

# Developing a New Driver Assistance System for Overtaking on Two-Lane Roads using Predictive Models

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## Abstract

The complexity of an overtaking maneuver on two-lane roads merits a thorough method for developing an assistance system to prevent accidents, thus reducing the number of fatalities and the associated economic costs. This research aims to introduce a new Driver Overtaking Assistance System (DOAS). This system is based on the proactive prediction of the possibility of overtaking any preceding vehicle(s) both accurately and safely. To provide a comprehensive system, different factors related to the driver, the vehicle, the road, and the environment which have an impact on the maneuver have been taken into consideration. In addition to considering the main overtaking strategies including accelerative, flying, piggybacking, and the 2+. The proposed system is a vehicle-based safety system based on the collection of contextual information from the driving vicinity through Hello beacon messages and a set of sensors that are used as part of the reasoning process of the context-aware architecture to safely initiate the overtaking maneuver. A classification model was implemented for both the Artificial Neural Network (ANN) and Support Vector Machine (SVM) learning algorithms. A vehicle driving simulator STISIM Drive® was used to conduct driving experiments for 100 participants of different ages, gender, and levels of mental awareness. The results obtained from the DOAS show high accuracy in aiding a safe overtaking maneuver. The classification model shows promising results in the predictions, through perfect accuracy and a very low level of outcome errors.

## Keywords

overtaking assistance, accident classification, microscopic traffic simulation, Neural Network, Support Vector Machine, two-lane roads

## 1 Introduction

In the majority of countries, two-lane rural roadways comprise approximately 90% of the roadway network. Such roadways result in more than 60% of traffic fatalities worldwide and the deaths of approximately 500,000 annually (Lamm et al., 2006). Overtaking maneuvers are frequent on these types of roads and are highly demanding of the driver. Such overtaking can be considered a dangerous maneuver due to the need to use the opposing traffic lane for an extended period and, generally, at a high speed. The opposite lane may be occupied by an oncoming vehicle; therefore, overtaking maneuvers on these roads can be considered a particular challenge for the majority of drivers, depending on traffic conditions and road geometry. The difficulty of this maneuver is that there are a limited number of real solutions that can be introduced.

As a primary source of accident data (Stats19) for overtaking on two-lane roads, the UK's Department for Transport

(DfT) was considered. This data for the period 2012–2015 was analyzed to find records for accidents caused by overtaking maneuvers on two-lane roads. The data set obtained comprises a total of 2,211 usable records from police reports on these accidents. During this period, these accidents were the main reason for 3,565 casualties among drivers and motor-vehicle occupants ranging from slight to fatal injuries and also causing damage to 4,909 vehicles.

Considering the statistics of the world's road casualties, and the prediction of World Health Organization (WHO) more than 50 million people will suffer injuries each year from traffic collisions. This imposes the necessity to develop a real solution to assist drivers in performing the overtaking maneuver to reduce casualties and any economic costs, in addition to exploiting the widespread and rapid developments in communication technologies, especially in the Vehicle Ad-hoc Network (VANET).

Many researchers in the past years adopted context-awareness as an intelligent system benefiting from the adaptability to detect multi-class states (Al-Sultan et al., 2013; Fasanmade et al., 2019). Context-aware systems in cooperating multi-layer architecture are divided into three phases (sensing, reasoning, and acting) (Pradeep and Krishnamoorthy, 2019).

Therefore, this paper introduces a new context-aware Driver Overtaking Assistance System (DOAS), which takes into consideration most factors related to the driver, vehicle, road, and the environment, all of which have a serious impact on the overtaking maneuver. In addition, different types of overtaking strategies, including accelerative, flying, piggybacking, and the 2+, have been considered in designing the DOAS; refer to (2.3). The combined models for data classification were trained through the use of a dedicated dataset collected during this research via a microscopic vehicle simulator STISIM Drive® (Rosenthal, 1999), which consists of 18 variables. These models consist of multiple topologies that are designed using the Support Vector Machine (SVM) and the Artificial Neural Network (ANN). Thus, the results are divided into two parts.

Here, will present the classification models using both ANN and SVM. The results of the data regression for both machine learning methods will be presented in a future paper. In summary, the main contributions of this study are:

- A new Driver overtaking assistance system on two-lane roads, considering multiple factors related to the driver, the vehicle, the road, and the environment.
- Newly developed predictive models of the ANN and SVM.
- Implementation of the accelerative, flying, piggybacking, and overtaking strategies in the proposed system.
- Application of a Microscopic traffic simulation to collect a new dedicated dataset for 100 participants of different ages, gender, and levels of mental awareness to be used by other scholars.

The rest of the sections are organized as follows. Subsection 1.1 presents a literature review of related work. Section 2 introduces the model dataset highlighting the participants, the experimental design, and the maneuver strategies. Section 3 describes the predictive models of both ANN and SVM and provides a comprehensive evaluation and metrics. Sections 4 and 5 present the DOAS model and the system preliminaries, respectively. Section 6 presents the results of the predictive models. Whereas,

Section 7 presents a research discussion of the output. Section 8 concludes. Lastly, Sections 9 and 10 present the system limitation and the future work, respectively.

### 1.1 Related work

Despite the assistance systems utilized by many high-class vehicle manufacturers as overtaking assistance systems (OAS), the literature review shows that none of the work available in the literature (to the best of our knowledge) has considered a comprehensive solution to this type of maneuver to date.

A driver assistance system called dynamic pass prediction (DPP) was described as an overtaking assistance system to perform the maneuver more safely (Loewenau et al., 2006). The DPP directs the driver to a section of the road where it is safe to start an overtaking maneuver and specifies how long that road section will be. In practice, the system combines the digital map data from the vehicle's global positioning system (GPS) to state its position, acceleration, and velocity with data; combining vehicle data with roadway geometry from the vehicle navigation system provides the driver with a clear picture of the current traffic situation.

Another study investigated the operational effects of passing lanes on two-lane highways using field and simulation data (Jafari et al., 2020). Field data were collected from two study sites in Oregon to calibrate the traffic simulation program to evaluate the effective length of passing lanes under different traffic levels and numbers of no-passing zones. The results showed that the effective length of the overtaking lane is a function of the traffic level as well as of the number of no-passing zones for any segment of two-lane roads. In addition, the results supported the operational advantages of overtaking lanes for a significant distance downstream of the overtaking lane, with this distance varying in the range between 3 and 20 miles depending on the traffic level and the number of no-passing zones.

This same study further developed an autonomous system to assist with overtaking maneuvers (Milanés et al., 2012). This design was based on the use of stereo vision to trigger an autonomous OAS when detecting a preceding vehicle in the same driving lane. The system can detect the length and width of any type of preceding object on the road, such as motorbikes, vehicles, or trucks. A vision system for automating overtaking maneuvers was applied to multi-lane trajectories; to emulate human actions while overtaking, a controller based on a fuzzy logic model was used. A positioning-based system and the vision system

are the source input information for the system, whereas the output is a set of actions for controlling the vehicle's throttle, brake pedals, and steering wheel.

The design of an Android app called EYES is reported in (Patra et al., 2015). This app is intended to function as an overtaking assistant system and offers real-time video for oncoming vehicles traveling in the opposite direction before overtaking. A fifth report assessed the efficiency of a Dedicated Short-Range Communication (DSRC) method for wireless communication, V2X, on rural two-lane highways (Motro et al., 2016). This method was used to enhance safety during overtaking maneuvers by predicting the possibility of an accident and by warning the driver before they initiate the maneuver. The authors examined the prediction of unsafe overtaking maneuvers via DSRC in terms of three factors: driver behavior, vehicular kinematics, and DSRC features. The heterogeneity of the three factors was determined using 18,000 overtaking maneuvers and around 10,000 accidents.

Microsimulation was identified as a valuable instrument for analyzing traffic operations (Llorca et al., 2015). This group focused on the development of a microsimulation model using the Aimsun software on rural two-lane highways over three stages: the desire to pass, the decision, and the execution. The data used in this study were collected from 1,752 maneuvers on ten rural highways in Spain.

Behavioral differences in different groups of drivers, as classified by age and gender were also studied (Farah, 2011). The authors used a driving simulator to collect data for 100 drivers (69 males and 31 females) for different scenarios on two-lane rural highways and consider different road design geometries and traffic conditions. The results revealed the principal aspects that have a significant impact on drivers' behavior: driving speed, following distance, duration of the overtaking maneuver, critical overtaking gaps, and the frequency of overtaking maneuvers.

A separate study (Vlahogianni, 2013) likewise modeled the overtaking maneuver to detect the factors affecting the duration of overtaking for both male and female drivers on two-lane rural roads, based on data provided from a driving simulator. It involved 57 participants who had each held a driving license for at least 1 year. The findings of the research revealed that overtaking duration depends on driver gender – which represents a critical factor – the speed of the oncoming traffic, the speed difference compared to the preceding vehicle, and whether the driver is involved in conducting multiple maneuvers.

Finally, a methodology was proposed, using a driving simulator, to monitor overtaking maneuvers on two-lane

roads and to study the impacts of the preceding vehicle's speed, vehicle type, and the overtaking sight distance on the following gap distance as an indicator of driving behavior (Figueira and Larocca, 2020). Around 640 overtaking maneuvers by 80 participants were studied. The results showed that at the beginning of overtaking, the speed of the preceding vehicle had a greater impact on the following gap distance than the length of the overtaking sight distance and the type of the preceding vehicle.

An in-depth review of all relevant studies and the overtaking assistance systems implemented to date has therefore shown that considerable limitations are consistently encountered in these studies. In particular, there is no comprehensive system currently available that focuses accurately and proactively on recognizing the possibility of performing an overtaking maneuver. This involves calculating the available distance for overtaking, as well as considering the effects of all factors that have an impact on maneuvering from the perspective of context-awareness. In our study, all these limitations are addressed in the design of the proposed assistance system.

## 2 Model dataset

The DOAS we present is based on the use of a specific data set obtained from driving experiments using the microscopic driving simulator STISIM Drive® (Rosenthal, 1999). The collected data includes 18 variables related to performing overtaking maneuvers on two-lane rural highways. All variables used here are significant in terms of careful consideration of the more influential factors in performing such a maneuver. In the final version of the outcome data set, these variables will be used with the SVM and ANN machine learning models to train and test the proposed assistance system, as explained below.

The data set collected comprises a total of 1,557 records divided into two classes: 1,012 records representing the completed maneuver, and the remaining 545 records representing incomplete maneuvers or accidents. The number of accidents in the accelerative, flying, and piggybacking strategies in these experiments were 190, 355, and 0, respectively. It is worth noting that there are 588 safely completed maneuvers in the collected dataset and the separating distance between the subject and oncoming vehicles was less than 65.61 feet.

### 2.1 Participants

100 participants were chosen for our experiment from different countries, ages, genders, driving experience, and educational levels. To be eligible for the driving

experiment, volunteers had to hold a valid driving license. The mean driving experience was about 16.3 years, with a distribution of 1–52 years. Likewise, driver ages ranged from 18 to 72 years with a mean of 37.96 years of age and a standard deviation of 15.40 years. Male participants constituted 65% of the total number of participants, with the remaining 35% being female drivers. The educational level ranged from low education to undergraduate, and postgraduate, including university professors.

### 2.2 Experimental design

Our experiments were conducted using the STISIM Drive® vehicle simulator to collect data on the overtaking maneuver. Participants were asked to drive, in two separate scenarios, for 7.6 miles (12.92 km) on two-lane rural roadways. Roadways were designed according to UK legislation and marked with a dashed centerline, meaning there are no legal limitations on performing the overtaking maneuver throughout the driving route. There were also two continuous (solid) lines on each side of the roadway.

The experimental scenarios were designed using different conditions including, weather (e.g. clear or foggy), light status (daylight or darkness), road curvature (straight, curved, uphill, and downhill), and roadway surface (dry and icy). Based on these different conditions we have alternated between the above-mentioned conditions to perform the overtaking maneuvers. This means the conditions of the driving environment and road characteristics were changed throughout the test, and consequently, the participants tested all available conditions on the road. The speed of all vehicles was set to be between 14 and 75 mph. The subject vehicle was not limited in either speed or direction. The distribution of vehicles along the direction of travel and in the opposite lane was created with no fixed distance separating the vehicles, to achieve a reasonable level of realism. This is in contrast to other researchers (Hegeman, 2008) who programmed the arrival of oncoming vehicles with increasing fixed gaps of 4, 6, and 8 s, and so on. This study also set fixed speeds for the preceding vehicles, using three different speed regimes: the first was programmed at 46.6 mph, the second at 58.8 mph, and the third changed speed every 8 s between 47.2 and 56.5 mph.

### 2.3 Maneuvering strategies

In our driving experiments, alternate drivers were instructed to overtake one or more preceding vehicles. The strategies employed fall into three categories:

- **Accelerating:** the subject vehicle alternates its speed until the emergence of an overtaking opportunity.

- **Flying:** the subject vehicle can start overtaking the preceding vehicle without the need to reduce its speed whilst performing the maneuver.
- **Piggybacking:** a vehicle in front overtakes the preceding vehicle (impeding vehicle) and the subject vehicle (the overtaker) follows this vehicle to perform the maneuver, both vehicles overtake the preceding vehicle in the same maneuver. The need for acceleration is still present, as is the necessity to pass the preceding vehicle and complete the maneuver.

Maneuvers were further categorized into overtaking a single vehicle or two or more vehicles (2+). The total number of maneuvers recorded in our experiments are 489 accelerating, 995 flying, and 73 piggybacking ones, respectively. The driving experiments were conducted on the premise that the driver must overtake one or more preceding vehicles.

The boxplots of the subject's initial vehicle speed in feet per second (ft/s) at the beginning of a maneuver, categorized by strategy, are shown in Fig. 1 (for overtaking a single vehicle) and Fig. 2 (for overtaking multiple vehicles). In Fig. 1,

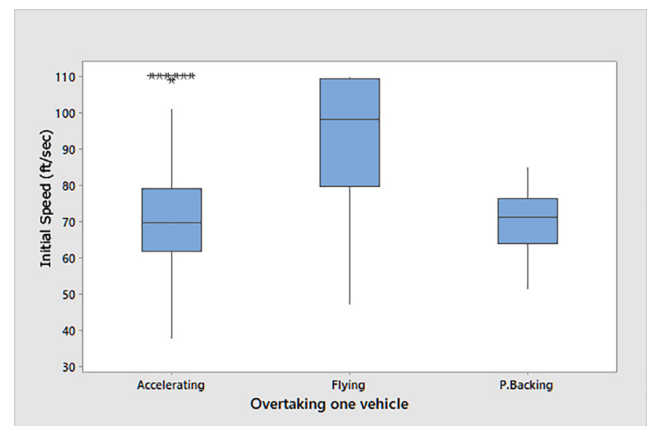


Fig. 1 Boxplot of initial speeds for overtaking a single vehicle

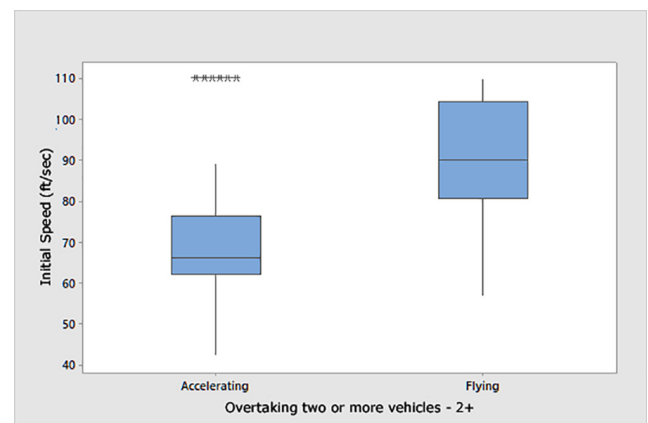


Fig. 2 Boxplot of initial speeds for overtaking two or more vehicles

the minimum and maximum initial speeds in the accelerative strategy were 37.48 and 101.25 ft/s, respectively; for the flying strategy, minimum and maximum initial speeds were 47.02 and 110.00 ft/s, respectively; for the piggybacking strategy, these values were 51.04 and 85.14 ft/s.

Comparing the centers of distribution for the three boxes, the median value for accelerating, flying, and piggybacking were 69.56, 98.15, and 71.27 ft/s, respectively; while the spreads (interquartile range, IQR) of these distributions were 17.58, 29.58, and 12.36 ft/s, respectively. The shape of the distribution for accelerating was more similar to piggybacking than flying, with little skewing at the bottom end of these distributions; on the other hand, the distribution for the flying strategy was skewed only at the bottom. Outliers were found only in the accelerating strategy, with speeds of 108 and 110 ft/s.

When overtaking two or more vehicles, as shown in Fig. 2, there are only two types of maneuvers to consider: the accelerative and flying strategies. Piggybacking to ultimately overtake two or more vehicles in the same trial seems unrealistic and represents a particular challenge. The minimum and maximum initial speeds for the subject vehicle were 42.12 and 89.09 ft/s, respectively, for accelerating and 56.79 and 110 ft/s for flying.

The median values for accelerating and flying were 66.20 and 89.97 ft/s, respectively, while the IQR was 23.57 and 14.26 ft/s, respectively. The shape of each strategy's distribution was different: both distributions were skewed at the bottom end, but the flying distribution was skewed more than that of the accelerating strategy. No outliers were found for either strategy.

## 2.4 Maneuvering process

It is worth mentioning that the required information as stated in Subsection 2.4 is always being gathered depending on the surrounding situation and the related factors. The completed overtaking maneuver includes two parts, the start and the end of the maneuver. The beginning of the maneuver starts once the front tire of the vehicle touches the centerline. The end of the maneuver completes once the vehicle has completely returned to the driving lane and the second rear tire of the vehicle passes the centerline. The information gathered to complete the maneuver safely are:

- Distance from preceding vehicle,
- Distance from an oncoming vehicle,
- Distance from approaching vehicle,
- Speed of the subject vehicle,
- Speed of the preceding vehicle,

- Speed of the oncoming vehicle,
- Speed of approaching vehicles,
- Maneuver distance.

## 3 Predictive models

We used a binary classification model, for both ANN and SVM, based on class labels for of either 0 or 1, where 0 refers to a completed maneuver ("not accident"), and 1 refers to an accident. Therefore, one variable represents the output in terms of accidents and is used with the classifying function for predicting an accident or otherwise.

In data classification, there are two different techniques. The first is to model; this provides the probability of class membership in addition to the class label for the data item. This technique is used most prominently in ANN, logistic regression, decision trees, and k-nearest neighbors. In the second technique, only the dichotomous distinction between the two classes is taken into consideration, and the unknown data points are assigned with the class labels 0 or 1. SVM is the most common application of this technique (Dreiseitl and Ohno-Machado, 2002).

In our study, we trained the ANN using the backpropagation algorithm (BPA). The supervised training method used two ranges of K-fold cross-validation to evaluate the predictive models; these are 5-fold and 10-fold types, applied with 20 iterations for each fold type.

The ANN model we used has multiple inputs, two or more hidden layers, and one output. The input of the network consists of various attributes related to the driver, the vehicle, the road, and the environment, as listed in Table 1.

Some of the input variables for the ANN network are of a categorical type, consisting of more than one state, whereas the others are continuously valued variables.

Several different parameters have an impact on the ANN level of generalization and accuracy. Among these parameters are training data, initial weight and bias, learning rate, momentum parameter (Gómez et al., 2014), activation function, and the number of hidden neurons. Practically, the initial weights and biases in this study were randomly generated; the value of the momentum parameter was set to 0.01 and the learning rate was 0.008, to keep the size of changes in weight and bias to a low level in learning the BPA. The training was constrained to six validation levels and 1000 epochs. While training the ANN, the error was represented by the difference between actual and expected outputs.

In the classification model, the default threshold value is set to 0.5 (safety threshold); refer to Eq. (1), the samples of

**Table 1** Description of the explanatory variables

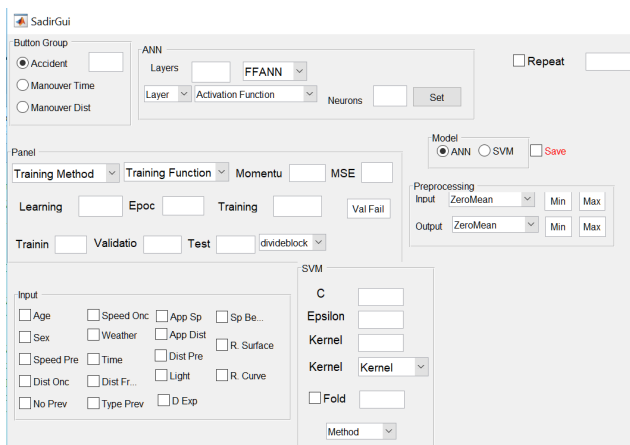
Explanatory Variables	Description
Weather	(Fine; Fog)
Light Condition	(Daylight; Darkness)
Road Surface	(Dry; Ice)
Road Curvature	(Straight; Curved; Uphill; Downhill)
Time	(Daytime; Night time)
Driver Age	(18–72 years)
Driver Gender	(Male; Female)
Driver Experience	(1–52 years)
Initial Speed	Speed of subject vehicle before maneuvering (14–75 mph)
Speed (Oncoming)	Speed of oncoming vehicle (14–75 mph)
Distance (Oncoming)	Distance from oncoming vehicle (79.46–4551.07 ft)
Speed (Preceding)	Speed of preceding vehicle (46.6–56.5 mph)
Distance (Preceding)	Distance from preceding vehicle (17.65–467.05 ft)
Speed (Approaching)	Speed of approaching vehicle (50–75 mph)
Distance (Approaching)	Distance from approaching vehicle (13.11–274.60 ft)
Front Distance	Length of front distance (55–1128 ft)
Vehicle Number	Number of preceding vehicles (1–5)
Vehicle Type	Type of preceding vehicles (15–60 ft) (light vehicle – trailer)

the output greater than or equal to 0.5 would be assigned to the "not accident" (completed maneuver) class, whereas the remaining samples would be assigned to the "accident" class.

$$f(x) = \begin{cases} 1 & \text{if } x \geq 0.5 \\ 0 & \text{Otherwise} \end{cases} \quad (1)$$

### 3.1 The ANN analysis model

A user-friendly graphical user interface (GUI) was developed in the MATLAB environment, as depicted in Fig. 3,



**Fig. 3** Graphical user interface for the DOAS

to ease model implementation. To utilize the best quality results from the ANN and SVM by covering the widest number of the adopted functions, the developed GUI consists of the different components, as shown in Table 2.

### 3.2 The SVM analysis model

In recent years, SVMs have been used in a wide range of application domains such as classification, optimization, prediction, pattern recognition, image analysis, and so on, (Nayak et al., 2015). SVM is one of the supervised machine learning algorithms that can be used to detect an optimal hyperplane to separate a set of inputs into two classes. The selected hyperplane has to provide a maximum margin or separation between these two classes.

The vertical distance between the closest data points that denote the support vectors and the decision boundary is called a margin (Nagalla et al., 2017). The separating hyperplane might not exist when a low dimensionality of input features is used; in such a case, nonlinear mapping into a high-dimensional feature space is applied (Iliya, 2016). This mapping into a high-dimensional feature space

**Table 2** The ANN analysis model components

Component	Description
Input/output data pre-processing functions	Zeromean, AbsMax, Sigmoid, Transigmod, PCA, Zscore, Minmax, and FullMinMax.
Activation function	Tansig, Hardlim, Purelin, Poslin, and Logsig.
Number of layers	1–5 layers.
Network Topology	Feed-forward backpropagation networks (FFANN), cascade-forward backpropagation networks (CFFANN), feed-forward backpropagation networks with feedback from output to input (OFBANN), and Layered-Recurrent networks (LRANN).
Training method (Adapt / Train)	Adapt  Trainlm (Levenberg-Marquardt), Trainbfg (BFGS Quasi-Newton), Trainbr (Bayesian regularization backpropagation), Traincgb (Conjugate Gradient with Powell/Beale Restarts), Traincgp (Polak-Ribière Conjugate Gradient), Traingd (Gradient descent), Traingdm (Gradient Descent with Momentum), Traingda (Gradient descent with adaptive learning rate).
Momentum	0.008
MSE (Mean square error)	The expected default value for the MSE is set to 0
Learning rate	0.001
Epoch	1000
Training time	Infinity

solves the problem of no separable classification in low dimensionality and is linearly separable in that feature space (Teng et al., 2008).

SVM is intended to solve the following optimization problem (Boser et al., 1992; Cortes and Vapnik, 1995): Given a training set of attribute-target pairs  $(x_i, y_i)$ ,  $i = 1, 2, \dots, n$ , where  $x_i \in R^n \wedge y \in \{1, -1\}^n$ :

$$w, b^{\min}, \xi \frac{1}{2} w^T w + C \sum_{i=1}^n \xi_i, \quad (2)$$

subject to:

$$y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i, \quad (3)$$

where  $\xi_i \geq 0$ .

In this study, three kernel functions (linear kernel, radial basis function (RBF), and polynomial) are used to classify the target output of the assistance system in terms of whether it belongs to the "accident" or the "not accident" class, as shown in Eqs. (4), (5), and (6), respectively:

$$K(x, x_i) = x^T x_i + c, \quad (4)$$

$$K(x, x_i) = e^{(-\gamma \|x - x_i\|^2)}, \quad (5)$$

$$K(x, x_i) = (\alpha x^T x_i + c)^d, \quad (6)$$

where  $c$  is set to zero in the linear kernel equation as a constant parameter,  $\gamma$  indicates the kernel parameter, and  $x$  represents the input vector. Selecting an RBF model as one of the kernel functions for conducting a classification model is based primarily on the results obtained from the developed models. In addition, there are extensive recommendations in the literature to adopt the RBF as the first choice of the kernel (Cherkassky and Mulier, 1998).

#### 4 DOAS model

The acquired information is used in machine learning to calculate the possibility of performing the overtaking maneuver safely. This system is based on the three phases/stages of a context-aware system; the output is displayed on the driver interface via green and red lights. The green light represents a safe opportunity to start overtaking at that moment, as the available gap for overtaking is greater than or equal to the minimum convenient distance required for overtaking. The green light starts flashing whenever the distance approaches the minimum suitable distance for overtaking as discussed in Subsection 4.1. When the available distance for overtaking is less than that required, the red light will be displayed. These changes between green,

flashing green, and red lights continue as long as the assistance system is switched on and the vehicle is moving on the two-lane roadway.

Having collected the contextual information, the DOAS operation steps (Overtaking Algorithm), as depicted in Fig. 4, is based on the following steps:

1. **Stage 1 (Sensing):** This stage mainly focuses on collecting and analyzing all relevant information (raw data) to be passed to the reasoning phase.
  - *Step 1.1:* Using Hello beacon messages (periodic messages used by nodes (vehicles) to the main purpose is to allow each node in the network to inform other surrounding nodes about its existence and provide them with its current situation such as its location, velocity, and direction) and a relevant set of sensors (e.g. GPS, Lidar), the DOAS collects the speed, location, and direction of the oncoming vehicle and other vehicles in the vicinity. The DOAS will use radio access technology to communicate between vehicles; in this study, we used IEEE 802.11p DSRC. This ensures reliable and effective communication between all vehicles in the vicinity, and with the infrastructure in the area.
  - *Step 1.2:* The system continues updating all values for all variables through vehicle input sensors.
  - *Step 1.3:* The assistance system measures the total length of the overtaking distance until the

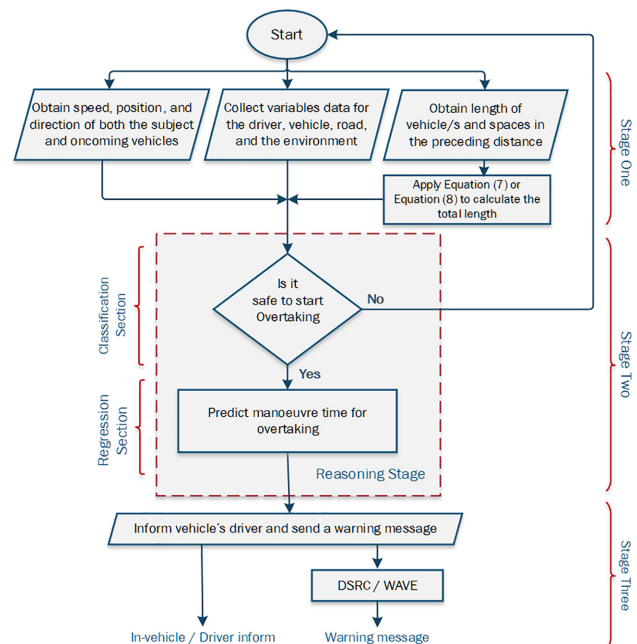


Fig. 4 The DOAS model

first convenient gap occurs that would allow for a safe overtake. This distance includes the length of all preceding vehicles, in case there is more than one preceding, in addition to the length of the separating spaces between vehicles. The collection of this information is achieved via the Hello beacon messages that are exchanged between vehicles and through input sensors.

2. **Stage 2 (Reasoning):** The machine learning algorithms SVM and ANN are applied to the collected information from various input resources. Inferring functions such as the classifier (when the output is discrete) and the regression functions (when the output is continuous) is the task of the machine learning from supervised training data. For any valid input object, the inferred function should predict the corresponding correct output value (Mohri et al., 2012). Thus, in this study, the inferring functions form the basis for both ANN and SVM. In particular, the SVM can refer to the classification method in terms of Support Vector Classification (SVC). This stage includes several steps as follows:

- *Step 2.1:* In this pre-processing step, the data from all input resources, including the communication devices, sensors, and HMI need to be transformed into a format appropriate to the SVM and ANN packages. This pre-processing leads to improved performance and efficiency of the machine learning algorithms (Kantardzic and Srivastava, 2005; Hsu et al., 2003). Once the input data is processed and is ready to be used by the machine learning algorithms, the data are fed to both the SVM and ANN. The next step is therefore to classify the input data for predicting the target values of accidents.
- *Step 2.2:* In the classification model, the application of the SVM and ANN algorithms is to predict whether the data from the input vector would lead to an accident. When the target value belongs to the "not accident" class (i.e., continuing the overtaking maneuver is safe), the process can continue to the regression model. If the target value belongs to the "accident" class, the trial for the maneuver will be canceled.
- *Step 2.3:* After the input vector is classified as "not accident", the maneuver time is predicted (i.e., how much time is required to overtake one or more preceding vehicles in any of the three

overtaking strategies: accelerating, flying, and piggybacking). The prediction of the target values in the regression models is conducted using the ANN and SVR models. This step will be presented in a future paper.

3. **Stage 3 (Action):** After receiving the predicted time required to perform the overtaking maneuver from the regression functions derived from the SVM or ANN models, the last step involves informing the driver about the safety of initiating the overtaking maneuver via an appropriate in-vehicle visual mechanism. During the maneuver, all other vehicles in the vicinity will be alerted proactively about the commencement of this overtaking maneuver through the dissemination of a warning message.

#### 4.1 Measuring the overtaking distance

When overtaking two or more vehicles, the length of the queue of vehicles to be overtaken is a vital issue. Overtaking more than one vehicle is more difficult than just a single vehicle, as it increases the length of time the subject vehicle must remain in the overtaking lane.

The available safety distance  $d_{saf}$  in front of the preceding vehicle has to be sufficient to enable the subject vehicle to return to its own lane, as shown in Fig. 5. Equation (7) can thus be adopted for measuring the distance  $d_{ov}$  in the DOAS for overtaking one preceding vehicle, whereas Eq. (8) is adopted when overtaking two or more vehicles:

$$d_{ov} = d_{prec} + l_{sub} + l_{prec} + d_{saf}, \quad (7)$$

where:

- $d_{ov}$ : overtaking distance in feet;
- $d_{prec}$ : distance between the subject and preceding vehicle before starting overtaking in feet;
- $l_{sub}$ : length of the subject vehicle in feet;
- $l_{prec}$ : length of the preceding vehicle in feet;
- $d_{saf}$ : safety distance for returning to the original lane in feet;

and:

$$d_{ov} = d_{prec} + l_{sub} + l_{prec} + d_x + l_x + d_{saf}, \quad (8)$$

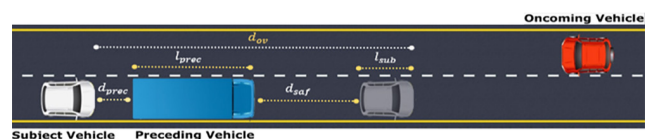


Fig. 5 Overtaking distances



where  $l_x$  is the total length of all vehicles in front of the preceding vehicle and  $d_x$  is the total length of all distances between vehicles in front of the preceding vehicle.

## 5 Preliminaries

### 5.1 Model training

Due to the stochastic nature of the ANN, selecting a network configuration that gives the best generalization result is a difficult task (Torres-Ramírez et al., 2015). Therefore, to achieve the best performance using ANN, our first step was to train and test the four adopted ANN architectures, 4,443 times in total. The ANN architectures included were the feed-forward backpropagation network (FFANN), the cascade-forward backpropagation network (CFFANN), feed-forward backpropagation networks with feedback from output to input (OFBANN), and the layered-recurrent network (LRANN). The training included 1,296 networks for each of the FFANN and CFFANN, 972 networks for OFBANN, and the remainder for LRANN.

The main purpose of the training was to test the performance of the majority of available network structures to find the optimum ANN topologies through applying different activation functions, the number of layers (from 1 to 5), ranges of neurons (from 5 to 40), input and output normalization methods, training methods, training functions, and finally learning rate and momentum.

It is worth noting that we chose the above numbers of layers and neurons based on two factors: first, the literature in different research fields, and second, the poor results we achieved from test experiments with more than 5 layers and 40 neurons. Of the nine training functions used to train the ANN networks, the *trainlm* (Levenberg-Marquardt backpropagation) and, in the second level, the *trainbr* (Bayesian regularization backpropagation) showed the best performance and levels of generalization in training compared with the other functions in the classification model.

Most of the classification experiments for ANN have been conducted using two common activation functions of the sigmoid family in the hidden layers: the logistic and hyperbolic tangent functions. For the output neurons, some linear transfers were used in addition to the sigmoidal functions. MATLAB software (The MathWorks, Inc., 2017) was utilized to estimate the ANN and the SVM models.

On the other hand, the parameters used in SVM need to be predetermined; training includes selecting the regularization parameter  $C$  and proper kernel function parameters such as  $\epsilon$ ,  $\gamma$ , and order of the polynomial. Four kernel functions were investigated in this research, including the linear, RBF, Gaussian RBF, and polynomial kernels.

The investigation was conducted for the SVM classification model. The results of the predictive models are summarized in Section 6.

At this stage, we chose the best configuration of all possible models after training the various models considered and applying all possible changes to the design of the network to obtain the best results. The next step included the performance estimation of the selected models on the test data (data never previously used in training the model). Therefore, K-fold cross-validation has been used as the main tool for computing estimates of the learning algorithms' performances.

### 5.2 Evaluation of performance

Indeed, introducing the proposed prediction models with only one test set (generalization sets) can be inconclusive, impractical, and far from any of the previous studies of the ANN and SVM models. For this reason, K-fold cross-validation has been used to give a reliable estimation of the model accuracy. The data set used has been partitioned into several disjoint folds; the entire data set is used to train the model except for one-fold that is used to assess the model's predictive accuracy. The implemented models for ANN and SVM were tested using five- and ten-fold cross-validation of 20 iterations to reveal the validity and the performance of the models introduced. Each model was tested 100 and 200 times, i.e., the number of folds multiplied by the number of iterations. The total test errors are averaged over the total number of test times. The results for these tests are listed below for the classification model.

## 6 Results

To highlight the performance of the proposed ANNs, the results obtained have been compared with the SVM for the classification models because of the unavailability of a similar work to be used in the comparison. The combined models for data classification consist of multiple topologies that are designed using ANN and SVM. Thus, section A presents the results of the classification models used for both ANN and SVM. To investigate the accuracy of the predictive models, four measuring metrics have been employed with the classification models.

### 6.1 Classification models

The trained ANN and SVM classifiers were tested with unseen data to classify between the "accident" and "not accident" states of the target variable. The dataset used was obtained from driving experiments using a microscopic simulator. The results obtained from the predictive

models demonstrated the effectiveness and the good generalization of the networks.

The four ANN topologies consisted of two hidden layers and one output layer. There are different numbers of neurons in the first and second hidden layers, as summarized in Table 3. The neuron numbers were approximately the same for each of the ANN topologies; the lowest number was for LRANN. The best performance of the activation functions was achieved for the sigmoid family of functions, such as log-sigmoid transfer function (logsig) and tan-sigmoid transfer function (tansig), while the linear transfer functions "purelin" and "poslin" are used in the output neurons in addition to log-sigmoid transfer function.

To normalize the input and output data, the performance of the sigmoid and Z-Score functions was found to be better than other functions. The performance of the "trainlm" (Levenberg-Marquardt backpropagation) represented the best set of network training functions, followed by the "trainbr" (Bayesian regularization backpropagation). Finally, the classification thresholds for the ANN classifier ranged between 0.7 and 0.8.

Concerning the SVM classifier, three kernel functions were used namely the linear, the RBF, and the polynomial, as shown in Table 4. To obtain the best results in predicting the results from unseen data, the parameters of each particular kernel function need to be optimized. This optimization can be achieved in terms of adjusting the optimal values for parameters such as the cost function, gamma, and the polynomial order.

### 7 Discussion

Before using the trained classifiers for predicting whether performing an overtaking maneuver will lead to an accident, an evaluation of the performance of the classification models is necessary.

Therefore, experiments were conducted to analyze and compare the performance of the four ANN topologies and three SVM kernel functions. We used four measuring metrics (confusion matrix, percentage of error (PE), F-measure, Precision, and Recall) in the evaluation process to investigate the accuracy of the predictive models.

PE is calculated to measure the misclassification error for each ANN topology and SVM kernel, as in Eq. (9):

$$PE = ((K + L) / N) * 100, \tag{9}$$

where *PE* is the percentage error, *K* is the total number of samples belonging to the "not accident" class which are classified as accidents, *L* is the number of "accident" samples that were classified as belonging to the "not accident" class, and *N* is the total number of samples. Hence, the PE is the ratio of incorrect predictions to the total number of predictions.

The average PEs and the average F-measure, in addition to the other metrics such as Precision and Recall, are listed in Tables 5 and 6, where the best and worst results are highlighted in bold. Tables 5 and 6 contain test data only and not the data used to train the classification models.

Tables 5 and 6 show the classification accuracy achieved when testing all the various ANN topologies and SVM kernels. These tabulated results are for both 5- and 10-fold cross-validation using 20 iterations.

In Table 5, the 5-fold cross-validation for the FFANN performed better than other topologies in terms of the lowest PE (1.04%) and also achieved the highest accuracy in terms of an F-measure, Precision, and Recall of 99.19%, 99.69%, and 98.70%, respectively. The CFFANN was found to be the second-best performer. In the ten-fold cross-validation, the CFFANN was found to perform the best, followed by FFANN. Compared with other topologies, the LRANN, performed the worst for both 5- and 10-fold cross-validation with a PE of 9.87% and classification accuracies of

**Table 3** ANN topologies specification

Network type	Threshold.	Training function	Network layers			No. of neurons			Processing functions	
			Hidden	Hidden	Output	Hidden	Hidden	Output	Input	Output
FFANN	0.7	trainlm	logsig	logsig	logsig	30	20	1	sigmoid	sigmoid
CFFANN	0.8	trainbr	tansig	tansig	purlin	36	18	1	Z-score	Z-score
OFBANN	0.7	trainbr	tansig	tansig	purlin	36	18	1	Z-score	Z-score
LRANN	0.7	trainlm	tansig	tansig	poslin	25	15	1	Z-score	Z-score

**Table 4** SVM kernel parameters

	C	Gamma	D
LINEAR	12.00	-	
RBF	20.00	1.30	
gPolynomialL	74.00	2.00	2

**Table 5** Classification accuracy of ANN models

	K = 5				K = 10			
	PE	F-measure	Precision	Recall	PE	F-measure	Precision	Recall
FFANN	1.04	99.19	99.69	98.70	2.48	98.11	99.78	96.50
CFFANN	1.48	98.86	99.92	97.83	1.32	98.98	99.91	98.08
OFBANN	4.10	96.93	99.90	94.14	3.85	97.11	99.89	94.48
LRANN	9.87	92.92	99.89	86.87	8.11	94.11	99.86	88.99

**Table 6** Classification accuracy of SVM models

	K = 5				K = 10			
	PE	F-measure	Precision	REcall	PE	F-measure	Precision	Recall
Linear	0.77	99.40	99.30	99.50	0.70	99.45	99.10	99.80
RBF	4.56	96.55	98.41	94.76	4.25	96.76	97.91	95.63
Poly.	2.95	97.71	97.42	98.01	2.96	97.69	96.92	98.48

92.92%, 99.89%, and 86.87% for the F-measure, Precision, and Recall, respectively.

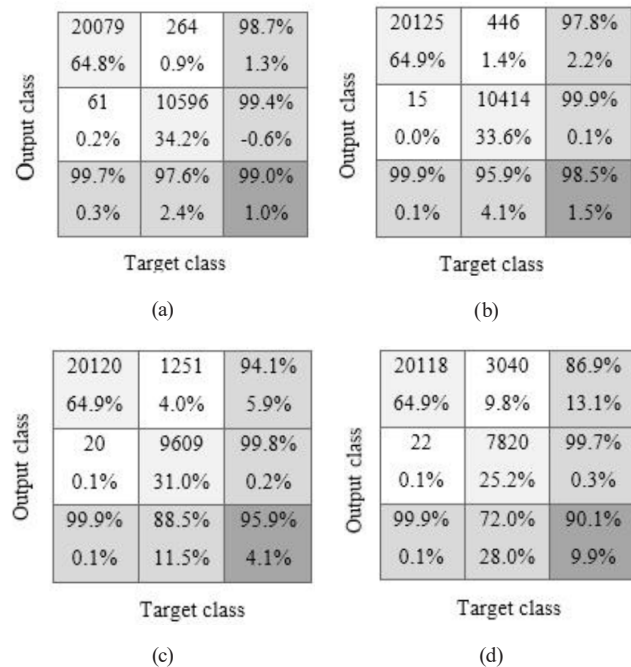
Using the confusion matrix measure, the columns represent the actual class instances, while the rows denote the predicted class instances. The observations of the "not accident" class are labeled as positive, whilst the accidents class is labeled as negative.

The terms of the confusion matrix are represented as follows, according to the data set used in this research:

- True Positive (TP): predicted to be not-accident and the actual value is also not-accident;
- False Positive (FP): predicted to be not-accident but the actual value is an accident;
- True Negative (TN): predicted to be an accident and the actual value is also accident;
- False Negative (FN): predicted to be an accident but the actual value is not-accident.

The test set of each fold has been carefully verified to avoid bias in the averaged confusion matrix. The classification accuracies used for the ANN networks for five-fold cross-validation are given in Fig. 6. The matrices show both the number of samples that were classified correctly and the number of the misclassified samples for both classes, i.e. "accident" and "not accident". The highest accuracy was reached via the use of FFANN at 99.00%, followed by CFFANN, whereas the worst accuracy was returned by the LRANN.

The percentage of the true positive rate in this confusion matrix was 98.70%, and 99.42% for the true negative rate of the samples classified. According to these results, FFANN might be considered a straightforward type of network that associates inputs with outputs with no feedback (loops) as



**Fig. 6** ANN confusion matrices of 5 folds; (a) FFANN; (b) CFFANN; (c) OFBANN; (d) LRANN

compared to LRANN. Thus, this type of network is ideally suited to modeling the relationships between a set of predictor variables and one or more response variables.

In Table 6, we see that the best classification accuracy for the SVM kernels was achieved by the linear kernel function. This kernel had the lowest classification error among the various options considered, at 0.77%, and it further achieved the highest classification accuracy reached in the F-measure (99.40%), Precision (99.30%), and Recall (99.50%) metrics. Therefore, the superior performance of the linear kernel can give us an indication of a linear boundary between the two classes "accident" and "not accident".

Meanwhile, the RBF kernel had the highest PE, at 4.56%. It should be noted that the performance of the linear kernel was also found to be best for the 10-fold cross-validation.

Referring to the confusion matrices in Fig. 7, these illustrate that the linear kernel has the highest classification accuracy among the other kernels (99.2%) followed by the polynomial kernel (97.0%), while the worst performance was found for the RBF kernel (95.4%). The matrices show a high percentage for the true classified samples for the "accident" and "not accident" classes, at 64% and 31-34%, respectively, compared to percentages of misclassified samples.

Finally, the results obtained show that both classifiers, ANN and SVM, demonstrated outstanding generalization abilities when dealing with the unseen data. Thus, in terms of the accuracy category, the linear kernels and FFANN topology might be considered excellent models as they show the lowest PEs of 0.70% and 1.04%, respectively, whereas the CFFANN and polynomial kernels might be considered good models, with PEs of 1.48% and 2.95%, respectively. The OFBANN and RBF kernel group might be considered acceptable models, with PEs of 4.10% and 4.56%, respectively.

The worst-performing classifier was the LRANN topology, which had the highest classification error of 9.87%. Both the SVM and the ANN classifiers emerged as promising in terms of DOAS classification. Overall, the linear kernel function is promising for application in the proposed model as it showed superior results compared to other models.

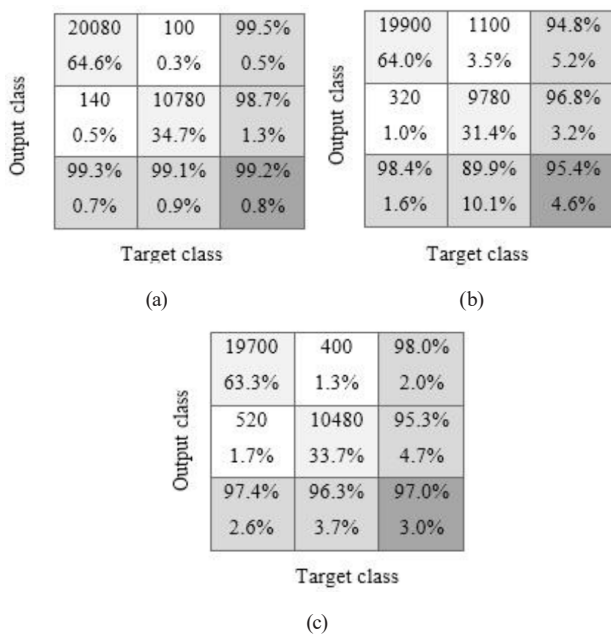


Fig. 7 SVM confusion matrices; (a) Linear; (b) RBF; (c) Polynomial

### 8 Conclusion

The general objective of the work in this research is to present a thoroughly researched DOAS system to provide drivers with a realistic solution for an accurate predictor of overtaking maneuvers on two-lane rural roads. The system is designed to consider the most influential variables when performing this maneuver to improve performance and provide a much safer driving environment.

Reliable results can provide crucial assistance in avoiding accidents and introduce a better understanding of the relationship between accident factors, i.e., driver characteristics, road conditions, the vehicles involved in the maneuver, and finally the environmental conditions.

This work has validated the performance of the proposed DOAS in classifying "accident" and "not accident" situations and in predicting the time required to perform an overtaking maneuver. The accuracy of the outcome from the DOAS is a vital step that is of particular importance to this type of dangerous maneuver.

Based on the experiments carried out in this study, different ANN topologies and SVM kernel functions have been used to perform the training and testing experiments, namely FANN, CFFANN, OFBANN, and LRANN, while the SVM kernels used were the linear, RGB, Gaussian RGB, and polynomial.

The final output showed promising results in classifying between accidents and predicting the success of the maneuver. In the classification model, the linear kernel and the FFANN topology showed the most attractive performance of those considered for each. Whereas, the worst-performing classifier was the LRANN topology, which had the highest classification error. Both the SVM and the ANN classifiers emerged as promising in terms of DOAS classification. Overall, the linear kernel function is promising for application in the proposed model as it showed superior results compared to other models.

### 9 Limitation

In this research, the data was collected via laboratory experiments using a microscopic driving simulator STISIM Drive®. Field data is difficult to obtain from real-world experiments due to the heightened risk associated with the overtaking maneuver, in addition to which the maneuver can be performed on any section of the road. Thus, there are many advantages of using the driving simulator for gathering the dataset that is used for validating the proposed work in this research. The behavior of participants using the simulators might be different from

performing experiments in real driving conditions and this might add some effects to the obtained results and to the level of realism (Godley et al., 2002).

Also, the maneuver might lead to a hazardous situation while overtaking. Three hazardous situations have been identified in DOAS before and during an overtaking maneuver. This includes communication difficulties, unexpected component failures, or when the driving speed of the preceding and the oncoming vehicles change while performing the maneuver. Using context-aware uncertain reasoning provides dynamism i.e. aborting the maneuver

and continuing to examine the road situation for further overtaking opportunities.

## 10 Future work

Implementing the second stage of the DOAS model is the regression model. The purpose of this model is to predict the maneuver time, i.e., the time required to complete one overtaking maneuver starting from crossing the centerline when moving to the opposite driving lane until the moment of fully crossing the centerline to return to the original driving lane.

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