included weaving, sudden braking, and everyday driving.
[44]	CNN; LSTM; GRU	22	HACKING AND COUNTERMEASURE RESEARCH LAB. [45]	A unified end-to-end DL framework based on convolutional and recurrent neural networks is proposed for time series CAN-BUS sensor data. This method is capable of learning driving and temporal information without prior knowledge. The method can access rich feature representations of driving behaviours from multi-sensor data.
[105]	NCAE; MC-CNN;	1	HACKING AND COUNTERMEASURE RESEARCH LAB. [45]	The researchers first propose utilizing an unsupervised three-layer nonnegativity-constrained autoencoder to search for the sliding window's optimal size and then build a deep nonnegativity-constrained autoencoder network to complete driver identification. Their method can search for optimal window

				size and save many data compared to conventional sparse autoencoder, dropout-autoencoder, random tree, and random forest algorithms. Also, their technique helps classifiers distinguish the differing class boundaries. Finally, their method helps increase the prediction time and reduce model overfitting.
[106]	Decision Tree; Random Forest;	13	https://insight.shrp2nds.us	ML is suggested to identify secondary tasks drivers use while driving. First, drivers' distraction is found, and second, unique kinds of distractions are discovered. Nine classification methodologies are utilized to identify three secondary tasks (hand-held cellphone calling, cellphone texting, and interaction with an adjacent passenger). The models use five driving behaviour parameters (including standard deviations) as inputs. The paper's findings show that using a proposed methodology for characterizing drivers' involvement in secondary tasks (like texting) helps drivers identify driving hazards and alert them to problems on the road.
[107]	CNN; RNN	9	Gathered by themselves	This paper proposes a DL framework for behaviour extraction. The machine used for their method models temporal features captures salient structure features and fuses CNN and RNN with an attention unit. Gathering a driving behaviour dataset also takes into consideration gravity's effect. Device-independent sensor data is collected. The preferred sensor information is furnished by this method.
[108]	CNN; FC; LSTM;	0	Gathered by themselves	A driver's eyes are the primary source of information while they are driving. Data show that drivers' gazes precede and correlate with driving maneuvers. Thus, GazMon is designed to detect and predict driving maneuvers. The "GazMon" facial analysis uses facial landmarks, including facial features and head posture, to evaluate the effects. Their GazMon outperforms the competing products in predicting and reducing distracting behaviours. It is easy to customize and will work with existing smartphones.
[109]	DenseNet	6	https://www.kaggle.com/c/state-farm-distracted-	This paper stresses D fusion techniques. For the first time, three novel DL-based fusion models for abnormal driving behaviour detection are proposed. WGD network,

			driver-detection/data	WGRD network, and AWGRD network are three DL-based fusion models equivalent to their functional characteristics. The actual model structure of WGD is modelled using DenseNet.
[110]	Autoencoders	10	Gathered by themselves	This paper studies encoding, clustering, and modelling driver behaviours to build an autonomous vehicle agent. A typical Japanese suburban area driver provided driving speed, braking, steering, and acceleration data. A fully Connected Deep Autoencoder was used to long datasets of consecutive measurements to collect driving data for clustering purposes. Data were modelled and validated in a ROS car simulator.
[111]	t-SNE; CVAE;	2	Gathered by themselves	This paper offers a DL approach to vehicle driving styles. The neural network groups short behavioural segments into a latent space. The driving dataset had 59 drivers on a highway. Embedded driving behaviour data were clustered into clusters using a topological map. Elements exhibit probabilistic distributions that compactly describe driving episodes.
[112]	DCNN	1	Gathered by themselves	This paper focuses on the end-to-end technique that emulates human drivers' decisions, such as steering angle, acceleration, and deceleration. Ignoring previous states is investigated by comparing predicted accuracy and variation, using data collected in a simulation study.
[113]	DNNR-Ensemble	0	N/A	By using PAYD, insurance carriers can avoid unjust and inefficient policies. The authors propose a PAYD method that incorporates user behaviour factors from multiple dimensions. This first dimensionally divides all factors. Treating each dimension of the factors separately improves the model's efficiency. “DNNRegressor” is used to make each classification dimension weak. The DNNRegressor classifier yields the final output.
[114]	LSTM;	51	Next Generation Simulation (NGSIM)	This paper proposes an LSTM NN-based car-following (CF) model to capture natural traffic flow characteristics. The proposed CF model is calibrated and validated using NGSIM data. Three driving-related characteristics are investigated: hysteresis, discrete driving, and intensity difference. The

				simulation results show the CF model's good traffic flow features reproduction.
[115]	R-CNN	1	Gathered by themselves	In this paper, vehicle-mounted camera-based driver detection that utilizes Faster R-CNN is proposed. First, a residual structure is added to the ZF network. BN replaces LRN, which increases parameter stability and accelerates network convergence.
[116]	NK-DNA	6	Gathered by themselves	A new security model using driving data and the neural knowledge DNA is proposed in this paper. A novel knowledge representation method helps computers discover, store, reuse, improve, and share knowledge.
[56]	Autoencoder and Self-organized Maps (AESOM)	21	Shenzhen Urban Transport Planning Center, Shenzhen, China	A hybrid unsupervised DL model for modelling driving behaviour and risky patterns was developed for this paper. The extraction method uses Autoencoders and Self-Organized Maps (AESOM).
[117]	deep convolutional neural network; LSTM;	6	Gathered by themselves	Because many traffic accidents occur at intersections due to unsafe driving behaviours, this paper presents a smartphone-based system for analyzing driving behaviour at intersections. A deep convolutional neural network-based model is proposed to detect traffic lights, crosswalks, and stop lines. The LSTM-based model estimates vehicle speed using an accelerometer and gyroscope embedded in the smartphone.
[118]	DSAE	4	N/A	A driving behaviour time series is assumed to be generated from a single-dimensional dataset that everyone has access. Sensor time-series data is faulty because of a sensor failure. Another essential function is to limit the negative impact when extracting low-dimensional time-series data. Using a “DSAE,” low-dimensional time-series data is extracted.

Table 5 Summarized articles

NN	timestep	normalization	Evaluation	loss	accuracy	precision	recall	F1 Score
GRU	60	Min-Max	Seen	0.5617	0.776	0.687	0.822	0.748461233
GRU	60	Standardization	Seen	0.4212	0.822	0.775	0.789	0.78193734
GRU	120	Min-Max	Seen	1.0759	0.781	0.736	0.714	0.724833103
GRU	120	Standardization	Seen	0.379	0.867	0.81	0.877	0.842169532
GRU	180	Min-Max	Seen	0.8107	0.736	0.689	0.629	0.657634294
GRU	180	Standardization	Seen	0.4329	0.878	0.843	0.857	0.849942353
GRU	60	Min-Max	Unseen	0.2487	0.896	0.805	0.711	0.755085752
GRU	60	Standardization	Unseen	0.3219	0.846	0.619	0.83	0.709137336
GRU	120	Min-Max	Unseen	0.5059	0.801	0.533	0.802	0.640398502
GRU	120	Standardization	Unseen	0.3903	0.87	0.643	0.927	0.759313376
GRU	180	Min-Max	Unseen	0.4403	0.828	0.58	0.789	0.668546384
GRU	180	Standardization	Unseen	0.2088	0.845	0.588	0.991	0.738072198
LSTM	60	Min-Max	Seen	0.3348	0.822	0.762	0.816	0.788076046
LSTM	60	Standardization	Seen	0.2913	0.858	0.821	0.829	0.824980606
LSTM	120	Min-Max	Seen	0.2997	0.923	0.963	0.841	0.897874723
LSTM	120	Standardization	Seen	0.0544	0.984	0.973	0.987	0.97995
LSTM	180	Min-Max	Seen	0.0602	0.981	0.974	0.98	0.976990788
LSTM	180	Standardization	Seen	0.0124	0.996	0.994	0.997	0.99549774
LSTM	60	Min-Max	Unseen	0.4245	0.837	0.632	0.664	0.647604938

LSTM	60	Standardization	Unseen	0.3991	0.832	0.619	0.675	0.645788253
LSTM	120	Min-Max	Unseen	0.7365	0.86	0.667	0.727	0.695708752
LSTM	120	Standardization	Unseen	0.5766	0.893	0.764	0.746	0.754892715
LSTM	180	Min-Max	Unseen	0.4201	0.903	0.771	0.778	0.774484183
LSTM	180	Standardization	Unseen	0.4131	0.93	0.855	0.809	0.831364183

Table 6 Experiments details

References:

[1] W. H. Organization, "Road Traffic Injuries," 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries. [Accessed: 25-Oct-2021].

[2] W. H. Organization, "World Health Organization, 2018. Global Safety Report on Road Safety.," 2018.

[3] National Highway Traffic Safety Administration, "Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey," *Natl. Highw. Traffic Saf. Adm.*, no. February, pp. 1–2, 2015.

[4] B. Ryder, B. Gahr, P. Egolf, A. Dahlinger, and F. Wortmann, "Preventing traffic accidents with in-vehicle decision support systems - The impact of accident hotspot warnings on driver behaviour," *Decis. Support Syst.*, vol. 99, pp. 64–74, 2017, doi: 10.1016/j.dss.2017.05.004.

[5] M. Čubranić-Dobrodolac, L. Švadlenka, S. Čičević, and M. Dobrodolac, "Modelling driver propensity for traffic accidents: a comparison of multiple regression analysis and fuzzy approach," *Int. J. Inj. Contr. Saf. Promot.*, vol. 27, no. 2, pp. 156–167, 2020, doi: 10.1080/17457300.2019.1690002.

[6] P. Intini, N. Berloco, P. Colonna, V. Ranieri, and E. Ryeng, "Exploring the relationships between drivers' familiarity and two-lane rural road accidents. A multi-level study," *Accid. Anal. Prev.*, vol. 111, pp. 280–296, 2018, doi: 10.1016/j.aap.2017.11.013.

[7] J. Kalsi, T. Tervo, A. Bachour, and M. Partinen, "Sleep versus non−sleep-related fatal

road accidents," *Sleep Med.*, vol. 51, pp. 148–152, 2018, doi: 10.1016/j.sleep.2018.04.017.

[8] J. Archer, "A strategic approach to aggression," *Soc. Dev.*, vol. 10, no. 2, pp. 267–271, 2001, doi: 10.1111/1467-9507.00163.

[9] J. L. Deffenbacher, R. S. Lynch, E. R. Oetting, and R. C. Swaim, "The Driving Anger Expression Inventory: A measure of how people express their anger on the road," *Behav. Res. Ther.*, vol. 40, no. 6, pp. 717–737, 2002, doi: 10.1016/S0005-7967(01)00063-8.

[10] S. Afkhami Goli, "Location Estimation and Trajectory Prediction for Collision Risk Assessment in Connected Vehicle Environment," p. 160, 2019.

[11] B. F. Farid Talebloo, Emad A. Mohammed, "Deep Learning Approach for Aggressive Driving Behaviour Detection."

[12] M. Noaeen, "Managing Urban Traffic Networks Using Data Analysis, Traffic Theory, and Deep Reinforcement Learning," 2021.

[13] N. C. for I. P. and C. Centers for Disease Control and Prevention, "Motor Vehicle Crash Deaths." [Online]. Available: https://www.cdc.gov/vitalsigns/motor-vehicle-safety/index.html.

[14] "KITTI dataset." [Online]. Available: http://www.cvlibs.net/datasets/kitti/raw_data.php.

[15] C. Zhang *et al.*, "A crash risk identification method for freeway segments with horizontal curvature based on real-time vehicle kinetic response," *Accid. Anal. Prev.*, vol. 150, 2021, doi: 10.1016/j.aap.2020.105911.

[16] G. Hermawan and E. Husni, "Acquisition, Modeling, and Evaluating Method of Driving Behavior Based on OBD-II: A Literature Survey," *IOP Conf. Ser. Mater. Sci. Eng.*, vol.

879, no. 1, 2020, doi: 10.1088/1757-899X/879/1/012030.

[17] Y. Xing *et al.*, “Identification and Analysis of Driver Postures for In-Vehicle Driving Activities and Secondary Tasks Recognition,” *IEEE Trans. Comput. Soc. Syst.*, vol. 5, no. 1, pp. 95–108, 2018, doi: 10.1109/TCSS.2017.2766884.

[18] F. Talebloo, “Dynamic Survey of DL Approaches for Driving Behaviour Analysis.” [Online]. Available: https://datastudio.google.com/s/pV5qYf0Mg-A.

[19] F. Talebloo, “Driving Behavior Analysis Dynamic Survey Developments.” [Online]. Available: https://github.com/faridtalebloo/Driving-Behavior-Analysis-Dynamic-Survey.

[20] Cambridge, “ANALYSIS | meaning in the Cambridge English Dictionary.” [Online]. Available: https://dictionary.cambridge.org/dictionary/english/analysis.

[21] Merriam-Webster, “Behavior | Definition of Behavior by Merriam-Webster.” [Online]. Available: https://www.merriam-webster.com/dictionary/behavior.

[22] Oxford, “driving_1 noun - Definition, pictures, pronunciation and usage notes.” [Online]. Available: https://www.oxfordlearnersdictionaries.com/definition/english/driving_1.

[23] History, “Automobile History - HISTORY.” [Online]. Available: https://www.history.com/topics/inventions/automobiles.

[24] oldcarbrochures, “Directory Index: Duesenberg/1922_Duesenberg_Model_A_Catalogue.”

[25] Hsing-Shenq Hsieh, Kuo-Liang Ting, and Ruey-Min Wang, “An image processing system for signalized intersections,” pp. 28–34, 2002, doi: 10.1109/vnis.1995.518814.

[26] G. Ciaburro and B. Venkateswaran, “Neural network with R: Smart models using CNN, RNN, deep learning, and artificial intelligence principles,” *Packt*, vol. 91, pp. 399–404,

2017.

[27] Y. B. Ian Goodfellow, Yoshua Bengio, Aaron Courville, *Deep learning*. MIT Press.

[28] SuperDataScience Team, "Convolutional Neural Networks (CNN): Step 1- Convolution Operation." [Online]. Available: https://www.superdatascience.com/blogs/convolutional-neural-networks-cnn-step-1-convolution-operation.

[29] A. Dertat, "Applied Deep Learning - Part 4: Convolutional Neural Networks."

[30] D. Han, Q. Liu, and W. Fan, "A new image classification method using CNN transfer learning and web data augmentation," *Expert Syst. Appl.*, vol. 95, pp. 43–56, 2018, doi: 10.1016/j.eswa.2017.11.028.

[31] N. M. Rezk, M. Purnaprajna, T. Nordstrom, and Z. Ul-Abdin, "Recurrent Neural Networks: An Embedded Computing Perspective," *IEEE Access*, vol. 8, pp. 57967–57996, 2020, doi: 10.1109/ACCESS.2020.2982416.

[32] Stanford, "Architecture of a traditional RNN." [Online]. Available: https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks#overview.

[33] P. Baldi, "Autoencoders, Unsupervised Learning, and Deep Architectures," in *ICML Unsupervised and Transfer Learning*, 2012, pp. 37–50, doi: 10.1561/2200000006.

[34] R. Atienza, *Advanced Deep Learning with Keras: Apply Deep Learning Techniques, Autoencoders, GANs, Variational Autoencoders, Deep Reinforcement Learning, Policy Gradients, and More*. 2018.

[35] O. G. Yalçın, *Applied Neural Networks with TensorFlow 2*. 2021.

[36] T. Kohonen, “The Self-Organizing Map,” *Proc. IEEE*, vol. 78, no. 9, pp. 1464–1480, 1990, doi: 10.1109/5.58325.

[37] W. Dong, J. Li, R. Yao, C. Li, T. Yuan, and L. Wang, “Characterizing Driving Styles with Deep Learning,” 2016.

[38] X. Yang, F. Ding, D. Zhang, and M. Zhang, “Vehicular Trajectory Big Data: Driving Behavior Recognition Algorithm Based on Deep Learning,” *Commun. Comput. Inf. Sci.*, vol. 1253 CCIS, pp. 324–336, 2020, doi: 10.1007/978-981-15-8086-4_30.

[39] “Driver Telematics Analysis | Kaggle.” [Online]. Available: https://www.kaggle.com/c/axa-driver-telematics-analysis.

[40] P. Wang, P. Wang, Y. Fu, Y. Zheng, J. Zhang, and C. Aggarwal, “You Are How You Drive: Peer and Temporal-Aware Representation Learning for Driving Behavior Analysis,” *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, pp. 2457–2466, 2018, doi: 10.1145/3219819.3219985.

[41] A. B. Ellison, M. C. J. Bliemer, and S. P. Greaves, “Evaluating changes in driver behaviour: A risk profiling approach,” *Accid. Anal. Prev.*, vol. 75, pp. 298–309, 2015, doi: 10.1016/j.aap.2014.12.018.

[42] Y. L. Zhu, X., Yuan, Y., Hu, X., Chiu, Y. C., & Ma, “A Bayesian Network model for contextual versus non-contextual driving behavior assessment,” *Transp. Res. Part C Emerg. Technol.*, 2017.

[43] S. M. Simmons, A. Hicks, and J. K. Caird, “Safety-critical event risk associated with cell phone tasks as measured in naturalistic driving studies: A systematic review and meta-

analysis," *Accid. Anal. Prev.*, vol. 87, pp. 161–169, 2016, doi: 10.1016/j.aap.2015.11.015.

[44] J. Zhang *et al.*, "A deep learning framework for driving behavior identification on in-vehicle CAN-BUS sensor data," *Sensors (Switzerland)*, vol. 19, no. 6, 2019, doi: 10.3390/s19061356.

[45] "HACKING AND COUNTERMEASURE RESEARCH LAB. (EST. IN 2010)." [Online]. Available: https://ocslab.hksecurity.net/Datasets/driving-dataset.

[46] J. Lee and K. Jang, "A framework for evaluating aggressive driving behaviors based on in-vehicle driving records," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 65, pp. 610–619, 2019, doi: 10.1016/j.trf.2017.11.021.

[47] "U-AH Dataset." [Online]. Available: http://www.robesafe.uah.es/personal/eduardo.romera/uah-driveset/#download.

[48] E. G. Mantouka, E. N. Barmpounakis, and E. I. Vlahogianni, "Identifying driving safety profiles from smartphone data using unsupervised learning," *Saf. Sci.*, vol. 119, pp. 84–90, 2019, doi: 10.1016/j.ssci.2019.01.025.

[49] "T-Drive trajectory dataset." [Online]. Available: https://www.microsoft.com/en-us/research/publication/t-drive-trajectory-data-sample/.

[50] "The Warrigal dataset." [Online]. Available: http://its.acfr.usyd.edu.au.

[51] H. Liu, T. Taniguchi, Y. Tanaka, K. Takenaka, and T. Bando, "Visualization of Driving Behavior Based on Hidden Feature Extraction by Using Deep Learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 9, pp. 2477–2489, 2017, doi: 10.1109/TITS.2017.2649541.

[52] M. Enev, A. Takakuwa, K. Koscher, and T. Kohno, “Automobile Driver Fingerprinting,” *Proc. Priv. Enhancing Technol.*, vol. 2016, no. 1, pp. 34–50, 2016, doi: 10.1515/popets-2015-0029.

[53] J. Elander, R. West, and D. French, “Behavioral correlates of individual differences in road-traffic crash risk: An examination of methods and findings.,” *Psychol. Bull.*, vol. 113, no. 2, pp. 279–294, 1993, doi: 10.1037//0033-2909.113.2.279.

[54] F. Sagberg, Selpi, G. F. Bianchi Piccinini, and J. Engström, “A review of research on driving styles and road safety,” *Hum. Factors*, vol. 57, no. 7, pp. 1248–1275, 2015, doi: 10.1177/0018720815591313.

[55] D. Potoglou, F. Carlucci, A. Cirà, and M. Restaino, “Factors associated with urban non-fatal road-accident severity,” *Int. J. Inj. Contr. Saf. Promot.*, vol. 25, no. 3, pp. 303–310, 2018, doi: 10.1080/17457300.2018.1431945.

[56] J. Guo, Y. Liu, L. Zhang, and Y. Wang, “Driving behaviour style study with a hybrid deep learning framework based on GPS data,” *Sustain.*, vol. 10, no. 7, 2018, doi: 10.3390/su10072351.

[57] N. Lin, C. Zong, M. Tomizuka, P. Song, Z. Zhang, and G. Li, “An overview on study of identification of driver behavior characteristics for automotive control,” *Math. Probl. Eng.*, vol. 2014, 2014, doi: 10.1155/2014/569109.

[58] P. Wasielewski, “Speed as a measure of driver risk: Observed speeds versus driver and vehicle characteristics,” *Accid. Anal. Prev.*, vol. 16, no. 2, pp. 89–103, 1984, doi: 10.1016/0001-4575(84)90034-4.

[59] D. J. French, R. J. West, J. Elander, and J. M. Wilding, “Decision-making style, driving style, and self-reported involvement in road traffic accidents,” *Ergonomics*, vol. 36, no. 6, pp. 627–644, 1993, doi: 10.1080/00140139308967925.

[60] Y. T. Pang, S. W. Syu, Y. C. Huang, and B. H. Chen, “An Advanced Deep Framework for Recognition of Distracted Driving Behaviors,” *2018 IEEE 7th Glob. Conf. Consum. Electron. GCCE 2018*, pp. 270–271, 2018, doi: 10.1109/GCCE.2018.8574512.

[61] Y. Zhang, J. Li, Y. Guo, C. Xu, J. Bao, and Y. Song, “Vehicle Driving Behavior Recognition Based on Multi-View Convolutional Neural Network with Joint Data Augmentation,” *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4223–4234, 2019, doi: 10.1109/TVT.2019.2903110.

[62] J. Z. Varghese and R. G. Boone, “Overview of Autonomous Vehicle Sensors and Systems,” *Int. Conf. Oper. Excell. Serv. Eng.*, pp. 178–191, 2015.

[63] G. Milner, “What is GPS?,” *J. Technol. Hum. Serv.*, vol. 34, no. 1, pp. 9–12, 2016, doi: 10.1080/15228835.2016.1140110.

[64] P. E. Ceruzzi, *GPS*. Cambridge, Massachusetts : The MIT Press. 2018.

[65] T. Ganegedara, “Natural Language Processing with TensorFlow,” p. 473, 2018.

[66] E. Romera, L. M. Bergasa, and R. Arroyo, “Need data for driver behaviour analysis? Presenting the public UAH-DriveSet,” *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, pp. 387–392, 2016, doi: 10.1109/ITSC.2016.7795584.

[67] M. Khashei and M. Bijari, “An artificial neural network (p, d, q) model for timeseries forecasting,” *Expert Syst. Appl.*, vol. 37, no. 1, pp. 479–489, 2010, doi:

10.1016/j.eswa.2009.05.044.

[68] M. A. Khodairy and G. Abosamra, "Driving Behavior Classification Based on Oversampled Signals of Smartphone Embedded Sensors Using an Optimized Stacked-LSTM Neural Networks," *IEEE Access*, vol. 9, pp. 4957–4972, 2021, doi: 10.1109/ACCESS.2020.3048915.

[69] G. Bénédict, V. Koops, D. Odijk, and M. de Rijke, "sigmoidF1: A Smooth F1 Score Surrogate Loss for Multilabel Classification," 2021.

[70] "The Didi Chuxing GAIA Initiative to the research community." [Online]. Available: https://outreach.didichuxing.com/research/opendata/en/.

[71] M. Siami, M. Naderpour, and J. Lu, "A Mobile Telematics Pattern Recognition Framework for Driving Behavior Extraction," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1459–1472, 2021, doi: 10.1109/TITS.2020.2971214.

[72] K. Saleh, M. Hossny, and S. Nahavandi, "Driving behavior classification based on sensor data fusion using LSTM recurrent neural networks," pp. 1–6, 2018, doi: 10.1109/itsc.2017.8317835.

[73] S. Yin, J. Duan, P. Ouyang, L. Liu, and S. Wei, "Multi-CNN and decision tree based driving behavior evaluation," *Proc. ACM Symp. Appl. Comput.*, vol. Part F1280, pp. 1424–1429, 2017, doi: 10.1145/3019612.3019649.

[74] H. Wu, W. Sun, and B. Zheng, "A fast trajectory outlier detection approach via driving behavior modeling," *Int. Conf. Inf. Knowl. Manag. Proc.*, vol. Part F1318, pp. 837–846, 2017, doi: 10.1145/3132847.3132933.

[75] C. H. Lee and C. H. Wu, “A data driven approach to create an extensible EV driving data model,” *ACM Int. Conf. Proceeding Ser.*, 2016, doi: 10.1145/2955129.2955164.

[76] H. Abu-Gellban, L. Nguyen, M. Moghadasi, Z. Pan, and F. Jin, “LiveDI: An Anti-theft Model Based on Driving Behavior,” *IH MMSec 2020 - Proc. 2020 ACM Work. Inf. Hiding Multimed. Secur.*, pp. 67–72, 2020, doi: 10.1145/3369412.3395069.

[77] C. H. Lee and C. H. Wu, “An incremental learning technique for detecting driving behaviors using collected EV big data,” *ACM Int. Conf. Proceeding Ser.*, vol. 07-09-Ocob, 2015, doi: 10.1145/2818869.2818935.

[78] X. Zhang, M. Qiao, L. Liu, Y. Xu, and W. Shi, “Collaborative cloud-edge computation for personalized driving behavior modeling,” *Proc. 4th ACM/IEEE Symp. Edge Comput. SEC 2019*, pp. 209–221, 2019, doi: 10.1145/3318216.3363310.

[79] Y. Wang, Y. Qin, W. Xu, W. Zhang, Y. Zhang, and X. Wu, “Machine learning methods for driving risk prediction,” *Proc. 3rd ACM SIGSPATIAL Int. Work. Use GIS Emerg. Manag. EM-GIS 2017*, 2017, doi: 10.1145/3152465.3152476.

[80] Y. Wang and I. W. H. Ho, “Joint Deep Neural Network Modelling and Statistical Analysis on Characterizing Driving Behaviors,” *IEEE Intell. Veh. Symp. Proc.*, vol. 2018-June, pp. 2060–2065, 2018, doi: 10.1109/IVS.2018.8500376.

[81] P. Ping, Y. Sheng, W. Qin, C. Miyajima, and K. Takeda, “Modeling Driver Risk Perception on City Roads Using Deep Learning,” *IEEE Access*, vol. 6, pp. 68850–68866, 2018, doi: 10.1109/ACCESS.2018.2879887.

[82] L. Liao *et al.*, “Time Difference Penalized Traffic Signal Timing by LSTM Q-Network to

Balance Safety and Capacity at Intersections," *IEEE Access*, vol. 8, pp. 80086–80096, 2020, doi: 10.1109/ACCESS.2020.2989151.

[83] M. N. Azadani and A. Boukerche, "Performance Evaluation of Driving Behavior Identification Models through CAN-BUS Data," *IEEE Wirel. Commun. Netw. Conf. WCNC*, vol. 2020-May, 2020, doi: 10.1109/WCNC45663.2020.9120734.

[84] Y. Hu, M. Lu, and X. Lu, "Spatial-Temporal Fusion Convolutional Neural Network for Simulated Driving Behavior Recognition," *2018 15th Int. Conf. Control. Autom. Robot. Vision, ICARCV 2018*, pp. 1271–1277, 2018, doi: 10.1109/ICARCV.2018.8581201.

[85] Z. Bai, W. Shangguan, B. Cai, and L. Chai, "Deep reinforcement learning based high-level driving behavior decision-making model in heterogeneous traffic," *Chinese Control Conf. CCC*, vol. 2019-July, pp. 8600–8605, 2019, doi: 10.23919/ChiCC.2019.8866005.

[86] T. Kagawa and N. P. Chandrasiri, "Analysis of driving skills based on deep learning using stacked autoencoders," *Int. Conf. Electr. Eng. Comput. Sci. Informatics*, vol. 2017-Decem, 2017, doi: 10.1109/EECSI.2017.8239200.

[87] C. Zhao, J. Gong, C. Lu, G. Xiong, and W. Mei, "Speed and steering angle prediction for intelligent vehicles based on deep belief network," *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, vol. 2018-March, pp. 301–306, 2018, doi: 10.1109/ITSC.2017.8317929.

[88] M. H. Alkinani, W. Z. Khan, and Q. Arshad, "Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges," *IEEE Access*, vol. 8, pp. 105008–105030, 2020, doi: 10.1109/ACCESS.2020.2999829.

[89] K. Sama *et al.*, "Extracting Human-Like Driving Behaviors from Expert Driver Data Using Deep Learning," *IEEE Trans. Veh. Technol.*, vol. 69, no. 9, pp. 9315–9329, 2020, doi: 10.1109/TVT.2020.2980197.

[90] P. Ping, W. Qin, Y. Xu, C. Miyajima, and K. Takeda, "Impact of driver behavior on fuel consumption: Classification, evaluation and prediction using machine learning," *IEEE Access*, vol. 7, pp. 78515–78532, 2019, doi: 10.1109/ACCESS.2019.2920489.

[91] S. Luo, A. P. Leung, X. Qiu, J. Y. K. Chan, and H. Huang, "Complementary deep and shallow learning with boosting for public transportation safety," *Sensors (Switzerland)*, vol. 20, no. 17, pp. 1–16, 2020, doi: 10.3390/s20174671.

[92] J. Li, L. Yao, X. Xu, B. Cheng, and J. Ren, "Deep reinforcement learning for pedestrian collision avoidance and human-machine cooperative driving," *Inf. Sci. (Ny).*, vol. 532, pp. 110–124, 2020, doi: 10.1016/j.ins.2020.03.105.

[93] J. Hu, X. Zhang, and S. Maybank, "Abnormal Driving Detection with Normalized Driving Behavior Data: A Deep Learning Approach," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 6943–6951, 2020, doi: 10.1109/TVT.2020.2993247.

[94] N. Zaghari, M. Fathy, S. M. Jameii, M. Sabokrou, and M. Shahverdy, "Improving the learning of self-driving vehicles based on real driving behavior using deep neural network techniques," *J. Supercomput.*, vol. 77, no. 4, pp. 3752–3794, 2021, doi: 10.1007/s11227-020-03399-4.

[95] A. Alamri, A. Gumaei, M. Al-Rakhami, M. M. Hassan, M. Alhussein, and G. Fortino, "An Effective Bio-Signal-Based Driver Behavior Monitoring System Using a Generalized Deep Learning Approach," *IEEE Access*, vol. 8, pp. 135037–135049, 2020, doi:

10.1109/ACCESS.2020.3011003.

[96] A. Bichicchi, R. Belaroussi, A. Simone, V. Vignali, C. Lantieri, and X. Li, “Analysis of road-user interaction by extraction of driver behavior features using deep learning,” *IEEE Access*, vol. 8, pp. 19638–19645, 2020, doi: 10.1109/ACCESS.2020.2965940.

[97] K. Mani, M. Kaushik, N. Singhania, and K. M. Krishna, “Learning adaptive driving behavior using recurrent deterministic policy gradients,” *IEEE Int. Conf. Robot. Biomimetics, ROBIO 2019*, pp. 2092–2098, 2019, doi: 10.1109/ROBIO49542.2019.8961480.

[98] D. F. Xie, Z. Z. Fang, B. Jia, and Z. He, “A data-driven lane-changing model based on deep learning,” *Transp. Res. Part C Emerg. Technol.*, vol. 106, pp. 41–60, 2019, doi: 10.1016/j.trc.2019.07.002.

[99] Y. Hao, L. Xu, X. Wang, Y. Li, and G. Chen, “Aggressive lane-change analysis closing to intersection based on UAV video and deep learning,” *ICTIS 2019 - 5th Int. Conf. Transp. Inf. Saf.*, pp. 496–502, 2019, doi: 10.1109/ICTIS.2019.8883543.

[100] Z. Wu, C. Li, J. Chen, and H. Gao, “Learning driving behavior for autonomous vehicles using deep learning based methods,” *2019 4th IEEE Int. Conf. Adv. Robot. Mechatronics, ICARM 2019*, pp. 905–910, 2019, doi: 10.1109/ICARM.2019.8834039.

[101] Y. Moukafih, H. Hafidi, and M. Ghogho, “Aggressive Driving Detection Using Deep Learning-based Time Series Classification,” *IEEE Int. Symp. Innov. Intell. Syst. Appl. INISTA 2019 - Proc.*, 2019, doi: 10.1109/INISTA.2019.8778416.

[102] Y. Hu, M. Lu, and X. Lu, “Driving behaviour recognition from still images by using

multi-stream fusion CNN," *Mach. Vis. Appl.*, vol. 30, no. 5, pp. 851–865, 2019, doi: 10.1007/s00138-018-0994-z.

[103] M. Monselise, O. S. Liang, and C. C. Yang, "Identifying Important Risk Factors Associated with Vehicle Injuries Using Driving Behavior Data and Predictive Analytics," *2019 IEEE Int. Conf. Healthc. Informatics, ICHI 2019*, 2019, doi: 10.1109/ICHI.2019.8904860.

[104] H. Nassuna, O. S. Eyobu, J. H. Kim, and D. Lee, "Feature selection based on variance distribution of power spectral density for driving behavior recognition," *Proc. 14th IEEE Conf. Ind. Electron. Appl. ICIEA 2019*, pp. 335–338, 2019, doi: 10.1109/ICIEA.2019.8834349.

[105] J. Chen, Z. Wu, J. Zhang, and S. Chen, "Driver identification based on hidden feature extraction by using deep learning," *Proc. 2019 IEEE 3rd Inf. Technol. Networking, Electron. Autom. Control Conf. ITNEC 2019*, pp. 1765–1768, 2019, doi: 10.1109/ITNEC.2019.8729442.

[106] O. A. Osman, M. Hajij, S. Karbalaieali, and S. Ishak, "A hierarchical machine learning classification approach for secondary task identification from observed driving behavior data," *Accid. Anal. Prev.*, vol. 123, pp. 274–281, 2019, doi: 10.1016/j.aap.2018.12.005.

[107] J. Zhang *et al.*, "Attention-Based Convolutional and Recurrent Neural Networks for Driving Behavior Recognition Using Smartphone Sensor Data," *IEEE Access*, vol. 7, pp. 148031–148046, 2019, doi: 10.1109/ACCESS.2019.2932434.

[108] X. Fan, F. Wang, D. Song, Y. Lu, and J. Liu, "GazMon: Eye Gazing Enabled Driving Behavior Monitoring and Prediction," *IEEE Trans. Mob. Comput.*, vol. 20, no. 4, pp.

1420–1433, 2021, doi: 10.1109/TMC.2019.2962764.

[109] W. Huang, X. Liu, M. Luo, P. Zhang, W. Wang, and J. Wang, “Video-based abnormal driving behavior detection via deep learning fusions,” *IEEE Access*, vol. 7, pp. 64571–64582, 2019, doi: 10.1109/ACCESS.2019.2917213.

[110] K. Sama, Y. Morales, N. Akai, H. Liu, E. Takeuchi, and K. Takeda, “Driving Feature Extraction and Behavior Classification Using an Autoencoder to Reproduce the Velocity Styles of Experts,” *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, vol. 2018-Novem, pp. 1337–1343, 2018, doi: 10.1109/ITSC.2018.8569245.

[111] O. Shouno, “Deep unsupervised learning of a topological map of vehicle maneuvers for characterizing driving styles,” *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, vol. 2018-Novem, pp. 2917–2922, 2018, doi: 10.1109/ITSC.2018.8569331.

[112] T. M. Hsu, C. H. Wang, and Y. R. Chen, “End-to-end deep learning for autonomous longitudinal and lateral control based on vehicle dynamics,” *ACM Int. Conf. Proceeding Ser.*, pp. 111–114, 2018, doi: 10.1145/3293663.3293677.

[113] Y. Wang, W. Zhang, X. Pan, and W. Xu, “Fresh: A multi-dimensional factors method for Payd with deep ensemble learning,” *Proc. 4th ACM SIGSPATIAL Int. Work. Saf. Resilience, EM-GIS 2018*, 2018, doi: 10.1145/3284103.3284120.

[114] X. Huang, J. Sun, and J. Sun, “A car-following model considering asymmetric driving behavior based on long short-term memory neural networks,” *Transp. Res. Part C Emerg. Technol.*, vol. 95, pp. 346–362, 2018, doi: 10.1016/j.trc.2018.07.022.

[115] M. Lu, Y. Hu, and X. Lu, “Driver Detection Based on Deep Learning,” *J. Phys. Conf.*

Ser., vol. 1069, no. 1, 2018, doi: 10.1088/1742-6596/1069/1/012118.

[116] F. Li *et al.*, “Toward Intelligent Vehicle Intrusion Detection Using the Neural Knowledge DNA,” *Cybern. Syst.*, vol. 49, no. 5–6, pp. 412–419, 2018, doi: 10.1080/01969722.2017.1418788.

[117] Q. Wang, Y. Liu, J. Liu, Y. Gu, and S. Kamijo, “Critical areas detection and vehicle speed estimation system towards intersection-related driving behavior analysis,” *2018 IEEE Int. Conf. Consum. Electron. ICCE 2018*, vol. 2018-Janua, pp. 1–6, 2018, doi: 10.1109/ICCE.2018.8326122.

[118] H. Liu, T. Taniguchi, K. Takenaka, and T. Bando, “Defect-repairable latent feature extraction of driving behavior via a deep sparse autoencoder,” *Sensors (Switzerland)*, vol. 18, no. 2, 2018, doi: 10.3390/s18020608.