

CLASSIFICATION AND MODELING OF DRIVER BEHAVIOR DURING YELLOW INTERVALS AT INTERSECTIONS

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ABSTRACT:

The violation of traffic rules is, nowadays, the most important cause of accidents. Passing an intersection or a red light can be fatal for a driver and lead to serious damage. In fact, when the driver encounters a signal change from green to yellow, he or she is required to make a decision to stop or to go based on many factors. Making the wrong decision will result in a red-light violation or an abrupt stop at the intersection. Researchers typically focus on the connection between driving behavior and decision-making because of its importance in controlling aggressive drivers' behavior. This work aims to compare the potential of machine learning techniques to classify driver behavior at intersections and follows a data preparation process to expect interesting performance results. A comparative study was therefore conducted to explore the various data source and algorithms employed to classify driver behaviors at intersections and to address the most important techniques used. Two experiments were also developed in this paper. The first experience attempts to classify driver behavior in intersections into (1) stopping and (2) going at intersections. The second experience was based on stopping observations when approaching intersections. We classified these drivers into two categories: those who stop beyond the line (1) are considered dangerous or unsafe stops, and those who stop before the line (2) are considered safe stops. As a result, XBoost archive the best performance with 92.19% of accuracy and 94.38% of precision in the first experience and RF gives the best performance in the second experience with an accuracy of 99.38%.

1. INTRODUCTION

Road traffic accidents are one of the most important issues facing the world today, resulting in a large number of deaths and injuries every year (Bouhsissin et al., 2022). Speeding was a factor in 29% of all traffic fatalities in 2020 (Stewart, 2020). Also, in Morocco, about 18% of all road fatalities in 2019 were caused by speeding (Ronan, 2021). Therefore, the behavior of road users is an important determinant of a country's road safety performance, especially at intersections. In addition, intersections are one of the major road safety challenges for road users.

Driver behavior is one of the most important factors in the emergence of problems in intersections and the safety of human vehicles. In addition, road intersections are generally considered to be the riskiest areas of road networks. When a yellow indicator is activated, the intersection is investigated and represented as a binary decision problem to stop or go. Therefore, research on driver behavior in the yellow gap at signalized intersections can lead to useful information for improving road safety. The area where it could be challenging for a driver to choose whether to stop or continue through the intersection at the beginning of the yellow signal indication is known as a dilemma zone (Zhang et al., 2014). Due to drivers' reluctant decision-making, the dilemma zone has been identified as a significant cause of traffic accidents and infractions at signalized junctions, and this has sparked an increase in attention from studies across the globe.

This paper presents the results of research that focuses on the classification of driver behaviors when they face a yellow signal. To achieve our goal, we used the most commonly used machine learning models found in our literature review on driver behaviors classification on stopping decisions (stop and go) and stopping methods (safe and unsafe).

This research paper is structured as follow. Section 2 exposes the related works in the field of driver behavior at intersections. In section 3, we presented a comparative study. Section 4 discussed our methodology and in section 5 we develop our experiments studies and exposes the results achieved. Conclusion and perspectives are discussed in section 6.

2. RELATED WORK

Understanding how drivers behave at stop-controlled intersections is of crucial importance for the control and management of an urban traffic system. Using a video system, driver behavior associated with signal change was observed at a high-speed signalized intersection in the paper (Elmitiny et al., 2010). Decision tree models were applied to analyze how the probabilities of a stop or start decision is associated with traffic parameters. Also, video data is used in (Pathivada and Perumal, 2017) with binary Logistic Regression model that achieved a prediction accuracy of 83.3%. In (Wen et al., 2021), they classified the behavior into four classes: full stop, slight rolling stop, rule stop, slow down without stop and running through at stop-controlled intersections via k-means and camera data. Using compiled intersection data from Shanghai and Decision tree classification algorithms, authors in (Dong and Zhou, 2020) demonstrates the conditions impacting stop/go decisions in rural areas. The relationship between drivers' stop/go decisions and these potential influencing elements is then revealed. From GPS, accelerometer, and sensors, the authors (Elhenawy et al., 2015a) have classified driver behavior in the dilemma zone into two classes: stop or go via Support vector machine (SVM) algorithm. The accuracy of the model is 90.09%. From the field observations, driver data is collected in (Shaaban et al., 2017). The authors use the binary and ordinal logistic regression algorithms to categorize driving behavior at small street stop sign junctions into no-stop, rolling-stop, and complete stop.

In proportion to the data extracted by the driving simulator, the research (Li et al., 2021) studies driver behavior in a dilemma zone using a mathematical modeling technique based on stochastic model predictive control (SMPC), in order to develop a system for simulating driver behavior and possibly enhance our comprehension of the interactions between drivers, vehicles, and environments in dilemma zones. In addition, for various road surface conditions, article (Elhenawy et al., 2015b) models the driver's stop/run behavior at the start of a yellow sign. For the classification of driving behavior, the authors employ the adaptive boosting (AdaBoost), Artificial Neural Networks (ANN), and Support Vector Machine (SVM) algorithms. The SVM algorithm expected 92.9% accuracy. Using the experimental dataset from National Advanced Driving Simulator (NADS) driving simulations, the paper (Chen et al., 2018) uses Bayesian network (BN) to study the decision patterns of drivers in a dilemma zone with phone use, the model achieved 82.9% of precision. In (Ali et al., 2021), a hybrid method based on decision tree and mixed logit panel algorithms examines drivers' decisions at the start of yellow traffic lights when assisted by prior information about traffic light changes. Moreover, a survival analysis model for stop time analysis was suggested in (Li et al., 2020) to better understand the stopping

behavior of drivers at junctions during the yellow interval. More, a statistical analysis is conducted to define the types of driver behavior into complete stops, rolling stops, and non-compliant stops at rail level crossings (RLX) in (Beanland et al., 2017).

In addition, the Back Propagation Neural Network (BPNN) method and the relative strength of Electroencephalogram (EEG) data are used in the paper (Zhou et al., 2019) to create a prediction model of drivers' stop or go decision-making at intersections. The model's accuracy rating is 91.44 percent.

3. COMPARATIVE STUDY

In this section, we developed a comparative study to explore the various approaches employed to classify driver behaviors and to address the most important techniques used. The comparison criteria adopted are:

- Driver behavior: various types of driver behavior.
- Data sources: which cover the data source and type.
- Features: characteristics.
- Algorithms: algorithm used.
- Evaluation measures: model performance.
- Results.

Ref	Driver behavior	Data sources	Features	Algorithm	Evaluation measure	Result
(Pathivada and Perumal, 2017)	Stop Go	Video collected	Approach speed Distance to stop line Type of intersections Light of yellow interval Vehicle types	Binary logistic regression	Accuracy	83.30%
(Ali et al., 2021)	Stop Go	Advanced Driving Simulator and questionnaire	Age, Gender Speed Distance to the stop line Driving experience Acceleration noise License type, Education	Decision tree (DT)	-	-
(Li et al., 2021)	Stop Go	CarSim 8.02 simulator	Traffic light Speed Traffic flow Distance from the stop-line	Stochastic predictive control (SMPC)	-	-
(Elhenawy et al., 2015a)	Stop Run	GPS and questionnaire	Time to intersection Speed Gender, age Roadway surface condition	AdaBoost Random forest (RF) Support vector machine (SVM) Logistic regression (LR)	Accuracy False positive	SVM: 90.02%
(Elhenawy et al., 2015b)	Stop Run	Simulator	Time to intersection Speed Vehicle type Roadway surface condition Gender, age Intercept and the new proposed driver aggressiveness predictor	AdaBoost Support vector machine (SVM) Artificial neural networks (ANN)	Accuracy False positive	SVM: 92.9%
(Chen et al., 2018)	Proceed Stop	Simulator	Yellow signal length Years Time to stop line Gender Pedal Change Direction Dramatic pedal change Handheld phone tasks Phone, Task Type	NB	F-measure ROC curve MPE TP Rate FP Rate Precision	82.9% 88.3% 0.0815 82.9% 19.3% 82.9%
(Beanland et al., 2017)	Complete stop Rolling stop	Simulator	Travel speed Visual checks	Analytical and statistical study:	-	-

	Non-compliant		Verbal protocols	χ^2 test				
(Shaaban et al., 2017)	No stop Rolling stop Complete stop	Data collectors – observers	Stopping behavior Gender, Heritage Age, Vehicle type Vehicle approaching Pedestrian approaching Time of day, Day of week Location type	Binary logistic regression Ordinal logistic regression	logistic	p-Value		p-value < 0.001
(Wen et al., 2021)	Full stop Slight rolling stop Ruling Stop Slow down without stop Running through	Mobile camera	Speed and position data	K-means		Sum of squared errors		-
(Elmitiny et al., 2010)	Stop Go	Video collected	Vehicle's distance Speed Position in the traffic flow	Classification models	tree	-		-
(Zhou et al., 2019)	Stop Go	EEG	32 features	Back propagation neural network (BPNN)		Accuracy		91.44%
(Dong and Zhou, 2020)	Stop Go	Data collectors	Speed Distance to the stop-line Vehicle type	Decision tree (DT)		Gini criterion		-

Table 1. Statistical description of independent variables.

Table 1 shows a comparison table between the studies on drivers' behaviors when stopping or going in intersections and in front of the yellow light. We can see that we can classify these behaviors mainly from simulator data, camera (video), GPS, electroencephalogram, and even through questionnaires. In fact, different data sources are valuable to develop these models, nevertheless they all have the same goal of categorizing the drivers' behaviors at the intersection.

In terms of features, we can see that the speed of the vehicle, the distance to the stop line, the light of the yellow interval, and the time before the intersection are the most used.

In the simulator data, the AdaBoost, RF, DT, SVM, NB, and LR algorithms are the most used, and the best result obtained is 92.9% accuracy from the SVM algorithm and 82.9% precision from the BN algorithm. When AdaBoost, RF, SVM, and LR are used for the data extracted by the GPS sensors, the SVM classifier obtains 90.02% accuracy. From the camera data, the classification of the drivers' behaviors is done by K-means, DT, and binary logistic regression, which expects 83.30% accuracy.

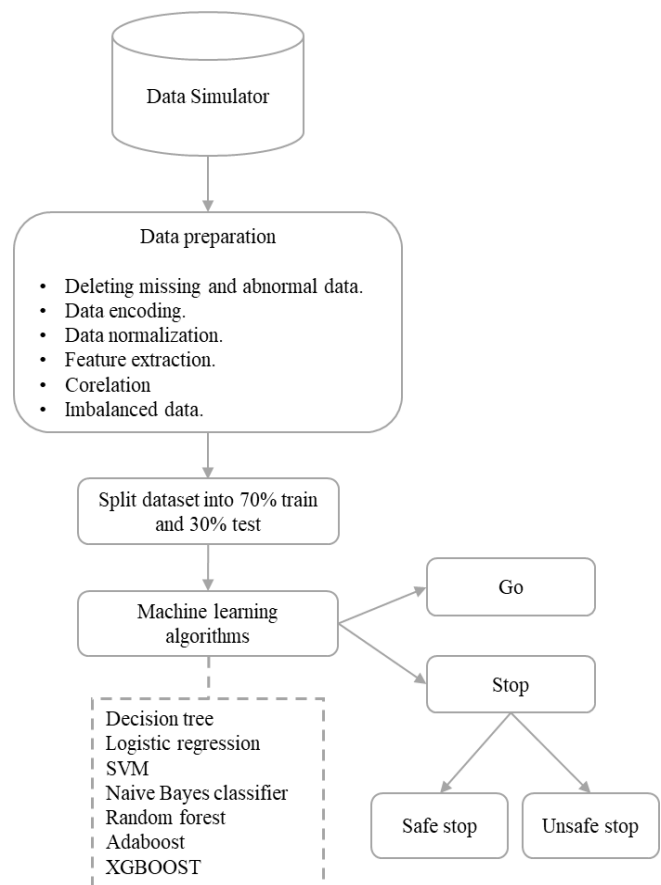
In general, we cannot affirm which is the best algorithm to classify driver behavior at intersections because the data sources are different, such as data sources of simulators, videos, and GPS. However, for the same data source, we can examine and compare the performance of different algorithms such as DT, LR, AdaBoost, SVM, NB, and RF on the same data source to explore them and analyze their performance for the stop/go classification in signal-controlled intersections.

4. METHODOLOGY

In this paper, different algorithms of machine learning were developed to model stopping behavior during yellow intervals at intersections. Our goal is to classify stop/go decisions at signalized intersections during signal change interval and classify the stopping vehicle as a safe or unsafe stop. We compare the ability of machine learning models to classify drivers' stopping behaviors during yellow intervals. In this

section, we present the methodology followed to achieve our objective. Figure 1 shows the workflow of our approach.

Figure 1. Our workflow.



From the data extracted by a driving simulator, we prepare this data by going through different phases of data preparation, such as pre-processing of data, feature extraction, and imbalanced data. Then we divide it into training and test datasets.

Using a set of machine learning algorithms, we trained the dataset in order to classify the behaviors of drivers at intersections into two categories: stop and go. Then, we classify stop instances as safe or unsafe.

4.1 Data Description

The data set is from the Transportation Research Board (TRB) Driver Behavior Analysis Competition in 2014 (“Human Factors and Statistical Modeling Lab - University of Washington,” n.d.; TRB Statistics Committee, 2014). The data study was conducted at the National Advanced Driving Simulator (NADS) at the University of IOWA (see Figure 2), which is a high-fidelity driving simulator, aimed at detecting driver behavior at signalized intersections.



Figure 2. National Advanced Driving Simulator (NADS).

Each reader had to make a yellow light judgment six times during the trial, which required each participant to complete the task 18 times. Additionally, secondary activities were conducted at random and exposed participants to three different cell phone interfaces: baseline (no phone call), outgoing call (calling out), and incoming call (answering a call). Before entering each sector, calls started coming in and going out. There are 1157 rows of data in the original dataset, which was compiled from 49 people. One yellow event's data is represented by one row. For every drive or visit, each participant should have a maximum of six rows.

The following data were collected:

- Driver's name, gender, age
- Call status, phone status
- The frame number when the traffic light changed from green to yellow, yellow to red, and red to green.
- The frame number and the direction at which the participant's foot moved the accelerator pedal by more than 10%: (released, depressed).
- Maximum acceleration and maximum deceleration.
- Distance to the stop line.
- Frame number when the vehicle first stops and when the participant has reached the stop line.
- Speed and distance of the participant when the light first changes from green to yellow.
- Speed when the light changes from yellow to red.

- Speed of the participant when he/she has reached the stop line.

4.2 Data Preparation

The data preparation was carried out before each construction of the model.

4.2.1 Data Pre-processing

To prepare data, some preprocessing techniques were applied such as following:

- Deletion of missing and abnormal data such as incomplete drive data or when there is an anomaly in the drive.
- Transformation of some features to international system of units like acceleration from foot per second squared (ft.s^{-2}) to meter per second squared (m.s^{-2}), speed from Miles per hour (Mph) to meter per second (m.s^{-1}), distance from feet to meters (m) and number of frames from frame to second (s) with 240 frames per second.
- Transformation of categorical data to numeric data using encoding.
- Data normalization with the linear scaling technique. Using the following simple formula:

$$x = \frac{x - x_{min}}{x_{max} - x_{min}}, \quad (1)$$

- Feature selection using the correlation between features. When two characteristics have a high correlation, we can remove one of the two characteristics. In our case, we have the correlation between the first stop frame, frame number when the traffic light changed from red to green, and stopping time calculated in section 4.2.2. We keep the latest feature. Also, between stop line time, the frame number when the traffic light changed from yellow to red and green to yellow. We reserve the first feature.

4.2.2 Feature Extraction

In machine learning and statistics, feature extraction is a method of dimensionality reduction by which data that is initially represented in a high-dimensional space is transformed into a representation in a lower-dimensional space. Feature extraction combines variables into functionalities, effectively reducing the amount of data to be processed, while accurately and completely describing the original dataset. In our case, we calculate the stopping time (ST) for stopping behavior, which is the time between the start of the yellow light and the complete stop of the vehicle.

4.2.3 Imbalanced Data

In recent years, the problem of class imbalance has been one of the emerging challenges in machine learning. Typically, unbalanced datasets are composed of two classes: the majority (negative) class and the minority (positive) class. Two possible solutions exist: undersampling or oversampling. Oversampling is used to increase the size of an unbalanced dataset by duplicating some minority instances. Downsampling consists of reducing the size of the data by removing certain majority instances in order to equalize the number of instances of each class. To overcome the problem of unbalanced data, we have used the SMOTE resampling strategy as there was an imbalance in the percentage of stop and go and an imbalance between safe

and unsafe stop. In order to raise the minority class proportion, the SMOTE algorithm produces artificially positive examples (Chawla et al., 2002).

4.2.4 Splitting Data

After collecting the data and preparing it, the next step is to split the data into training and test sets. The training set is used to train the machine learning model, while the test set is used to assess the performance of the model. It is important to split the data randomly so that the training and test sets are representative of the entire dataset.

There are a few different ways to split the data, in our situation the data was partitioned into a 70/30 split, where 70% of the data is used for training and 30% is used for testing.

4.3 Background Techniques

Once the data is prepared, the next step is to train the machine learning models. This is done by feeding the training data into the models.

4.3.1 Support Vector Machine

The Support Vector Machine (SVM) was introduced in the early 90s (Boser et al., 1992). The core concept of SVM is margin calculation. In this approach, each data element is represented as a point in an n -dimensional space, with each feature representing the value of a particular coordinate. This method is used to analyze the vectorized data and find a hyperplane that lies between the two inputs (Dey, 2016). Different margins are created between the various classes and the hyperplane so as to optimize the distance between the margin and the classes and minimize the mean square error.

4.3.2 Naive Bayes Classifier

Naive Bayes (NB) is a probabilistic classification technique. The algorithm is based on Bayes' theorem and depends on the nature of the probability model. Due to the assumption of independent variables, the Naive Bayes classification method only requires the variance of each class to be determined, not the whole covariance matrix (Dey, 2016; Dhall et al., 2020).

4.3.3 Decision Tree

Decision Tree (DT) is a supervised learning technique applied to classification issues. The DT is made up of branches and nodes, where a node indicates the characteristics of a group that needs to be categorised and a branch shows the possible values for a node (Dhall et al., 2020). In order to split the node, the algorithm uses information gain. Information gain is calculated using either the gini index or entropy. The gini index and entropy are measures of impurity of a node.

4.3.4 Random Forest

Random Forest (RF) is a simple supervised machine learning technique that constantly improves performance without the need for parameter modification. As the name implies, it builds a forest and partly randomizes it. In order to increase accuracy, the strategy should be such that there are more trees in the forest.

4.3.5 Logistic Regression

Logistic regression (LR) is a supervised learning method used to differentiate between two or more groups (targets). The method generates a yes (1) or no (0) answer depending on the value predicted by a linear equation with independent predictors (Dhall et al., 2020).

4.3.6 Adaboost

AdaBoost is an ensemble learning method, and it is part of the Boosting algorithm family. AdaBoost learns from the mistakes of weaker classifiers and turns them into stronger ones, thus improving the performance of the final classifier.

4.3.7 XGboost

XGBoost is an algorithm that has recently dominated the field of applied machine learning. XGBoost is an implementation of gradient boosted decision trees designed for speed and performance.

5. EXPERIMENTS AND RESULTS

5.1 Analytic study

Table 2 and Table 3 displays each variable's values and full descriptions. We have 838 observations after data preprocessing, including 306 go observations and 532 stop observations. Additionally, we have 476 vehicles stopping before line and 56 vehicles stopping beyond line. There are more data of young drivers than other categories with 309 observations and more men than women with 437 and 401 respectively. Noting that the average maximum acceleration is 3.465 m.s^{-2} and maximum deceleration is -6.113 m.s^{-2} . Moreover, the average speed of the vehicle at the beginning of the yellow light is 18.95 m.s^{-1} for stopped vehicle and 19.18 m.s^{-1} for the opposite, and the average distance is 62.36 meters for stopped vehicle and 61.98 meters for the opposite. According to the data set, traffic begins to stop at 3.63 seconds after the yellow signal appears and all vehicles stop within 12.97 s. The average stopping time is 6.24 s, and 75% of drivers stop in 7.68 seconds, 50% in 5.84 s, and 25% in 4.69 seconds. The stopping time statistics are presented in Table 4.

Variable	Description	Observations	Count	Mean	Std.Dev
MA (m.s^{-2})	Maximum acceleration	Go	306	1.343	1.338
		Stop	532	3.465	0.435
MD (m.s^{-2})	Maximum deceleration	Go	306	-2.338	2.488
		Stop	532	-6.113	1.532
GTYV (m.s^{-1})	Vehicle's speed at the onset of yellow light	Go	306	19.18	2.21
		Stop	532	18.95	2.27
GTYD (m)	The distance between the car and the stop line	Go	306	61.98	9.46
		Stop	532	62.36	10.56

Table 2. Statistical description of independent variables (Continuous).

Variable	Description	Observations	Count
Dependent variables			
Classification of Stop or Go Decision	Go	-	306
	Stop	-	532
Classification of stop instances to Safe or Unsafe	Before line	-	476
	Stop beyond line	-	56
Independent variables			
Age	Middle Old Young	Go	99
			102
			105
	Stop		197
			131
Gender	Female Male	Go	159
			147
	Stop		242
			290
Call state	Baseline (B) Incoming call (I) Outcoming call (O)	Go	121
			88
			97
	Stop		170
			182
Phone condition	HandsFree Handheld HeadSet	Go	100
			103
			103
	Stop		178
			185
		169	

Table 3. Description of dependent and independent variables (discrete).

Quartile	25%	50%	75%	Min	Max	Mean
Stopping time (s)	4.696	5.842	7.683	3.633	12.967	6.243

Table 4. Quartile statistics of stopping time.

5.2 Results and Discussion

The purpose of this experiment is to detect the most performant technique used to classify stopping decisions (stop or go) and stopping methods (safe or unsafe). This section develops into the results of the experiment conducted in this work see Table 5 and Table 6.

To implement this study, we used python programming language. These experiments were carried out on a Victus by HP laptop with an CPU AMD Ryzen 5 5600H with Radeon Graphics, 3301 MHz, 6 Cores, 12 Threads with (8 CPUS), 16 GB of ram and NVIDIA GeForce RTX 3050 Laptop GPU.

5.2.1 Performance Metrics

Numerous metrics are available to evaluate our models' performance in classification issues and to identify the most performance ones. To compare these algorithms more efficiently, we used the following measures in this study: accuracy, precision, sensitivity or recall, and F1-score.

5.2.2 Classification of Stop or Go Decision

For classification of stop/go decision, the results are presented in Table 5. XGBOOST around 92.19% of accuracy then RF

classifier 90.08% of accuracy, DT achieves the highest precision among all classifiers of 94.48%, and SVM achieves 99.40% of recall. The highest F1-score is 92.63% of F1-score followed by 92.35% for the RF algorithm.

Algorithms	Accuracy	Precision	Recall	F1-score
DT (using entropy)	88.49	94.48	86.71	90.43
DT (using Gini index)	84.69	87.27	83.72	85.46
LR	86.29	82.3	95.57	91.79
AdaBoost	88.49	91.41	90.85	91.13
XGBOOST	92.19	94.01	91.28	92.63
SVM	89.29	85.41	99.40	92.13
NB	89.29	85.79	99.37	92.08
RF	90.08	89.35	95.57	92.35

Table 5. Evaluation results of each model for stopping decision.

5.2.3 Classification of stop instances to Safe or Unsafe

In this experiment we went further than classifying stop or go driver behaviors at intersections but further classifying their stopping instances as Safe or Unsafe.

Algorithms	Accuracy	Precision	Recall	F1-score
DT	99.38	99.3	99.8	99.65
LR	96.88	97.89	98.58	98.23
AdaBoost	99.38	99.3	99.8	99.65
SVM	97.5	98.58	98.58	98.58
NB	94.38	96.48	97.16	96.82
RF	99.38	99.3	99.8	99.65

Table 6. Evaluation results of each model for safe or unsafe stop.

The following Table 6 shows the results for stop methods (safe or unsafe). This experience confirms that the performance of RF, DT and AdaBoost are the best classifier model with 99.38 of accuracy, 99.3% of precision, 99.8% of recall and 99.65% of f1-score.

5.2.4 Discussion

In this study, we explored the potential of a set of the most commonly used machine learning techniques over the same dataset to achieve the objective of driver behavior classification during yellow intervals at intersections. In addition, we proposed a machine learning process to develop these models and allow their performance.

In addition, this experience achieve 94.48% of precision and exceeds the result of authors in (Chen et al., 2018) where the best performance was 82.9% of precision with the same data source (simulator), but not the same data. Moreover, we found a better result at an accuracy level of 92.19% compared to the result in paper (Elhenawy et al., 2015b).

In this paper, we investigate the potential of machine learning techniques in the classification of driving behaviors at intersections.

We proposed a model's implementation process that improves the performance of the techniques through the data preparation steps and the training of different models. The process starts with understanding the data for data cleaning as well as studying correlations between features; then extracting features to minimize the dimensions of the dataset, and resolving the problems of imbalanced data before training the models (see Section 4). The results of this experiment are attractive because of this process.

6. CONCLUSION

This study investigated driver behavior at intersections during yellow-light period. We first, went through an in-depth study and analysis of articles on driver behavior at intersections. Then we conducted a comparative study of approaches based on the different machine learning algorithms, performance metrics and results to classify stopping decisions.

In this paper also developed two experiments. To begin with, we classify driver behavior at crossings into two categories: stopping at intersections and going to intersections. The second experiment, we classify drivers who stopped into two groups:

those who stopped beyond the line were classified as dangerous or unsafe, while those who stopped before the line was classified as safe.

We have developed a deep process for data preparation, starting with understanding the data set, then cleaning the data, extracting features, studying the correlation between features, and solving the data imbalance problem before training the models.

This study examined the effectiveness of machine learning algorithms in creating accurate and reliable classifiers. It shows that the XBoost algorithm seems to perform better than the other models with 92.19% of accuracy and 94.38% of precision in the first experience and RF gives the best performance in the second experience with an accuracy of 99.38%.

As a limitation, we have not tested our driver behavior evaluation models with different weather conditions, which are considered one of the most important factors of the driving environment that influence driver behavior. Based on the different steps of data preparation and data balancing shown in this paper, we suppose the results obtained will not significantly decrease even with the factor of weather conditions.

For future work, we wanted to work more on optimizing algorithm parameters and testing the performance of deep learning algorithms in the same dataset. Additionally, we want to exploit video collections datasets to analyze and classify drivers' behaviors with other approaches and algorithms. On the other hand, we plan to study and analyze driver behaviors in the external environment.

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