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Predicting and explaining lane-changing behaviour using machine learning: A comparative study

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ABSTRACT

Predicting lane-changing behaviour is an integral part of lane-changing decision models and has a significant impact on both traffic flow characteristics and traffic safety. A variety of lane-changing decision models have been developed for this purpose, with most of them focussing only on explaining lane-changing behaviour, while assessing the predictive capability of these models has comparatively received less attention. Meanwhile, machine learning techniques are often preferred for prediction purposes, but their application to predicting lane-changing behaviour is limited. However, the lack of interpretability of machine learning techniques is often criticised and needs a solution. Motivated by these research needs, this study explains and predicts driver's mandatory and discretionary lane-changing behaviours using a set of suitable machine learning techniques. Input features are objectively selected using the technique of Recursive Feature Elimination, and standard classification metrics are employed to select the best model. By accounting for class imbalance, this study finds that the Extra Trees classifier outperforms other machine learning techniques as well as a conventional utility theory-based model in predicting lane-changing behaviour. Furthermore, by keeping the model hyperparameters unchanged, this classifier shows good transferability in predicting lane-changing behaviour when tested on a completely new dataset. Finally, through explainable artificial intelligence, the output of the Extra Trees classifier is interpreted. The findings of this study advocate the use of machine learning techniques in future studies for explaining and predicting lane-changing behaviour.

1. Introduction

Lane-changing is a routine driving task, requiring adjusting the speed with the speeds of surrounding vehicles, finding a suitable gap in the adjacent lane, ensuring that a driver's own lane-changing intentions are recognised by others in the adjacent lane, and simultaneously controlling a driver's own vehicle dynamics. Thus, lane-changing is considered a complex driving manoeuvre and

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generally has adverse effects on traffic flow characteristics, road safety, and the environment (Ali, 2020). For instance, lane-changing has been frequently reported to trigger congestion (Zheng et al., 2011), cause stop-and-go oscillations (Sarvi et al., 2007), and create bottlenecks (Zheng et al., 2019). Similarly, lane-changing is also known to create hazardous traffic situations, thereby deteriorating traffic safety (Zheng et al., 2019).

In general, a lane-changing manoeuvre is classified as mandatory lane-changing and discretionary lane-changing. While the former manoeuvre is compulsory and must be carried out to follow a specific route such as entering or exiting a motorway, the latter manoeuvre is voluntary in nature and often performed to achieve better driving conditions such as gaining a speed advantage (Zheng, 2014). In the lane-changing decision-making process, for both mandatory and discretionary lane-changing manoeuvres, how available gaps are selected has a significant impact on traffic flow characteristics and, more importantly, on traffic safety. For instance, inaccurate and risky gap selection is frequently reported as one of the primary causes of safety–critical events (Ali et al., 2020b). Therefore, predicting lane-changing behaviour is of utmost importance for accurately reproducing traffic flow patterns. As such, this study focusses on predicting lane-changing behaviour, more specifically, predicting lane-changing decisions during the two types of manoeuvres. Note that lane-changing behaviour and decisions are interchangeably used in the rest of the paper.

Many lane-changing decision models have been developed in the literature, namely Gipps-type (rule-based) models (Gipps, 1986), utility theory-based models (Ahmed, 1999), cellular automata-based models (Maerivoet and De Moor, 2005), Markov process-based models (Singh and Li, 2011), fuzzy logic-based models (McDonald et al., 1997), and game theory-based models (Ali et al., 2019). Each model type has its own pros and cons, as discussed by Zheng (2014). For instance, Gipps-type models are rule-based in which lane-changing decisions are obtained through a set of deterministic rules, which may not realistically reflect how human drivers make decisions. Contrastingly, utility theory-based models follow gap acceptance theory to predict lane-changing behaviour, which suggests that drivers accept gaps larger than the critical gaps (Daamen et al., 2010), thereby imposing the assumption of consistent driving behaviour. This theory further states that if drivers do not find gaps larger than their critical gaps, they tend to continue travelling in the same lane without performing a lane-changing manoeuvre. In this case, particularly in a merging scenario where drivers are expected to merge from the acceleration lane to the freeway, they would travel to the end of the lane without merging (Marczak et al., 2013) and block upstream traffic in the same lane. This issue reflects the importance of accurately predicting lane-changing behaviour, which has rather received less attention in the literature because much of the research focus, unfortunately, remained on the explanatory analysis of lane-changing behaviour rather than predictive analysis.

Our understanding of the predictive capability of lane-changing models remains elusive primarily because of (a) the entangled nature of lane-changing decision models, limiting us to analyse the performance of these models solely in predicting lane-changing decisions, (b) the fact that only a few studies have focussed on assessing model's predictive performance (e.g., see Toledo et al. (2003) for a reference), therefore little is known on how good these models perform in predicting lane-changing behaviour, and (c) the scarce evidence of adopting a suitable technique for predicting lane-changing behaviour. Many existing microsimulation packages use rule-based models and overcome the negative impact of inadequately predicting lane-changing decisions by simply removing unconforming vehicles from simulations in a brute force manner (TSS, 2002, Zheng, 2014). As such, omitting vehicles from numerical simulations because of inadequate lane-changing predictions further highlights the importance of the predictive capability of lane-changing decision models, which is the focus of this study.

For prediction purposes, machine learning techniques have gained popularity because of their high accuracy in predicting simple as well as complex phenomena. Machine learning algorithms have been applied extensively to solve transportation problems due to their underlying precise and convenient mathematical models that can learn, generalise, and often reveal good predictive performance (Karlaftis and Vlahogianni, 2011). For instance, Huang et al. (2020) applied a convolutional neural network, logistic regression, decision tree, random forest, support vector classification, and *K*-nearest neighbours for predicting crash risk. Similarly, another study classified motor crash injury severity using a crash database by applying logistic regression, decision tree, neural network, gradient boosting model, and Naïve Bayes classifier (Jeong et al., 2018). There is also a wide body of literature focussing on the application of machine learning techniques for predicting lane-changing decisions at signalised and unsignalised intersections (Mafi et al., 2018, Nagalla et al., 2017, Sangole et al., 2011). Mafi et al. (2018), for instance, applied decision trees, instance-based learning, and random forest models for predicting drivers' lane-changing decisions for unprotected right and left turning manoeuvres at signalised intersections. However, lane-changing behaviour at intersections differs significantly from that on motorways (Ali et al., 2020c). For example, during a mandatory lane-changing manoeuvre on motorways, a driver has to keep track of the remaining distance in the acceleration lane as well as control their vehicle dynamics in the current lane and simultaneously look for an appropriate gap in the adjacent lane, which makes the decision-making process more complex, increases the driver's workload, and exerts pressure on a lane-changer. However, such pressure is minimal during lane-changing on intersections. Moreover, the frequency with which drivers make gap selection decisions and its consequent impact on lane-changing behaviour has not been studied well. Finally, as machine learning-based models are criticised for poor interpretability, their application to understand and explain the lane-changing decision-making process, akin to explanatory models like a logistic model, is rather limited. These research needs motivate the present study.

More specifically, the present study aims to answer four key research questions: First, how do utility theory-based models perform in predicting lane-changing behaviour? Second, can a machine learning technique outperform conventional modelling approaches such as a binary logistic approach in predicting lane-changing behaviour? Third, how does the predictive performance vary across different machine learning techniques? Particularly, this study will compare the performance of various machine learning techniques in predicting lane-changing behaviour on motorways. Finally, how can the lane-changing decision-making process be explained through a machine learning model?

The contribution of this paper is threefold. First, this study adopts a total of eight suitable machine learning techniques for predicting lane-changing behaviour. The performance of these techniques is objectively assessed using standard performance metrics for a

Table 1
Summary of representative studies on the application of machine learning techniques for predicting lane-changing behaviour.

Study	Technique	Comparison	Data	LC	Metrics	Purpose	Class imbalance	Interpretability	Transferability
Sangole et al. (2011)	Neuro-Fuzzy	×	Video data	MLC	RMSE	GA	×	×	×
Wei et al. (2013)	Intention-integrated prediction & cost function	×	Simulation	MLC	×	DM	×	×	×
Peng et al. (2015)	NN	×	Naturalistic data	DLC	Accuracy	DM	×	×	×
Dou et al. (2016)	NN	SVM	NGSIM	MLC	Accuracy	Style	×	×	×
Nie et al. (2016)	SVM	Nagel	NGSIM	DLC	Accuracy	Execution	×	×	×
Motamedidehkordi et al. (2017)	NB	SVM, DT, RF, BLR	NGSIM	MLC	Accuracy	GA	×	×	×
Nagalla et al. (2017)	SVM	RF and DT	Naturalistic data	MLC	Skill scores	GA	×	×	×
Gao et al. (2018)	NN	SVM, LSTM	Video data	NA	Accuracy	DM	×	×	×
Mafi et al. (2018)	C4.5 DT	RF, BLR	Driving simulator	MLC	F_1 score	GA	×	×	×
Benterki et al. (2019)	NN	SVM	NGSIM	DLC	F_1 score	DM	×	×	×
Deng et al. (2019)	HMM	NN, RF, SVM	Driving simulator	DLC	Accuracy	Execution	×	×	×
Liu et al. (2019)	NN	SVM, XGB, LightGBM	NGSIM	DLC	F_1 score	Execution	×	×	×
Gu et al. (2019)	RF	×	NGSIM	DLC	Accuracy	Style	×	×	×
Ren et al. (2019)	NN	NB, logistic, and J48-DT	NGSIM	DLC	Accuracy	Style	×	×	×
Xie et al. (2019)	NN	×	NGSIM	MLC	Accuracy	DM and impact	×	×	×
Mahajan et al. (2020)	SVM & LSTM	×	highD	NA	F_1 score	Class	×	×	×
Dong et al. (2021)	RF and NN	MOBIL	NGSIM	MLC	Accuracy	Capacity drop	×	×	×
Wang et al. (2020)	C4.5 DT	NB	Video data	NA	Accuracy	Style	×	×	×
Xing et al. (2020)	NN	LSTM	Naturalistic data	DLC	F_1 score	DM	×	×	×
Zhang et al. (2020)	NN	×	highD	DLC	F_1 score	DM	×	×	×
Choi and Lee (2021)	RF	SVM, LSTM, GRU	NGSIM	DLC	F_1 score	DM	×	×	×
Sun et al. (2021)	RF	LSTM	Naturalistic data	MLC	Accuracy	Trajectory	×	×	×
Wang et al. (2021)	LSTM	×	NGSIM	DLC	Accuracy	DM	×	×	×
Wei et al. (2021)	LSTM	SVM, DT	Naturalistic data	DLC	Accuracy	DM	×	×	×
Xu et al. (2021)	NN	×	Video data	MLC	Accuracy	Trajectory	×	×	×
This study	RF, XGB, SVM, ET, GBM, NB, ANN, BLR	Utility-theory model	NGSIM (2 datasets)	MLC & DLC	F_1 score, AUC-ROC	DM	✓	✓	✓

Abbreviations: NA: not mentioned; DT: Decision Trees; RF: Random Forests; NN: Neural Networks; NB: Naïve Bayes; SVM: Support Vector Machine; LSTM: Long-Short Term Memory; GRU: Gated Recurrent Neural Network; XGB: Extreme Gradient Boosting; LightGBM: Light Gradient Boosting Machine; HMM: Hidden Markov Chain; ET: Extra Trees, BLR: Binary logistic regression; LC: lane-changing; MLC: mandatory lane-changing; DLC: discretionary lane-changing; RMSE: root mean square error; AUC-ROC: area under the receiving operating curve; Note that columns containing cross sign (×) indicate that the corresponding aspect is not missing (or not performed) by the particular study; GA: gap acceptance; DM: decision-making; Class: classification of driving style; Accuracy is defined as ratio of correct predictions to total predictions made.

classification task, illustrating the appropriateness of different techniques for predicting lane-changing decisions; and the performance of the best performing machine learning model is also compared with a traditional utility theory-based model to demonstrate the effectiveness of the adopted technique for predicting lane-changing behaviour. Second, to account for the inherent imbalanced nature of lane-changing data obtained from a trajectory dataset, we adopt a treatment and quantify its impact on machine learning models' performances. Third, we show how the output of machine learning models can be interpreted in a manner similar to statistical models using an explainable artificial intelligence technique. Further, a transferability analysis of machine learning models is performed to evaluate their generalisation capabilities when applied to a new dataset.

The rest of the paper is structured as follows. Section 2 reviews some representative studies on machine learning in the context of lane-changing. Section 3 explains the study methodology, including a brief description of different machine learning techniques, treatment of class imbalance, and performance metrics. Section 4 describes the dataset, pre-processing of the data, and selection of input features for the considered models. Section 5 presents the performance of these models and explains the best performing model using explainable artificial intelligence. Section 6 rigorously evaluates the performance of the models, including comparison with a utility theory-based model, impact of class imbalance, and transferability to a new dataset. Finally, study findings and future research directions are presented in Section 7.

2. Literature review

A thorough literature review was carried out to investigate which machine learning techniques have been applied for predicting lane-changing behaviour, what type of data and performance metrics were used in earlier studies, whether they have compared their predictive performance with other techniques, and whether past studies rigorously tested the performance of their models on some basic yet important aspects of machine learning, like class imbalance, transferability, and interpretability.

As summarised in Table 1, the literature survey reveals a number of noteworthy observations. First, a wide range of machine learning techniques has been applied for various purposes in the context of lane-changing. Second, most studies did not compare their model performance with conventional lane-changing decision models, with a few exceptions. Third, some studies compared their model with some other machine learning models; however, a comprehensive comparison of various machine learning models for lane-changing prediction is missing. Fourth, the majority of studies focussed on mandatory lane-changing prediction while comparing machine learning models' performance for predicting both types of lane-changing manoeuvres (including discretionary lane-changing) remains unexplored. Fifth, none of the existing studies investigated the impact of class imbalance of lane-changing data on the predictive performance of their model. As lane-changing data are heavily dominated by non-lane-changing events (more details in Section 4), machine learning techniques are susceptible to yielding biased results towards the dominant class (Ali et al., 2019). As such, understanding and inferring about the true predictive capability of machine learning techniques, considering class imbalance, become paramount. Sixth, as machine learning models are often called '*black box*' due to their poor interpretability (Karlaftis and Vlahogianni, 2011), no study in the literature has attempted to interpret the lane-changing decision-making process using the model output. Despite the advent of explainable artificial intelligence, its application to understand and explain complex driving tasks, like lane-changing, remains nascent. As such, our understanding remains elusive whether machine learning models can provide an intuitive interpretation of the lane-changing decision-making process. Finally, as machine learning models are often reported to work well with training and testing datasets, transferability of these models is not tested to a completely new dataset, which restricts its adaptability and usage in different parts of the world.

Our study aims to address the aforementioned research gaps by (i) comprehensively comparing representative machine learning models, (ii) testing their sensitivity to class imbalance, (iii) understanding lane-changing relationship with its corresponding factors, and (iv) assessing their predictive performance to a completely new dataset.

3. Methodology

Unlike existing studies that consider the modelling of lane-changing behaviour as a conventional regression problem (Toledo et al., 2005), this study frames lane-changing behaviour modelling as a classification task. More specifically, a binary classification problem is formulated with '*lane-changing*' as one class and '*non-lane-changing*' as the other class. Although these two driver's decisions are not exclusively available in a trajectory dataset, a methodology is presented in this study to obtain these two decisions (more explanation to follow in Section 4.2). To predict each lane-changing decision during mandatory and discretionary lane-changing, this study considers eight commonly used machine learning classification techniques that are briefly summarised below. Providing a comprehensive and exhaustive review of these machine learning techniques is beyond the scope of this study.

3.1. Machine learning classification techniques

Random Forests: Random Forests are an ensemble learning method for classification and regression. Unlike the conventional decision tree analysis, where a single decision tree is employed for classification, random forests combine several tree-based classifiers, with each classifier having an independent and identically distributed random vector. For model development, random forests combine a sampling procedure and a subspace technique. For sampling, bootstrapping is commonly used to generate subtrees, whose predictions are used to select the class. For subspace, random forests also employ a random sampling technique, assisting in removing insignificant variables from the parsimonious random forest model. Compared to classical decision tree analysis, random forests are reported to perform well and robust against overfitting. Table 2 shows the hyperparameters selected for the random forest-based lane-changing model. Note that several other configurations of hyperparameters were tested for all the models and the best performing configuration (in terms of the highest accuracy) is reported in Table 2.

Gradient Boosting Machine: Gradient Boosting Machine can be regarded as a multitude of trees. By applying stochastic gradient boosting to a conventional decision tree, gradient boosting machine theoretically spreads and improves its accuracy. As this technique is a typical example of an ensemble method consisting of several simple decision tree models, it possesses all the properties of decision trees and simultaneously improves its robustness and accuracy. Gradient boosting machine is often preferred over conventional decision trees because of its capability to handle big data in raw form as well as cater for missing data, being less sensitive to outliers, and avoiding overfitting issues.

Extreme Gradient Boosting: Extreme Gradient Boosting is a specific implementation of gradient boosting machine, with the added advantage of computational efficiency. Extreme gradient boosting learns from underlying base learners, which are often conventional decision trees, for performing classification and regression. In extreme gradient boosting, following the gradient boosting, parameters of a strongly generated classifier are iteratively updated from the following classifier to minimise the gradient of a loss function.

Support Vector Machine: Support Vector Machine is based on statistical learning theory and the structural risk minimisation principle. To separate two or more classes of data, a support vector machine kernel maps the input feature vector into a high-dimensional feature space. A support vector machine algorithm creates a (or set of) hyperplane(s) in the specified high dimensional feature space to separate the outcome. The main goal of the classifier is to find the maximum separation between the linear decision boundaries as well as maximising the functional margin between the linear decision boundaries.

Extra Trees Classifier: Extra Trees classifier is a tree-based ensemble method that works by creating a large number of unpruned decision trees from a training dataset, and the final predictions are made by applying a bagging technique on the predictions of decision trees. However, it has a different mechanism for selecting the best split to separate the samples of a node into two groups compared to classical decision tree algorithms. An extra tree classifier splits nodes by choosing cut points fully at random and the selection of features is randomly performed, and the best split is chosen. Therefore, their structure is independent of the output values of the learning dataset. Moreover, unlike random forests that develop each decision tree from a bootstrap sample of a training dataset, an extra trees classifier uses the whole learning sample to grow the trees. This explicit randomisation combined with ensemble learning brings the benefit of reduced bias/variance and hence, decreases overfitting.

Naïve Bayes Classifier: Naïve Bayes classifier is a probabilistic learning technique, capable of handling the number of classes efficiently based on a probabilistic theory. More specifically, naïve Bayes follows the Bayes' theorem, assuming strong (naïve) independence among features for a given outcome. Contrary to other machine learning algorithms, naïve Bayes classifier assumes a *prior* information about the observed data. In this study, a Bernoulli distribution is assumed for parameter estimation and implementation of naïve Bayes classifier.

Binary Logistic Regression: Binary logistic regression is a statistical technique frequently applied to model a binary dependant variable. A binary logistic model consists of two classes, such as lane-changing and non-lane-changing events, often represented by an indicator variable whose values are labelled as 0 or 1. The maximum likelihood estimation method is used to estimate the parameters of a binary logistic model.

Artificial Neural network: An Artificial Neural Network (ANN) is a popular machine learning technique that joins connections between its elements, mimicking the neural structure in a human brain. ANNs typically consist of three layers, namely input, hidden, and output layers. ANNs are typically trained using a Stochastic Gradient Descent algorithm, which finds the optimal model weights that minimise the value of the loss function.

As machine learning models are prone to overfitting issues, the aforementioned models in this study are carefully used. More specifically, three strategies are implemented to avoid overfitting. First, by monitoring the training loss versus validation loss, we find that the gap between these losses is minimal when a model converges, reflecting no overfitting issues. Second, although the training accuracy of the models has not been reported herein due to brevity, the training accuracy was found to be close to the testing accuracy, reflecting no overfitting because a large disparity between training and testing accuracies indicates overtraining of models. Finally, this study employs a *k*-fold validation technique, which rigorously tests the generalisation capability of the models for various data portions and minimises overfitting issues.

Table 2
Configuration of the machine learning models adopted in this study.

Model	Hyperparameters selected
Random Forest	Number of trees: 100; split criterion: Gini; max number of features considered for splitting a node: square root of number of features
Extreme Gradient Boosting	Number of iterations: 100; max depth: 6; subsample: 0.5; subsample ratio of columns when constructing each tree: 0.6; lambda: 1; alpha: 0; and learning rate: 0.3
Support Vector Machine	Kernel: linear; Regularisation parameter: 1
Extra Trees classifier	Number of trees: 100; split criterion: Gini; max number of features considered for splitting a node: square root of number of features
Gradient Boosting Machine	Number of iterations: 100; loss: deviance; split criterion: Friedman mean square error; learning rate: 0.1; max depth: 3
Naïve Bayes	Alpha: 1.0
Binary logistic regression	Maximum iterations: 100
Artificial Neural Network	Number of neurons in hidden layer: 10; activation: ReLU; optimiser: Adam; learning rate: 0.001

3.2. Treating class imbalance

In general, machine learning models are regarded as heuristic techniques, often used for optimisation with a specific objective to minimise the difference between the observed class and the predicted class using a training dataset. Any inadequacy in the data, such as imbalance classes, may hinder the optimisation process, yield biased (and overestimated) results, or pose problems in generalisation to new datasets. Therefore, it is important to ensure that a balanced data (or class) proportion (of lane-changing and non-lane-changing events) is given to machine learning models for obtaining reliable predictions. To circumvent this problem, two data treatment techniques are often applied, namely undersampling and oversampling. Undersampling techniques reduce a significant portion of data to mitigate the class imbalance problem, resulting in loss of useful data as well as decreased accuracy (Ge et al., 2017). Oversampling, in contrast, synthesises artificial observations using interpolation and maintains the sanctity of the actual data, and therefore, it is often preferred in the literature (Parsa et al., 2020, Jeong et al., 2018) as well as in this study.

In this study, the lane-changing behaviour dataset has a highly imbalanced class distribution, with only 26 % and 19 % observations pertaining to Class 1 (i.e., lane-changing) for mandatory and discretionary lane-changing, respectively (see Table 4). To deal with the class imbalance, the synthetic minority oversampling technique (SMOTE), proposed by Chawla et al. (2002), has been adopted. More specifically, SMOTE generates artificial observations from the members of the minority class using a convex combination of nearby members in the same class. To this end, SMOTE learns each observation of the minority class and synthesises new observations along the line that joins them to their k nearest neighbours. SMOTE has been reported to work well with noisy, large, and sparse datasets (Parsa et al., 2020). Recognising these abilities of SMOTE, this technique has recently found its popularity in the safety literature (Parsa et al., 2020, Jeong et al., 2018).

3.3. Evaluation of the considered models

To evaluate the performance of the models considered in this study, popularly used classification metrics are employed, including precision, recall, F_1 score, and area under the receiver operating characteristics curve (see Table 3 for their explanations). Note that a detailed description of these indicators is omitted, and interested readers are referred to Nandi and Ahmed (2020) for more details. In general, a higher F_1 score is preferred. In this study, the goal is to select the best performing machine learning model with the highest performance metric scores for predicting lane-changing behaviour.

In order to evaluate the performance of the models, k-fold validation is conducted. More specifically, $k = 5$ non-overlapping subsets (folds) of data are formed. Each fold contains 20 % of the entire data, and k-1 folds are used for the training purpose in each of the k iterations, while the remaining onefold is used for the testing purpose. The overall accuracy of the models is considered as the average of all folds.

3.4. Model interpretation

As machine learning techniques are repeatedly criticised for their poor interpretability (Karlaftis and Vlahogianni, 2011), this study adopts SHapley Additive exPlanations (SHAP) for the interpretation of machine learning techniques' outputs. SHAP, proposed by Lundberg and Lee (2017), estimates the contribution of each feature to the model output based on game theory and local explanations. Obtaining the marginal contribution of a feature subset $S \subseteq F$, where F is the entire feature space, on the model output $[v\ |S|]$, the contribution (ϕ_i) (or SHAP values) of each feature (i) using SHAP can be obtained as.

$$\phi_i = \sum_{S \subseteq N[i]} \frac{|S|!(F - |S| - 1)!}{S!} [v(S \cup (i)) - v(S)] \tag{1}$$

Table 3
Performance metrics considered in this study.

Metric	Description
Precision	It is the ratio of correctly predicted positive observations ('lane-changing') to the total predicted positive observations. High precision implies low false positive rate. $Precision = \frac{TruePositive}{TruePositive + FalsePositive}$. True positive indicates the cases in which the predicted decision and the observed decision is lane-changing. False positive indicates the cases when the observed decision is non-lane-changing, while the predicted decision is lane-changing.
Recall (sensitivity)	It is the ratio of correctly predicted positive observations ('lane-changing') to the actual number of lane-changing events observed in the dataset. $Recall = \frac{TruePositive}{TruePositive + FalseNegative}$. False negative refers to the cases when the observed decision is lane-changing, while the predicted decision is non-lane-changing.
F_1 score	It is the weighted average of Precision and Recall as it accounts for both false positives and false negatives. F_1 score is particularly useful when data have uneven class distribution.$F_1 score = 2 \times \frac{Recall \times precision}{Recall + precision}$
Area under the curve (AUC)	AUC is the measure of the ability of a machine learning model to separate two classes. Of note, the higher the AUC score, the better the performance of a model in predicting two classes.
Receiver operating characteristic (ROC)	It is a plot of true positive rate (on y-axis) against the false positive rate (on x-axis) for a number of different candidate threshold values between 0 and 1.

Table 4
Representation of binary classes in the dataset.

Lane-changing	Class/ decision	Event	Training (80 %)	Testing (20 %)	Total	Sample size
Mandatory	0	Non-lane-changing	1249	313	1562	2139
	1	Lane-changing	461	116	577	
Discretionary	0	Non-lane-changing	2813	703	3516	4359
	1	Lane-changing	674	169	843	

Following the additive feature attribution method (Lundberg and Lee, 2017) that defines a model's output as a function of real values assigned to each feature, an explanation model, g, is formulated as a linear function of binary features as.

$$g(z) = \phi_0 + \sum_{i=1}^{M} \phi_i z_i \tag{2}$$

where $z \in [0,1]^M$ represents whether a feature is selected or otherwise; M is the number of input features; ϕ_0 indicates the model output with all simplified features toggled off (Lundberg and Lee, 2017).

4. Data and pre-processing

4.1. Data source

In this study, NGSIM dataset, more specifically, Interstate 80 (I-80) dataset, is used (FHWA, 2007). The I-80 site consists of six lanes, connected to an on-ramp and an off-ramp, as shown in Fig. 1. The I-80 dataset was collected for 45 mins and consists of vehicle speeds and positions recorded at a frequency of 10 Hz.

As this study considers both mandatory and discretionary lane-changing, a systematic approach is required to separate both types of lane-changing manoeuvres. While systematic mandatory lane-changing manoeuvres are expected to occur while entering or exiting a freeway, mandatory lane-changing manoeuvres performed to merge in the freeway are considered herein. On the other hand, discretionary lane-changing manoeuvres are considered from all inner lanes. Note that discretionary lane-changing to lane 1 are not considered as this lane is a high occupancy vehicle lane, and similarly, lane-changing manoeuvres from lane 5 to lane 6 are not considered due to ambiguity between mandatory and discretionary lane-changing.

4.2. Pre-processing

To predict a driver's lane-changing behaviour whether lane-changing will occur or not (i.e., lane-changing or non-lane-changing), trajectory data are used in this study. Since a trajectory is an illustration of space travelled against time (see Fig. 2(b)), it is challenging to pinpoint the exact time when a driver has made a lane-changing decision, thereby accepted a gap for lane-changing (i.e., the decision point). A Wavelet Transform (WT)-based method is employed to detect the starting point of lane-changing execution. Note that this point indicates the lane-changing decision point, implying that a driver has accepted a gap and initiates a physical execution of the manoeuvre. WT provides both frequency and time representation of a signal (here lateral movement of drivers), and any change in a lateral movement profile can be easily detected by moving the wavelet location and squeezing or dilating the wavelet. Note that since a driver's physical manoeuvring can be easily traced by their lateral movements, this study employs WT on lateral movement profiles, because such information is readily available in the I-80 dataset.

Fig. 2(a) displays a lateral movement profile subjected to WT (note that the Mexican hat wavelet is applied following the recommendation of Zheng and Washington (2012)), where the change points (B and C) are successfully detected by WT. Here, success is defined as the capability of WT to correctly identify the change points B and C. It is important to mention here that before applying WT on the real profiles, WT was extensively tested on synthetic profiles and such results are not presented herein for brevity purposes. In this study, the trajectory prior to Point B is considered as an input to the models, as this portion of the trajectory is part of the driver's decision-making process. In this study, the driver's decision time window of 2 s indicates the update interval of exactly 2 s. Note that while scanning the trajectory, a 2 s decision time window is updated in a backward direction, meaning that the last point of a trajectory (marked as a solid black circle in Fig. 2(b)) is considered a lane-changing event, while all other events occurring at 2 s interval are considered as non-lane-changing events (see white circles in Fig. 2(b)). Considering trajectory beyond Point B would lead to the issue of causal ambiguity, which will further increase data imbalance and may inflate model performance. More discussion on such data related issues can be found in Ali et al. (2022).

During mandatory lane-changing, as soon as drivers appear in the acceleration lane, they tend to look for a gap in the freeway lane. As such, a driver's decision time window, that is, the time interval a driver takes to evaluate traffic conditions and make a decision for a potential lane-changing is an important parameter in evaluating lane-changing behaviour since it has direct implications on data (or class) imbalance. For instance, if the driver's decision time window is considered as 1 s, 3,124 non-lane-changing events are generated against 577 mandatory lane-changing events. On the other hand, if a decision time window of 2 s is considered, then 1,562 non-lane-changing events are generated. This study selects a 2 s time window as it is considered the standard reaction time (AUSTROADS, 1993),

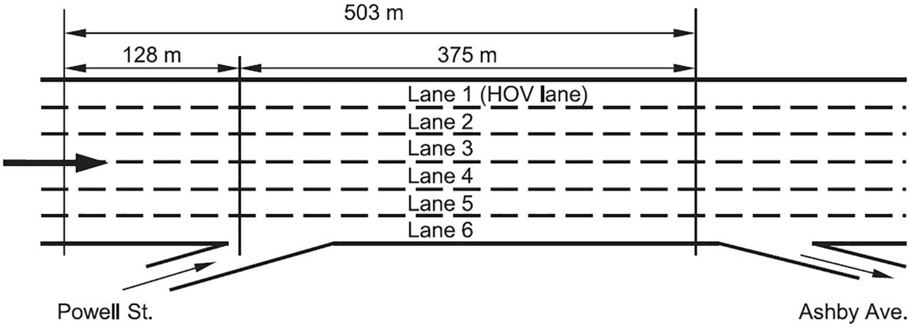


Fig. 1. I-80 study site.

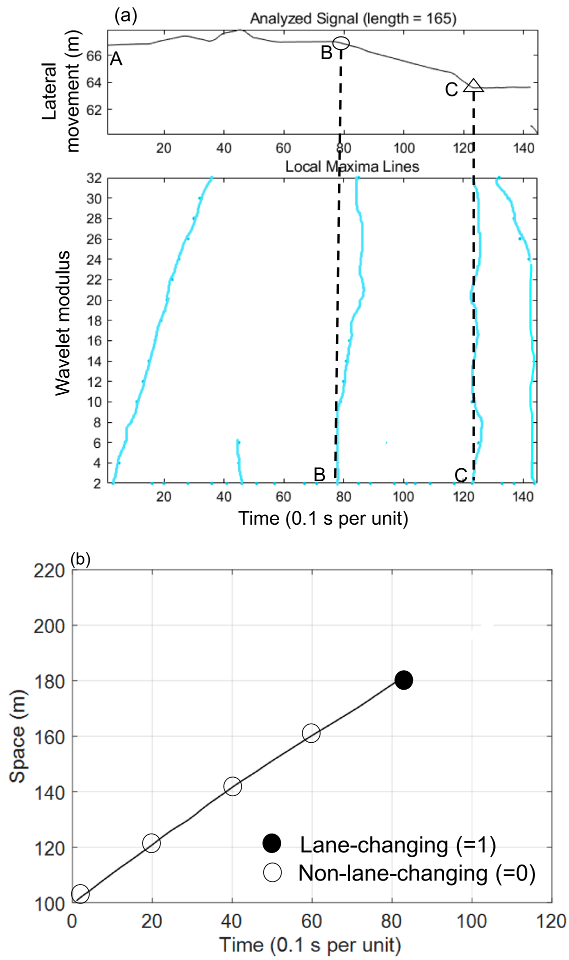


Fig. 2. Schematics: (a) A typical example of WT applied to the I-80 dataset, (b) extracting driver's lane-changing decisions from trajectory data between Points A & B; Points B and C respectively indicate the lane-changing decision point and the completion of a lane-changing manoeuvre.

and has been widely adopted as a reaction parameter in lane-changing studies (Ali et al., 2019). Each point in a driver's trajectory is classified as one of the two decisions: lane-changing or non-lane-changing (see Fig. 2(b)). As mentioned before, the last point, which is the lane-changing decision point, is the lane-changing event while all the previous points (at 2 s intervals) are non-lane-changing events. This leads to an imbalanced dataset (the number of non-lane-changing events is much larger than the number of lane-changing events), which may impact the performance of the models. This impact is evaluated and treated in this study (more discussion to follow in the next section).

Following the aforementioned approach, this study has 2,139 and 4,359 observations for mandatory lane-changing and discretionary lane-changing, respectively, as shown in Table 4. Note that 80 % of randomly selected data are used for training each model, while the rest are used for testing purposes.

4.3. Input features for the developed models

The performance of machine learning models highly depends on the input features provided to them. Therefore, it is of utmost importance to carefully select the input features. To this end, a thorough literature review is conducted, and a wide range of variables are identified that may affect lane-changing behaviour. Table 5 provides a summary of variables (or input features) used for the models developed in this study. In total, 10 and 11 variables were selected as input features for mandatory and discretionary lane-changing models, respectively. These variables are selected from a set of variables reported in the literature by monitoring the performance of the models for different feature combinations. Out of all the possible combinations of features, the considered models performed well for 10 (11) or lower number of features for mandatory lane-changing (discretionary lane-changing) models. Of note, keeping fewer but significant features as a model input often increases the predictive capability of the models and also helps in preventing overfitting issues.

5. Results

5.1. Performance of the models

As alluded above, eight machine learning classification techniques are tested in this study, and their modelling results are presented in Table 6 for mandatory and discretionary lane-changing. In particular, the performance is compared in terms of average F_1 score. Note that other classification metrics (such as precision, recall, and AUC-ROC) are only employed for further explaining the performance of the best performing model in case of mandatory and discretionary lane-changing. In addition, the performance of each model is compared by selecting the input features that offer the highest contribution in improving the performance. To objectively determine the optimal input features from the total set of input features, the technique of Recursive Feature Elimination (Chen and Jeong, 2007) has been used, which recursively discards features with lower feature importance. Note that for the testing dataset, each model predicts one of the two outcomes (or classes): lane-changing or non-lane-changing, which is compared with the actual observation.

Table 6 reveals the following observations for predicting mandatory lane-changing behaviour. First, given that lane-changing behaviour modelling is framed as a binary classification problem (i.e., lane-changing and non-lane-changing) and it is often reported that the accuracy of a machine learning model should be at least 0.5 (or 50 %) (Nandi and Ahmed, 2020), all of the considered models have an average F_1 score of over 0.5, suggesting that all the models possess a reasonable predictive power. Second, given the same model hyperparameters, the highest performance of a model is a function of the best set of input features (see shaded cells in Table 6). Further, it is not necessary that the best feature set should remain the same across all the models. For instance, the random forests model shows the highest performance when four features are selected (i.e., average F_1 score = 0.831), whereas the extreme

Table 5
Summary statistics of the input features used for machine learning models.

Variable	Symbol	Description of operational variables	Mean (SD)	
			Mandatory	Discretionary
Speed of SV	v_{SV}	Average speed of the subject vehicle (SV) during the decision time window (in m/s)	6.81 (4.53)	6.3 (3.15)
Acceleration of SV	a_{SV}	Average acceleration of the subject vehicle in the decision time window (in m/s^2)	0.18 (1.50)	0.01 (1.50)
Speed of LV_CL	v_{LV}^{CL}	Average speed of the leading vehicle during the current lane in the decision time window (in m/s)	1.80 (3.36)	0.57 (0.75)
Remaining distance*	D_R	The remaining distance available in the acceleration lane to complete a merging manoeuvre (in m)	30.58 (12.12)	—
Lag gap	G_{lag}	The distance between the subject vehicle and the following vehicle in the target lane (in m)	11.48 (10.95)	13.30 (7.50)
Speed of FV_TL	v_{FV}^{TL}	Average speed of the following vehicle (FV) in the target lane during the decision time window (in m/s)	5.61 (3.57)	6.45 (3.0)
Acceleration of FV_TL	a_{FV}^{TL}	Average acceleration of the following vehicle in the target lane during the decision time window (in m/s^2)	0.12 (1.68)	0.04 (1.51)
Lead gap	G_{lead}	The distance between SV and the leading vehicle in the target lane (in m)	10.42 (11.89)	9.12 (4.11)
Speed of LV_TL	v_{LV}^{TL}	Average speed of the leading vehicle in the target lane during the decision time window (in m/s)	4.88 (3.13)	6.65 (3.05)
Acceleration of LV	a_{LV}^{TL}	Average acceleration of the leading vehicle in the target lane during the decision time window (in m/s^2)	0.16 (1.70)	0.014 (1.52)
Relative speed-a	Δv_{LV-SV}	Average speed difference between the leader in the target lane and the subject vehicle in the current lane during the decision time window (in m/s)	—	0.34 (0.02)
Relative speed-b	Δv_{SV-FV}	The speed difference between the subject vehicle in the current lane and the follower in the target lane during the decision time window (in m/s)	—	0.15 (0.92)

* Remaining distance is computed only for mandatory lane-changing while during discretionary lane-changing, there is no urgency of performing discretionary lane-changing; S.D: standard deviation.

Table 6
Average F_1 score performance evaluation of the models for predicting lane-changing behaviour.

ML model	Number of features selected										Ranking	
	11	10	9	8	7	6	5	4	3	2	WS	WOS
Mandatory lane-changing												
RF	—	0.827	0.825	0.826	0.822	0.828	0.827	**0.831**	0.828	0.824	2	4
XGB	—	0.805	0.812	**0.823**	0.815	0.806	0.804	0.804	0.809	0.808	3	3
SVM	—	0.758	0.762	0.748	0.757	0.757	0.750	0.763	0.765	**0.765**	5	2
ET	—	**0.865**	0.863	0.806	0.857	0.859	0.856	0.854	0.864	0.862	1	5
GBM	—	0.786	0.784	0.782	0.785	0.785	0.781	0.786	0.785	**0.787**	4	6
NB	—	0.600	0.612	0.615	0.599	0.594	**0.620**	0.593	0.581	0.591	7	7
BLR	—	0.585	0.592	0.606	0.600	0.606	0.605	0.585	0.589	**0.614**	8	8
ANN	—	0.734	0.736	0.728	0.733	0.731	0.738	**0.739**	0.720	0.582	6	1
Discretionary lane-changing												
RF	**0.796**	0.786	0.786	0.787	0.794	0.785	0.793	0.794	0.783	0.786	2	4
XGB	0.734	0.742	0.738	0.742	0.743	0.745	0.747	**0.751**	0.735	0.746	3	2
SVM	0.630	0.642	0.643	0.646	**0.651**	0.651	0.632	0.643	0.644	0.640	5	1
ET	0.834	0.836	0.831	0.839	0.834	0.826	**0.843**	0.837	0.829	0.836	1	5
GBM	0.680	0.672	0.688	0.682	0.685	**0.692**	0.683	0.687	0.676	0.687	4	7
NB	**0.548**	0.546	0.542	0.541	0.539	0.533	0.536	0.546	0.533	0.535	7	6
BLR	0.513	**0.521**	0.506	0.516	0.518	0.509	0.505	0.507	0.505	0.507	8	8
ANN	0.595	**0.601**	0.582	0.581	0.573	0.558	0.596	0.592	0.529	0.506	6	3

Abbreviations: ML: machine learning; WS: with SMOTE; WOS: without SMOTE; Shaded cells (bold letters) indicate the machine learning model with the highest accuracy; RF: Random Forest; XGB: Extreme Gradient Boosting; SVM: Support Vector Machine; ET: Extra Trees classifier; GBM: Gradient Boosting Machine; NB: Naïve Bayes; BLR: Binary Logistic Regression; ANN: Artificial neural network; "—" not included in the model.

gradient boosting model reveals the worst performance against the corresponding number of features. Third, while most of the models indicate a fairly stable performance when the number of features are varied, the artificial neural network (ANN) model has shown the highest sensitivity to change in the number of features. Fourth, the best performing model (in terms of the highest average F_1 score) is the extra trees classifier model for a given number of features (with one exception of Random Forests), while the binary logistic model shows the poorest performance in predicting mandatory lane-changing behaviour in most cases.

Consistent with the findings for mandatory lane-changing, all the models used for predicting discretionary lane-changing behaviour have an average F_1 score of over 0.5. Results suggest that these models have sufficient predictive power for capturing discretionary lane-changing behaviour. Similarly, the highest predictive accuracy is a function of the best set of input features, keeping the model hyperparameters unchanged. In addition, the ANN model is found to be highly sensitive to change in the number of features. The best and poor performing models for discretionary lane-changing are the extra trees classifier and binary logistic models, respectively, akin to mandatory lane-changing models (Table 6).

As shown in Tables 6, the top three best performing models are Extra Trees, Random Forests, and Extreme Gradient Boosting, respectively. This ranking seems somewhat contradictory with some of the existing literature (Motamedidehkordi et al., 2017), which frequently reports that the extreme gradient boosting model should outperform other models because of its inherent boosting

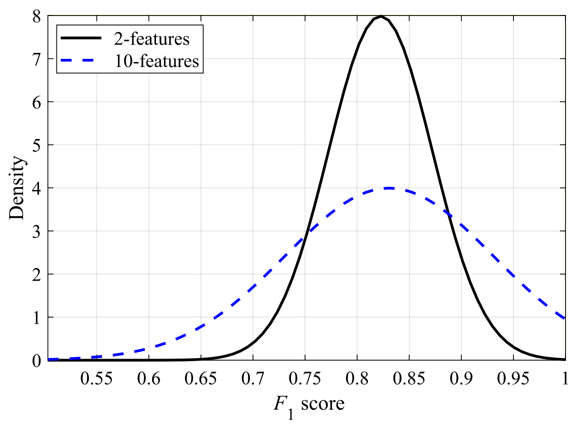


Fig. 3. Comparison of the 2-features versus 10-features extra trees classifier models for mandatory lane-changing.

mechanism that generally builds strong predictive models. The noisy nature of the NGSIM data (as researchers have frequently detected and reported significant noise in NGSIM (Ali et al., 2019, Punzo et al., 2011)) could be one of the possible reasons for this ranking, because ensemble techniques that fundamentally use a bagging mechanism (used by Extra Trees and Random Forests) tend to outperform those techniques that rely on boosting (used by Extreme Gradient Boosting) (Khoshgoftaar et al., 2010).

It can be noted from Table 6 that the performance difference between a 2-features model and a 10-features model appears to be relatively small. In this case, relying solely on average F_1 scores may be misleading in judging the performance of a model. For this purpose, we have statistically examined the difference between model predictions using a simulation approach presented in Ali et al. (2022), which generates a distribution of F_1 scores. For the sake of illustration, results for the extra trees classifier models for 2-features and 10-features for mandatory lane-changing are compared in Fig. 3. It is evident from the figure that F_1 score distributions are different for the 2-features and 10-features extra trees classifier models, suggesting different performances between these models. To complement this visual inspection, a Kolmogorov-Smirnov test is performed to determine whether these two distributions are the same. Results suggest that at a 95 % confidence level, these distributions are statistically different from each other (p-value < 0.001), implying that predictions of the 2-features extra trees classifier model are statistically different from those of the 10-features extra trees classifier model. Further, a paired t-test is also performed, and results reveal moderate evidence that the means of the distributions are statistically different (t-statistics = -2.35; p-value = 0.018), although this difference is very small. Note that similar results were found for other machine learning models and for discretionary lane-changing.

To obtain further insights into model performance, two microscopic indicators are used: time error and location error. While the time error indicates the time difference between the observed lane-changing decisions and the model's predicted lane-changing decisions, the location error is the spatial difference between the observed lane-changing decisions and the model's predicted lane-changing decisions. These indicators provide information about the readiness and suitability of a lane-changing model to be integrated with a car-following model in a microsimulation framework. Note that both time and location errors are calculated for the best performing model, which may correspond to a different number of input features. For instance, these errors are calculated for random forests and extreme gradient boosting models with four and eight input features, respectively. Fig. 4 displays time and location errors for mandatory and discretionary lane-changing models. Consistent with the findings of F_1 scores, both time and location errors are the smallest for the extra trees classifier model, while they are the largest for the binary logistic regression model. A time error of 1.75 s (for the extra trees classifier model for mandatory lane-changing) indicates that, on average, the time difference between the observed and the model predicted lane-changing decisions varies by 1.75 s. Similarly, the location error of 17.9 m for the same model implies that the difference in location of the observed and the model predicted lane-changing decisions differs, on average, by 17.9 m.

5.2. The best performing model

From the above results (Table 6), it is clear that the extra trees classifier model outperforms its competing model in predicting lane-changing behaviour during both types of lane-changing manoeuvres, and thus selected in this study for further analysis of its performance. This better performance of the extra trees models may be attributed to better handling of bias-variance analysis in predicting lane-changing using a high dimensional and noisy dataset (Motamedidehkordi et al., 2017). The precision of the extra trees classifier model is 0.82 (0.84), reflecting that 82 % (84 %) of lane-changing events are correctly predicted from the total lane-changing events predicted as lane-changing for mandatory lane-changing (discretionary lane-changing). Similarly, the recalls of the extra trees classifier model are respectively 0.91 and 0.84 for mandatory lane-changing and discretionary lane-changing, suggesting that the extra trees classifier model correctly identified 91 % and 84 % of the lane-changing events from all lane-changing events present in the dataset.

Fig. 5 displays the Receiver Operating Characteristic (ROC) curve of the extra trees classifier model, which shows the trade-off between true positive rate[1] and false positive rate for all thresholds and thus a curve is obtained. The farther the curve from the 45° line of equality, the better the classifier is at distinguishing two classes (i.e., lane-changing and non-lane-changing). Further, to quantify this ability of distinguishing two classes, area under the ROC curve (AUC-ROC) is obtained, which is 0.96 and 0.91, respectively, for mandatory lane-changing and discretionary lane-changing, demonstrating the excellent performance of the extra trees classifier model in accurately predicting lane-changing behaviour.

5.3. Features ranking and interpretation

From our literature review it was found that existing studies only focus on predicting lane-changing behaviour and did not attempt to interpret the output of machine learning models. In contrast, this study adopts explainable artificial intelligence to intuitively interpret model output similar to a statistical model. For this purpose, SHAP (SHapely Additive exPlanations) is used that not only provides an interpretation of the model output, but also ranks features according to their importance in predicting lane-changing behaviour. Note that this method takes into account the underlying model for the ranking of features as well as explaining the

[1] *The true positive rate measures the probability that an actual positive instance will be classified as positive. Mathematically, it can be calculated as* $Truepositiverate = \frac{TP}{TP+FN}$, *where TP stands for true positive and FN stands for false negative. Similarly, the false positive rate is essentially a measure of how often an actual negative instance will be classified as positive, and mathematically it can be obtained as* $Falsepositiverate = \frac{FP}{FP+TN}$, *where FP stands for false positive and TN stands for true negative.*

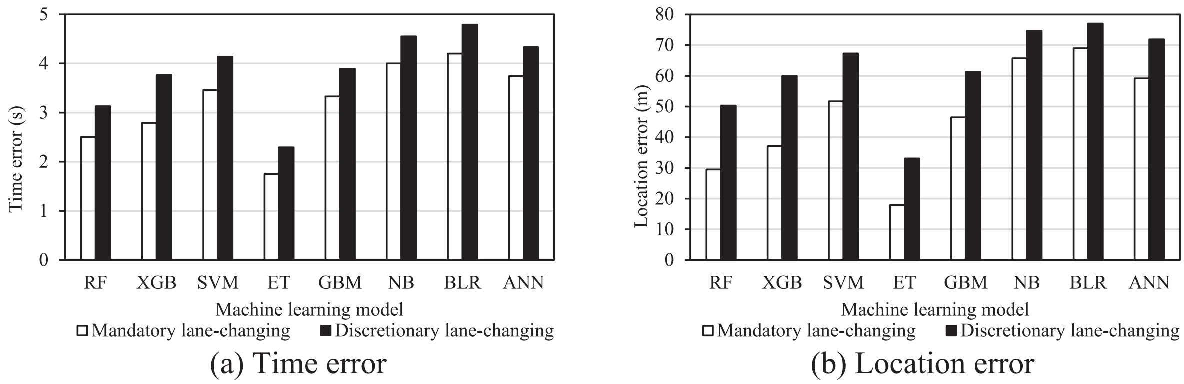


Fig. 4. Time and location errors of the selected models. **Model abbreviations**: RF: Random Forest; XGB: Extreme Gradient Boosting; SVM: Support Vector Machine; ET: Extra Trees Classifier; GBM: Gradient Boosting Machine; NB: Naïve Bayes; BLR: Binary Logistic Regression; ANN: Artificial Neural Network.

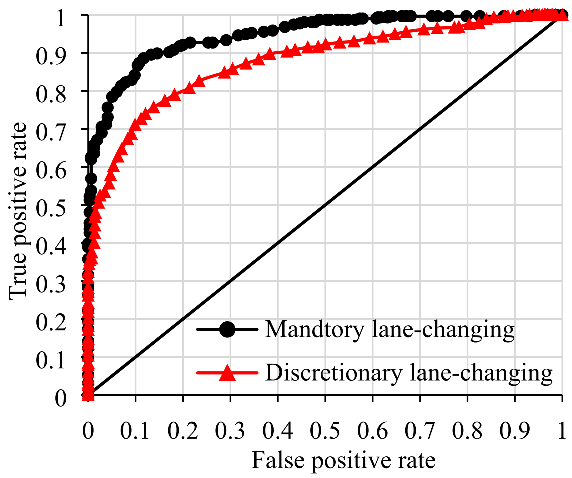


Fig. 5. ROC curve for the extra trees classifier model.

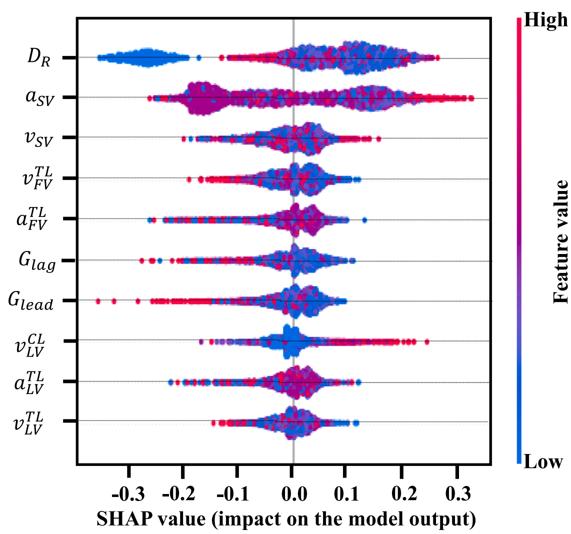
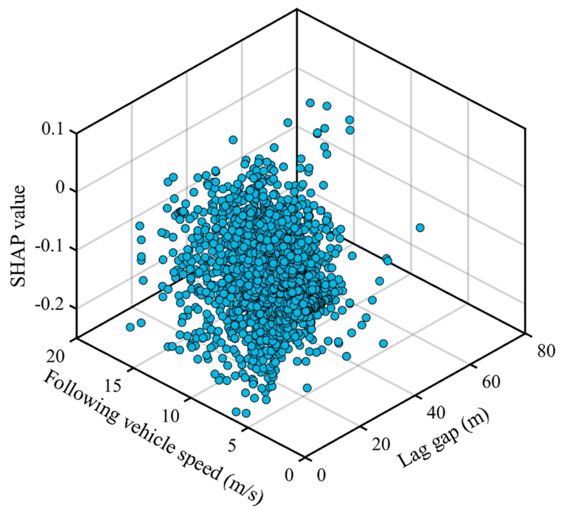


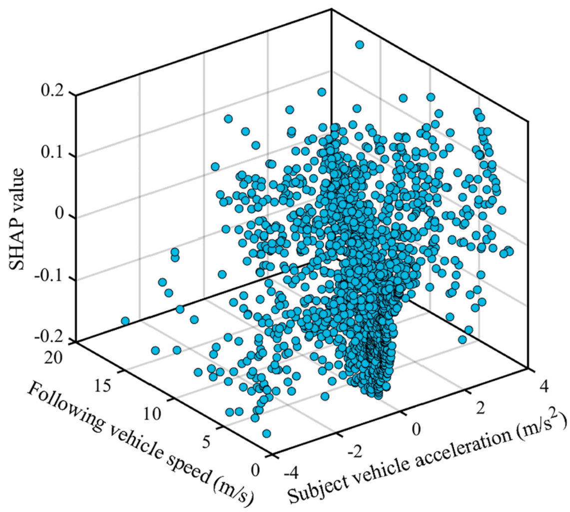
Fig. 6. SHAP summary plot for mandatory lane-changing.

relationships (i.e., the extra trees classifier model in this case).

Fig. 6 displays the ranking of features sorted according to their contribution to predicting lane-changing behaviour using SHAP values, with the most important feature being placed at the top. This ranking is obtained using the mean of absolute SHAP values of a feature. Note that the model input features (and their notations) are explained in Table 6. A SHAP plot can be interpreted as follows. The *y*-axis represents the input features, whereas the *x*-axis indicates SHAP values. The colour bar on the right side shows the feature value indicated by colour, whereby smaller values are indicated in blue and larger values are displayed in red. Note that each data point refers to one observation/case. In general, the absolute SHAP value represents the impact of a feature on the model output (i.e., the probability of lane change occurrence). Whereas the sign convention of SHAP values reflects the nature of the relationship of an input feature with the probability of lane change occurrence. More specifically, a negative (positive) value indicates an inverse (direct) relation of an input feature with the probability of lane-changing occurrence. More specifically, a negative (positive) value indicates an inverse (direct) relation of an input feature with the probability of lane-changing occurrence. Further, the magnitude of SHAP values relates to the probability of lane-changing occurrence whereby a higher value indicates a higher likelihood of lane-changing occurrence and vice versa. For instance, a smaller remaining distance (indicated by blue values) possesses a SHAP value of −0.3, reflecting an inverse relationship of remaining distance with the probability of mandatory lane-changing occurrence. This finding is intuitive and can be explained by the fact that when drivers tend to delay their mandatory lane-changing manoeuvres, they are likely to traverse to the end of the acceleration lane, whereby drivers have to accept a gap and find their way onto the freeway. This finding also corroborates with Ahmed (1999), where drivers are reported to be more likely to accept a gap with an increasing delay time. Moreover, Fig. 6 can assist in explaining potential heterogeneity in lane-changing behaviour corresponding to the same feature. For instance, a



(a)



(b)

Fig. 7. SHAP dependence plot for mandatory lane-changing.

larger remaining distance (indicated by red values) in performing a mandatory lane-changing manoeuvre is also associated with a higher probability of changing lanes. This finding and corresponding behaviour is plausible and can be explained by the possibility that there exists a class of drivers who tend to change lanes well before reaching the end of the acceleration lane, which is a common phenomenon observed during merging manoeuvres and often reported in the past literature (Ali et al., 2018, Ali et al., 2020c).

Similarly, the acceleration of the subject vehicle is the second most important feature in the model as shown in Fig. 6. A noteworthy observation in the acceleration of the subject vehicle is the existence of two peaks, one in positive and another in negative SHAP value, suggesting the presence of driver heterogeneity. The positive peak indicates that higher acceleration values that correspond to a higher likelihood of lane-changing occurrence while the negative peak implies that higher acceleration values may also correspond to a lower likelihood of lane-changing occurrence. This behaviour can be explained by the fact that some drivers, while accelerating in the acceleration lane, aim to merge in front of the following vehicle on the mainline by relying on the cooperation of the following vehicle (especially in heavy traffic). However, in some cases, the follower does not yield to the lane changer given that they have right-of-the-way, resulting in high crash risk associated with performing a lane change manoeuvre. As such, drivers with higher acceleration are often found to be forced to abort their physically executed lane change (i.e., failed lane-changing attempt, see Ali et al. (2020d) for more details).

Similar SHAP summary plots can be generated for discretionary lane-changing, and the importance of variables can be interpreted similarly. However, for brevity, they are not presented herein.

5.4. *Feature dependence plot*

SHAP is also used to create feature dependence plots, which are scatter plots showing the effect of changing the value of a single feature on the predictions of the extra trees classifier model. A second feature that is likely to have an interaction effect with the primary feature is also depicted in the plot. This plot allows us to investigate the impact of interaction effects of input features on predicting lane-changing behaviour, similar to an interaction effect in a statistical model. For the sake of illustration, feature dependency plots are presented only for the mandatory lane-changing case in this study, whereas for brevity purposes, plots related to discretionary lane-changing are omitted.

For illustration purposes, Fig. 7 shows two dependence plots (other plots have been omitted for keeping the paper as short as possible). These figures reveal the interaction effects of (i) lag gap and following vehicle speed (Fig. 7(a)) and (ii) following vehicle speed and subject vehicle acceleration (Fig. 7(b)), on the probability of mandatory lane-changing occurrence. As shown in Fig. 7(a), with a smaller lag gap and lower speed of the following vehicle, drivers are less likely to perform lane-changing, reflecting drivers' safer lane-changing behaviour as a lower lag gap increases crash risk. Ali et al. (2020a) analysed lane-changing interactions and reported that followers in the target lane tend to narrow down the gap to avoid a lane-changing action. Further, Fig. 7(b) indicates that with a lower (higher) speed (acceleration) of the following (subject) vehicle, the probability of drivers changing lanes increases. Toledo et al. (2003) reported that the speed of the following vehicle is negatively associated with lane-changing, as it increases crash risk and as such, drivers tend to avoid performing lane-changing manoeuvres when the following vehicle is travelling at a higher speed.

6. Discussion

6.1. *Impact of class imbalance on the models*

As machine learning models typically learn underlying relationships from data, imbalanced data are likely to deteriorate their

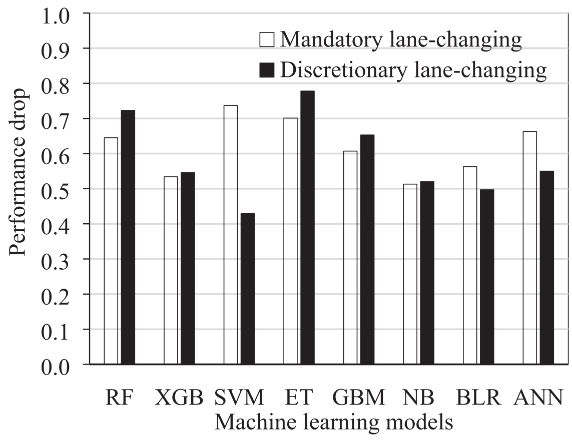


Fig. 8. Performance drop in the models without applying SMOTE. **Model abbreviations**: RF: Random Forest; XGB: Extreme Gradient Boosting; SVM: Support Vector Machine; ET: Extra trees classifier; GBM: Gradient Boosting Machine; NB: Naïve Bayes; BLR: Binary Logistic Regression; ANN: Artificial neural network.

performance by providing biased information towards the dominant class. As such, this study applies SMOTE (synthetic minority over-sampling technique) to oversample the minority class. Note that Fig. 8 reports the difference of F_1 scores (F_1 score with SMOTE - F_1 score without SMOTE), whereby the results of F_1 score without SMOTE are presented in Appendix A while the results with SMOTE are summarised in Table 6. By comparing the model performances with and without applying SMOTE (see Fig. 8), the following note-worthy observations are made. First, by accounting for class imbalance using SMOTE, the highest and lowest average F_1 scores are obtained for the extra trees classifier and binary logistic models, respectively. Second, the support vector machine and binary logistic models respectively indicate the highest and lowest average F_1 scores when SMOTE is not applied, suggesting that the support vector machine model is relatively robust to class imbalance. Third, Fig. 8 shows the maximum drop in the performance (measured in terms of average F_1 score) of the models when SMOTE is not applied to treat class imbalance. Results indicates that the support vector machine model shows the highest performance for discretionary lane-changing when there is a class imbalance as the support vector machine technique has the inherent capability, to some extent, to cater for class imbalance. Finally, the performance drop for mandatory lane-changing and discretionary lane-changing models is similar, whereas a higher performance drop for discretionary lane-changing models is observed, which can be attributed to a higher class imbalance in the discretionary lane-changing dataset. Thus, it is necessary to cater for class imbalance prior to selecting any machine learning technique for predicting lane-changing behaviour.

6.2. *Comparing the extra trees classifier model with other models from the literature*

To justify the choice of the best modelling method, the extra trees classifier model is compared with two lane-changing models from the literature. Most of the existing utility theory-based lane-changing models are based on gap acceptance theory, and their sole predictive capability has not been investigated due to their entangled nature in lane-changing decision models. As such, this section first compares the performance of the extra trees classifier model with two utility theory' models, which is based on gap acceptance theory, namely Ahmed's lane-changing model, (Ahmed, 1999) and Toledo's model (Toledo et al., 2005). The lane-changing behaviour in these models is defined by operational variables (such as relative speeds and remaining distance, etc.) and driver-specific terms—more details on these variables can be found in Ahmed (1999) and (Toledo et al., 2005). A maximum likelihood estimation method was used to estimate the parameters of these model using NGSIM data, and estimation results are not presented in this paper for brevity purposes. The Ahmed's mandatory lane-changing model performance, evaluated using the F_1 score, is 0.25 (see Fig. 9), which is about three times lower than that of the extra trees classifier model (i.e., 0.87). Similarly, the corresponding performance for Toledo's model is about 0.27, which is greater than Ahmed's model but still lower than the extra trees classifier model. The poor performance of utility theory models reflects the gap acceptance theory's inability to capture realistic driving behaviour. This finding is consistent with Marczak et al. (2013), which reported that drivers do not necessarily accept gaps that are larger than the critical gaps.

Further, this study compares the extra trees classifier model with a recent lane-changing model, which was previously used to model lane-changing behaviour using NGSIM data, i.e., the game theory-based lane-changing model developed by Talebpour et al. (2015). Details related to strategies, payoffs, and calibration framework of this model can be found in the original study. Using the same NGSIM dataset, the model performance is reported in Fig. 9. The F_1 score for the game theory-based mandatory lane-changing model is 0.33, which is about 2.5 times lower than the extra trees classifier model (i.e., 0.87). Although a relatively better performance of the game theory-based model is confirmed compared to the utility theory-based models, the extra trees classifier model tested in this study shows a better performance than the competing models from the literature and should be the preferred/recommended technique used for predicting lane-changing behaviour. Note that similar findings are observed when comparing the extra trees classifier model for discretionary lane-changing with the utility theory-based and game theory-based models for discretionary lane-changing.

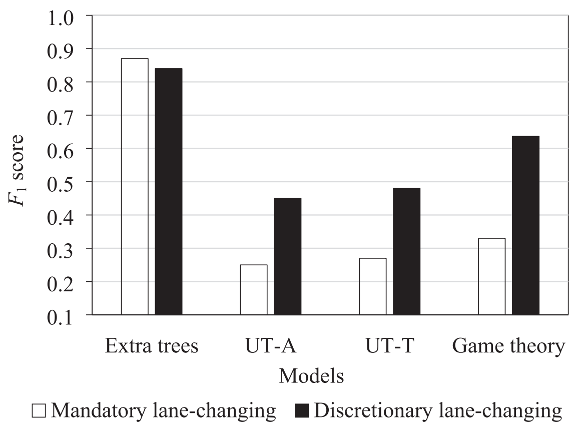


Fig. 9. Model performance for utility theory and game theory-based models. **Model abbreviations:** UT-A: Ahmed's utility theory model and UT-T: Toledo's utility theory model.

6.3. Impact of noisy data on model performance

Since NGSIM is known for containing errors in both longitudinal and lateral dynamics, mainly attributed to vehicle mistracking from camera video-processing (see Montanino and Punzo (2015) for more details), this study also used a reconstructed NGSIM I-80–1 dataset to investigate the performance difference. More specifically, machine learning models are applied to predict mandatory and discretionary lane-changing manoeuvres using the reconstructed and original I-80–1 datasets. Note that as the reconstructed I-80–1 dataset contains only 15-min data, the same 15-min data from the original I-80 dataset is considered for a fair comparison.

For the model comparison of with and without noise in the data, each best performing machine learning model with the application of SMOTE is selected (see Table 6) for a fair comparison. Apart from F_1 score, the relative error is calculated as $\frac{F_1^{reconstructed} - F_1^{original}}{F_1^{reconstructed}} \times 100$, indicating the difference in the model performance on the original dataset compared to the reconstructed one. Fig. 10 displays the comparison results. More specifically, all machine learning models tend to perform relatively better on noise-free data (i.e., reconstructed I-80–1 dataset), while their performance deteriorates when the data contains noise. Noise in the data has the highest impact on the binary logistic regression model (relative error of 15.7 %), while other machine learning models exhibit an error of less than 12 %. Sophisticated machine learning modelling techniques like Extra Trees and Random Forests have an inherent capability to work well with noisy data, and as such, their relative errors are lower than those of the other models.

In summary, this study confirms the performance difference between using noise-free and noisy data while its impact is found to be non-uniform across different models, mainly attributed to the inherent capability of different machine learning models to cope with noisy data (Schlimmer and Granger, 1986). As such, this study recommends that in future, if possible, models should be assessed first with noise-free data to obtain their true performance unconfounded by any noise.

6.4. Transferability analysis of the models

A good machine learning model should be able to generalise its predictive performance to new datasets, so that its adoption for prediction purposes is not restricted to the dataset on which it has been trained and tested. To this end, we have investigated the transferability performance (or replicability) of all the models. Note that here transferability refers to both spatial and temporal transferability. For this purpose, this study utilises a completely different dataset of NGSIM (i.e., US-101). This dataset was collected for 45 mins on the Hollywood Freeway, in Los Angeles, CA. The road segment length is about 640 m and consists of an on– and off-ramp where systematic mandatory lane-changing manoeuvres are expected, whereas all the inner lanes are used for discretionary lane-changing. This study considers both mandatory lane-changing and discretionary lane-changing manoeuvres as an example to illustrate the transferability of the models. Note that the number of observations for the US-101 dataset (590 (650) lane-changing versus 1,587 (2,657) non-lane-changing events for mandatory lane-changing (discretionary lane-changing)) is similar to that of the I-80 dataset, allowing a fair comparison of models using two different datasets. Moreover, the data pre-processing applied to the US-101 dataset is the same as that for the I-80 dataset. Further, all the models with the best performing number of input features are adopted for transferability analysis. For instance, the extra trees classifier model with input 10 features has been used for predictive analysis of mandatory lane-changing using the US-101 dataset.

6.4.1. Spatial transferability analysis

Using the same hyperparameters of the models, it can be observed that these models predict mandatory and discretionary lane-changing behaviours reasonably well (Fig. 11(a)). For instance, we find that the performance drop of the extra trees classifier model for mandatory lane-changing using the US-101 dataset is about 3 % (Fig. 11(a)) in comparison to the performance of the I-80 dataset (see Table 6). This finding reflects an excellent spatial transferability of the extra trees classifier model adopted in this study for predicting lane-changing behaviour. A similar finding is reported by Jiang et al. (2020) where machine learning models show a

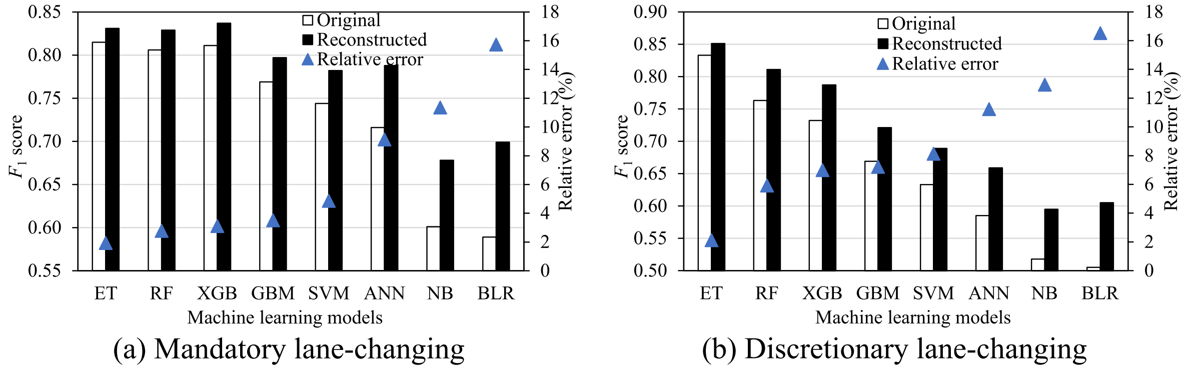
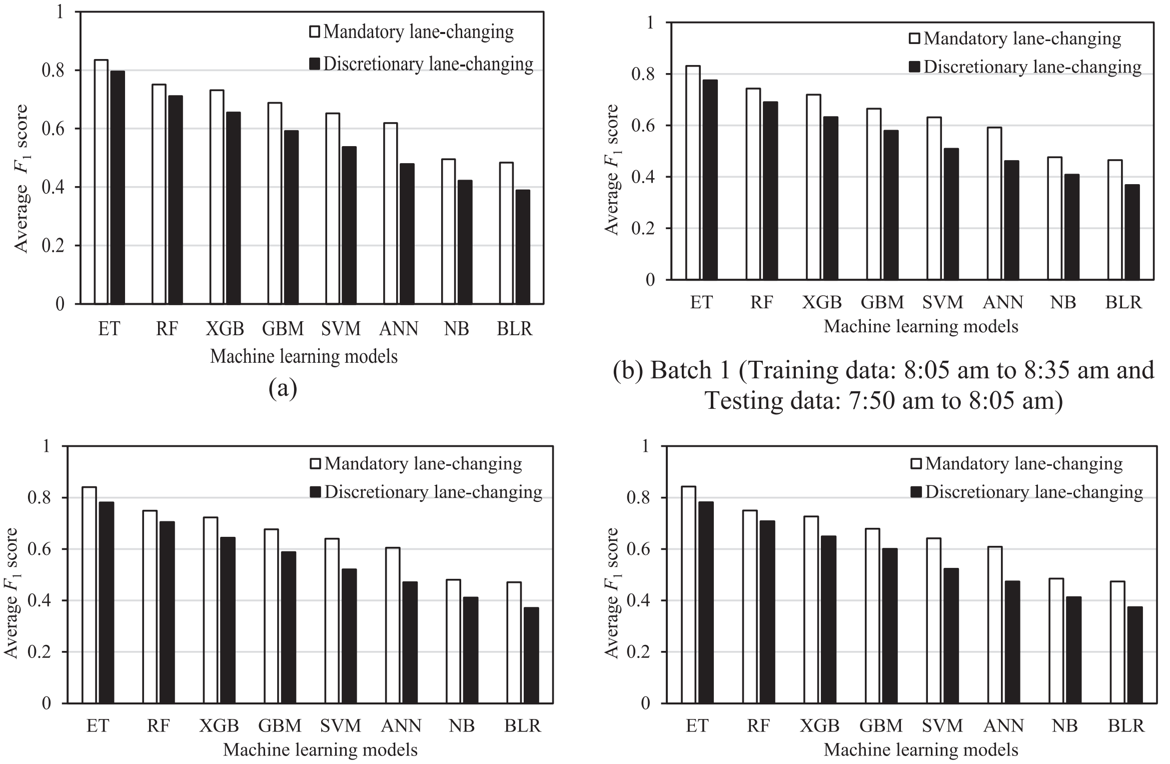


Fig. 10. Comparison of model performances with and without noise in the I-80 dataset. **Model abbreviations**: RF: Random Forest; XGB: Extreme Gradient Boosting; SVM: Support Vector Machine; ET: Extra Trees Classifier; GBM: Gradient Boosting Machine; NB: Naïve Bayes; BLR: Binary Logistic Regression; ANN: Artificial Neural Network.



(a)

(b) Batch 1 (Training data: 8:05 am to 8:35 am and Testing data: 7:50 am to 8:05 am)

(c) Batch 2 (Training data: 7:50 am to 8:05 am and 8:20 am to 8:35 am and Testing data: 8:05 am to 8:20 am)

(d) Batch 3 (Training data: 7:50 am to 8:20 am and Testing data: 8:20 am to 8:35 am)

Fig. 11. Summary of (a) spatial and (b-d) temporal transferability analyses using the US-101 dataset. **Model abbreviations**: RF: Random Forest; XGB: Extreme Gradient Boosting; SVM: Support Vector Machine; ET: Extra Trees Classifier; GBM: Gradient Boosting Machine; NB: Naïve Bayes; BLR: Binary Logistic Regression; ANN: Artificial Neural Network.

reasonable transferability performance in crash detection using two different datasets.

Further, the performance drop in the extra trees classifier model is much smaller than the other three top-performing models (i.e., Random Forests, Extreme Gradient Boosting, and Gradient Boosting Machine) for both mandatory and discretionary lane-changing. For instance, the performance drops of the random forests, extreme gradient boosting, and gradient boosting machine models for mandatory lane-changing are respectively 8 %, 9.2 %, and 9.9 %. Interestingly, the ranking of these models based on their average F_1 scores using the US-101 dataset is the same as we observed previously using the I-80 dataset. Similar observations have been found for discretionary lane-changing.

6.4.2. Temporal transferability analysis

To assess temporal transferability of all machine learning models, both NGSIM datasets (I-80 and US-101) were used. As 45-minutes time periods in these datasets were chosen to reflect build-up to congestion, moderate congestion, and severe congestion, the performance of all machine learning models is tested for each of these periods. More specifically, a 30-mins segment of dataset is used for model training, and the remaining 15-mins segment is used for model testing. For instance, batch 1 considers training data from 8:05 am to 8:35 am and testing data from 7:50 am to 8:05 am (for US-101 data); similarly, for batch 2, 7:50 am to 8:05 am and 8:20 am to 8:35 am data are used for training while 8:05 am to 8:20 am data are used testing, and so on. In doing so, the models are trained and tested with every segment of dataset, which will enable us to understand model performance corresponding to different times/ congestion levels.

Fig. 11 (b-d) show the temporal transferability analysis results using the US-101 dataset while the results for the I-80 dataset are omitted because of similar trends. Results indicate that the machine learning models capture mandatory and discretionary lane-changing behaviours with a reasonable accuracy during different time intervals/congestion levels. For instance, the variation in extra trees classifier mandatory lane-changing model predictions for all three congestion levels is about 0.64 % (calculated as variation in F_1 score across three batches), reflecting an excellent temporal transferability of the extra trees classifier model. Man et al. (2022) reported good temporal transferability of machine learning models for real-time crash prediction when these models were treated for class imbalance. Consistent with their findings, our study also handled the class imbalance issue using SMOTE and shows a reasonable temporal transferability performance of machine learning models in capturing lane-changing behaviour during different time periods.

Note that the ranking of the machine learning models remains unaffected by training and testing with different data segments, and similar observations have been found for discretionary lane-changing.

7. Conclusions

This study investigated the performance of machine learning techniques in predicting lane-changing behaviour using empirical data from NGSIM. Drivers' tactical lane-changing decisions were framed as a binary classification problem and eight representative machine learning techniques were employed to predict these decisions. To objectively select the number of input features for each machine learning model, the technique of Recursive Feature Elimination was employed. Using standard classification metrics, this study found that the extra trees classifier model outperformed other competing models from the literature. Further, classification metrics such as precision, recall, F_1 score, and area under the receiver operating characteristics curve, were employed to further assess the performance of the extra trees classifier model. Meanwhile, this study compared the extra trees classifier model with a utility theory-based model and found that the extra trees classifier model has vastly superior predictive performance.

Given that lane-changing behaviour data are often imbalanced (heavily dominated by non-lane changing events), this study applied the SMOTE oversampling technique. Results revealed that the models are sensitive to class imbalance as their true performance would be compromised if class imbalance is not treated. Thus, it is a prerequisite to apply a suitable data treatment prior to analysing their predictive performance. Since this study only applied SMOTE to account for class imbalance, a future research direction could be to apply different treatments and consequently analyse their effects on the performance of different models.

By employing explainable artificial intelligence, the output of the best performing model is interpreted using a SHAP summary plot and dependence plots. SHAP not only ranked the contribution of each feature toward predicting the overall lane-changing behaviour, but also uncovered its observation-level impact on lane-changing decisions, known as local interpretability. Furthermore, dependence plots allowed us to investigate the combined effect of different features on lane-changing behaviour. Since this study shows evidence of heterogeneity using SHAP, future research studies can further leverage explainable artificial intelligence to explain driver heterogeneity, which is often done using advanced statistical techniques like random parameters models or latent class models.

This study tested the performance of the selected machine learning models using another dataset from NGSIM to demonstrate their transferability. All the models showed a reasonable transferability performance, with the extra trees classifier model performing the best.

Several lane-changing decision modelling techniques have been used in the literature, including rule-based, utility theory-based, game theory-based, machine learning-based etc. (Zheng, 2014). However, their predictive capability remains questionable (e.g., the mean F_1 score of lane-changing decision models was found to be 0.3 using the I-80 dataset (Ali et al., 2022)). Meanwhile, data-driven techniques like machine learning models provide excellent predictive accuracy as well as explanation as demonstrated in this study. However, these models are not based on any theoretical framework (like game theory) and may yield erroneous estimates as well as inferences because of poor quality of data. A way forward in lane-changing decision modelling is to underpin machine learning models using a behaviourally sound decision-making framework (e.g., game theory and prospect theory). In doing so, machine learning models will not only rely on data but make decisions based on understanding drivers' lane-changing behaviour.

This paper mainly aims to provide an analysis framework for machine learning models in general and apply it to lane-changing in particular. Thus, selecting the best model from the candidate models should not be solely driven by one metric (such as F1 score). Instead, a thorough assessment through different indicators should be performed to ascertain the best performing machine learning model. Some suggestions in this direction are as follows. First, instead of focussing on average values of a performance indicator like F1 score, distributions of F1 scores should be used, which will further provide a base to statistically compare different models' performance. Second, microscopic indicators like time and location errors should be used to decide the performance of machine learning models at a micro level. Third, since the performance of machine learning models is susceptible to class imbalance, different proportion of class imbalance should be used to assess the veracity and soundness of machine learning models. Finally, the use of multiple data sources to confirm the performance of models in terms of spatial and temporal transferability will provide insights in generalisability of machine learning models.

Although this study has used a reasonable amount of data to build machine learning models, more data are required to increase their predictive capability. In particular, deep neural networks, which require a large dataset and have shown promising results for several problems, should be explored in future studies.

CRediT authorship contribution statement

Yasir Ali: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft. **Fizza Hussain:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft. **Michiel C.J. Bliemer:** Formal analysis, Funding acquisition, Investigation, Supervision, Validation, Writing – review & editing. **Zuduo Zheng:** Formal analysis, Funding acquisition, Investigation, Methodology, Supervision, Validation, Writing – review & editing. **Md. Mazharul Haque:** Formal analysis, Funding acquisition, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A:. Average F_1 score performance evaluation of the models for predicting lane-changing behaviour without considering SMOTE

ML model	Number of features selected									
	11	10	9	8	7	6	5	4	3	2
RF	—	0.206	0.197	0.196	0.177	0.233	0.226	0.211	0.211	0.212
XGB	—	0.336	0.296	0.289	0.324	0.285	0.295	0.313	0.31	0.318
SVM	—	0.359	0.045	0.044	0.042	0.038	0.028	0.041	0.031	0.028
ET	—	0.183	0.162	0.202	0.189	0.194	0.231	0.195	0.231	0.201
GBM	—	0.184	0.177	0.189	0.184	0.201	0.190	0.189	0.208	0.226
NB	—	0.094	0.110	0.112	0.108	0.116	0.107	0.111	0.110	0.107
BLR	—	0.039	0.049	0.049	0.050	0.046	0.042	0.049	0.050	0.052
ANN	—	0.222	0.111	0.098	0.072	0.079	0.075	0.105	0.518	0.060
RF	0.062	0.070	0.071	0.074	0.072	0.070	0.080	0.081	0.074	0.070
XGB	0.210	0.195	0.196	0.207	0.200	0.182	0.199	0.193	0.202	0.203
SVM	0.223	0.185	0.205	0.225	0.201	0.211	0.205	0.206	0.203	0.185
ET	0.060	0.053	0.061	0.050	0.063	0.068	0.049	0.055	0.048	0.062
GBM	0.043	0.031	0.038	0.038	0.055	0.045	0.033	0.038	0.035	0.036
NB	0.060	0.018	0.012	0.012	0.010	0.009	0.008	0.006	0.010	0.011
BLR	0.005	0.004	0.005	0.003	0.006	0.007	0.005	0.007	0.005	0.008
ANN	0.051	0.027	0.179	0.114	0.104	0.003	0.002	0.001	0.005	0.006

Abbreviations: *ML: machine learning; WS: with SMOTE; WOS: without SMOTE; Shaded cells (bold letters) indicate the machine learning model with the highest accuracy; RF: Random Forest; XGB: Extreme Gradient Boosting; SVM: Support Vector Machine; ET: Extra Trees classifier; GBM: Gradient Boosting Machine; NB: Naïve Bayes; BLR: Binary Logistic Regression; ANN: Artificial neural network; "—" not included in the model.*

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