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Vehicle Driving Behavior Prediction Under Different Weather Conditions Based on the Adaptive Network

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Abstract. Driving behavior is typically influenced to some extent by weather conditions, which is one of the important factors for the identification of driving behavior of adjacent vehicles by drivers during road travel. In this study, LightGBM and NN were employed as ensemble feature selection methods to consider the attributes with the highest information content in the driving behavior dataset. A stacked ensemble design of machine learning models was proposed under the framework of adaptive networks. The framework of the proposed model in this study consists of two layers, including the adaptive layer and the stacked layer. The performance of the model was evaluated based on classification metrics and compared with the most popular predictive models. The experimental results show that the prediction of the ensemble learning model under the adaptive framework is more stable and shows better comprehensive performance. It can achieve high accuracy and reliability in identifying driver's driving behavior.

Keywords. Ensemble learning, driving behavior, weather conditions, driving behavior prediction models.

1. Introduction

Current driving assistance systems primarily rely on traffic information evaluated for safety conditions and potential hazards based on inputs from laser radar or visual sensors. There is a high demand for the detection and prediction of driver's driving behavior in intelligent traffic road safety. Assisted driving systems are developed to assist drivers in better and safer driving. Assisted driving systems typically focus on predicting hazardous scenarios and issuing warning messages to prevent traffic accidents from occurring. In the driver behavior analysis system and collision warning, the prediction of driving behavior under different weather conditions is a fundamental and essential functionality. However, existing driving behavior prediction techniques often suffer from reduced accuracy and inadequate fitting due to the complexity of road conditions and limited visibility caused by varying weather conditions. Driver assistance systems may provide false or unnecessary alerts. This problem increases driver frustration and reduces trust, which increases the likelihood of traffic accidents [3]. During vehicle travel, drivers are

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typically influenced by the driving of adjacent vehicles, relying on the driving behavior of neighboring vehicles as a basis for their own vehicle operation. They need to consider the driving situations of the preceding and surrounding vehicles in order to perform actions such as acceleration, deceleration, and lane changes. Drivers are required to respond within a matter of seconds. As shown in Figure 1, the driving of Vehicle A relies on the information provided by adjacent vehicles. When Vehicle A needs to overtake or change lanes, it is necessary to predict the driving behavior of vehicles B, C, D, and others for at least the next three seconds. Once the driving behavior of adjacent vehicles is predicted, Vehicle A can use the predicted results to execute its own driving actions.

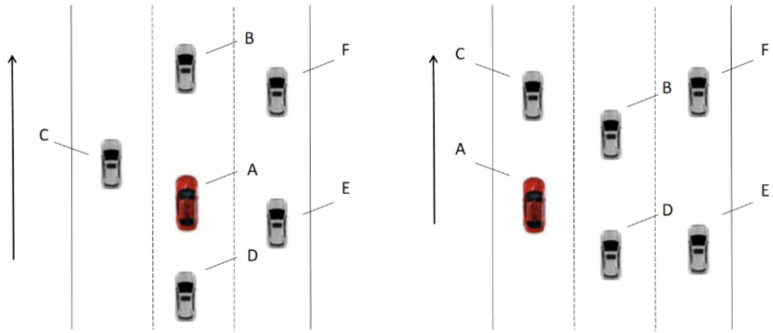

Figure 1. Road conditions for vehicle travel.

In the era of big data, allowing the concealment of target links from prediction by introducing minor perturbations to the network structure. Existing algorithms, such as traditional similarity metrics and newly developed network embedding methods, mostly focus on learning the structural features of static networks, while overlooking the dynamic characteristics of real-world systems. The traditional approach has encountered a bottleneck as it overly emphasizes the network's topology. Adaptive networks can assist in the analysis, where the prediction of vehicle driving behavior in the network involves forecasting driving behavior at different moments on the road. We assign varying weights to predict future vehicle driving behavior at different time intervals. Customized tasks can be executed by various nodes on the adaptive network through programmed handling of information passing through each node. For instance, a node can be programmed or customized to handle information points based on individual users or handle multi-point transmission of information distinct from other information points.

The research in this study is specifically focused on a classification task. As an integral component of artificial intelligence, machine learning can handle dynamic prediction models involving human-vehicle-road interactions. However, a single machine learning model has certain limitations in predicting driving behavior. Ensemble learning possesses higher predictive accuracy, faster computational speed, improved stability, and better generalization capabilities compared to individual machine learning methods. In this study, it is necessary to determine the optimal and appropriate strategy for stacking ensemble machine learning models. As a result, ensemble learning has gained popularity in various domains, such as healthcare, finance, and others.

In order to improve the accuracy and real-time performance of the prediction results, this paper uses the construction of an adaptive network framework combined with ensemble learning as the model of driving behavior prediction LightGBM and NN was employed as feature selection methods to construct the most informative features from the extracted dataset [4]. The key contributions of this study are as follows:

(1) The construction of an adaptive network framework enables the real-time and efficient performance of the prediction results..

(2) Ensemble learning uses XGBoost as a booster and SVM, MLP, and CatBoost as a basic learner.

(3) The attention mechanism is embedded, enabling the network to pay attention to relevant features.

2. Models

2.1. Adaptive module

An adaptive module was embedded in the experiments of this paper, which can compute the trajectories of the dynamic system. The proposed adaptive module ensures global robustness, with the system parameters being adjusted online to their optimal stable values, thereby accelerating the system's response. The adaptive parameters, including the center vector and feedback gain, are adaptively adjusted to the optimal values, so that the model has stability. In the system depicted in Figure 2, the transmission of the uplink link in the network is taken into consideration. In this study, appropriate modulation modes are chosen based on the near-instantaneous channel conditions in each transmission link. This results in the reduction of system transmission power and/or increase in the overall system throughput, thereby conserving bandwidth in the network. As a result, the received information frames are encoded by the system to construct corresponding parity check frames, which are then transmitted to the model during the cooperative phase.

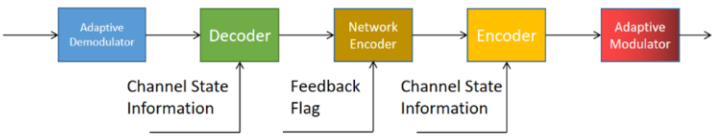

Figure 2. Adaptive Network architecture.

2.2. Ensemble learning module

The first step involves separating the raw data channels, followed by training the raw data set using the selected model. The experiment employs two model architectures to examine the dependency of each iteration. Then, each channel is trained using the model designed for the raw data set [5]. Figure 3 describes the operation flow of the model. If the low-accuracy models are combined, the results will be improved. For instance, while models A and B have an equal number of predictions, the predicted elements differ. This indicates that model A can make accurate predictions while model B fails to do so. Conversely, model B exhibits an advantage in prediction speed, but it does not accurately classify acceleration, unlike model A. When the two models are combined, the collective insight of the models contributes to a greater ability to accurately classify a larger number of outcomes. Here, $\begin{pmatrix} 1p_1^1 & \dots & 1p_1^m \\ 1p_2^1 & \dots & 1p_2^m \\ \vdots & \vdots & \vdots \\ 1p_n^1 & \dots & 1p_n^m \end{pmatrix}$, $\begin{pmatrix} 2p_1^1 & \dots & 2p_1^m \\ 2p_2^1 & \dots & 2p_2^m \\ \vdots & \vdots & \vdots \\ 2p_n^1 & \dots & 2p_n^m \end{pmatrix}$, and $\begin{pmatrix} 3p_1^1 & \dots & 3p_1^m \\ 3p_2^1 & \dots & 3p_2^m \\ \vdots & \vdots & \vdots \\ 3p_n^1 & \dots & 3p_n^m \end{pmatrix}$

represent the highest predicted probabilities for i, m refers to the number of data sets, and n denotes the number of predicted values.

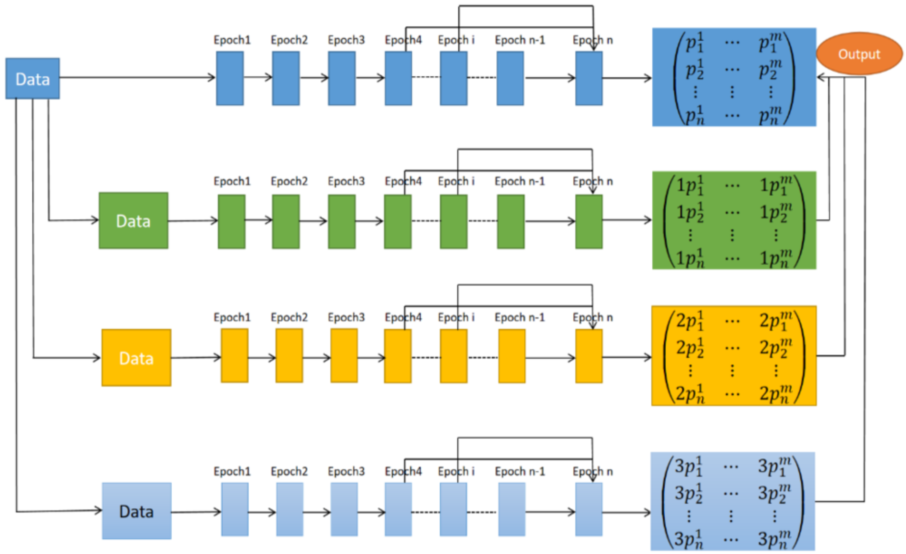

Figure 3. Ensemble Learning Network Architecture.

3. Method

3.1. Data

The dataset used in this study was provided by a local automotive company and includes variables such as driving speed, driving acceleration, and weather conditions during the testing dataset period, which spans from August 2019 to January 2020. The weather conditions encompass sunny, rainy, snowy, and foggy conditions. The vehicles on the road are represented by N units, and the speed and acceleration (measured periodically) of each vehicle are collected by various systems, forming the set $T_i, i \in N$. The whole data can be formulated as

$$Data = (V^i, A^i, W), i = 1,2,3, \dots, N \tag{1}$$

where U^i refers to the data measurement matrix collected by the systems, V^i represents the operating period of the systems, and W denotes the weather conditions during vehicle operation. The representation is as follows:

$$V^i = [v_1, v_2, v_3, v_4, \dots, v_{T_i}] \in R^{m \times T_i} \tag{2}$$

$$A^i = [a_1, a_2, a_3, a_4, \dots, a_{T_i}] \in R^{1 \times T_i} \tag{3}$$

where T_i represents the i-th overall operating period and $v_t = [v_t^1, v_t^2, \dots, v_t^m] \in R^{m \times 1}$ denotes an m-dimensional vector of system measurements at time t.

3.2. Integration aggregation module

To select the optimal duration from the training interval, a unique interval length L_k was pre-defined for each model.

$$L_k = \begin{cases} x, & if\ k = 1 \\ y, & if\ k = 2 \\ z, & if\ k = 3 \end{cases} \tag{4}$$

In Eq. (4), k represents the module, and x, y, z represent the list of specified training intervals. Within each interval, the optimal model for each module is selected to form an ensemble.

In Eq. (5), the top N prediction indices (P_i) are provided, determining the first N categories of the input data. The array D_g, which represents the prediction array achieved.

$$P_i = D_g \cdot argsort()[-N:][::-1] \tag{5}$$

Initially, each module separates data from the original dataset and creates a new dataset. Three data sets were divided into three modules, and each module was saved. By processing the data, four data sets were received: the original dataset and datasets for modules a, b, and c. Then, this study involves training the original data set using the proposed model architecture and saving the predicted results (P_0) of the test set. Next, module a is used to train the model architecture for the original dataset. Then, the optimal duration is obtained from certain training intervals identified from L_k. For module a, $L_k = x$ is utilized, where x represents the list of intervals. The optimal duration is selected only from two intervals, and the testing predictions from the chosen duration are collected and saved as (P_1). Next, module b adopts the same structure and utilizes the optimal duration from the intervals provided by k to obtain the predicted probabilities for the testing dataset. The final ensemble predictions from module b, denoted as (P_2), are saved. The same goes for module c. The intervals from p and their corresponding optimal durations are applied to the test set, and the obtained prediction results (P_3) are saved. Next, the top N predictions are selected from P_1, P_2, and P_3, and they are added to the respective categories of P_0. Finally, $P0^+ = P_1(P_i) + P_2(P_i) + P_3(P_i)$.

The data were inputted to the ensemble learning layer in the model. In the second step, batch normalization and max pooling were performed with a pooling size of 2×2. The batch normalization function, as given by Eq. (6), provides the normalized form of the input batch as the output [5].

$$M(\delta) = \frac{\gamma\big(a - mean(a)\big)}{\sqrt{var(a) + \varepsilon + \beta}} \tag{6}$$

$$ReLu = f(b) = \max(0, b) \tag{7}$$

$$\sigma(\eta)_i = \frac{e^{c_i}}{\sum_{j=1}^{k} e^{c_i}} \tag{8}$$

$$Crossentropyloss = \sum_{i=1}^{v} y_i \log p_i \tag{9}$$

The constants α, δ, ε, and β are learning bias coefficients and configurable constants. The activation function used in all layers of this model is rectified linear unit (ReLU) [5]. The softmax function takes a vector η of K-class predictions and normalizes it into K probabilities, where K is greater than 1. In Eq. (9), v represents the number of classes, y represents the input labels, and p_i represents the input predictions.

The prediction cycle, denoted as L, is adjusted if the index is unstable and the parameters need tuning. The optimal duration, denoted as T, is corrected. Based on the true value at time t, denoted as $P0^+$, the smoothed value, denoted as P_i, is obtained, which allows the calculation of the optimal duration T. A new constant, denoted as C, is introduced in this paper and is typically set between 0.1 and 0.5. The optimal duration T is then determined.

$$T = C\frac{P0^+}{P_i} + (1 - C)L \tag{10}$$

3.3. Models Evaluation

Additionally, the ROC curve and area under the curve (AUC) [1] were considered to assess the performance and stability of the model for estimating binary classifiers, as shown in Table 1. This paper also tests the accuracy, sensitivity, precision, and F1 score of the proposed model. The relevant formulas are specified by [1].

Table 1. Actual versus predicted classes.

		Actual Class	
		Positive Class	Negative Class
Predicted Class	Positive Class	TP	FN
	Negative Class	FP	TN

TP = True Positive, FP = False Positive1
FN = False Negative and TN = True Negative2

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{11}$$

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$F1score = \frac{2 * (Recall * Precision)}{Recall + Precision} \tag{13}$$

The AUC serves as an unbiased estimator for the classification predictive model e in determining whether the test positives are ranked higher than the negatives:

$$AUC(e) = \frac{\sum t_0 \in D^0 \sum t_1 \in D^1 1[e(t_0) < e(t_1)]}{|D^0| * |D^1|} \tag{14}$$

where D^0 represents a set of negative examples, D^1 represents a set of positive examples, and $1[e(t_0) < e(t_1)]$ is an indicator function that returns 0 when $e(t_0) < e(t_1)$ occurs and 1 otherwise.

In addition, Mean Absolute Error (MAE), Root Mean Square error (RMSE), and coefficient of determination (R^2) are also used in this paper, which is calculated using the following equations:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{15}$$

$$RMSE = \sqrt{\frac{1}{MN}\sum_{I=1}^{M}\sum_{j=1}^{N}\left(y_j^i - \hat{y}_j^l\right)^2} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(y_j^i - \overline{y_j^l}\right)^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(y_j^i - \bar{Y}\right)^2} \tag{17}$$

where y_i represents the actual values, $\hat{y}_i$ represents the predicted values, and $\bar{Y}$ represents the average score of all outputs with equal weights.

4. Results and Analysis

The model was trained on the NGSIM dataset [2] in this study to validate the driver behavior recognition model. $Data(t) = \{x_1(t), x_2(t), x_3(t), \dots, x_i(t), \dots, x_n(t)\}$. n represents the number of training samples, and $x_i(t)$ represents the feature variables corresponding to the time period t. The selected feature variables in this study are weather conditions and vehicle population. $Label(t) = \{y(t)\}$, where $y(t)$ represents the classification labels of the model at each node, $y(t) \in \{-1,1\}$. The model was trained using the Gaussian radial basis function (RBF) kernel, which has fewer kernel parameters compared to other commonly used kernels such as the polynomial kernel. The training time was 0.2473 s, and the number of iterations was 42.

4.1. Results

The driving behavior of neighboring vehicles is recognized and predicted every three seconds in this study, allowing the system to provide new driving strategies to the driver based on the driving behavior of adjacent vehicles. In this section, the support vector machine (SVM) model was employed and compared with the proposed model on the driving dataset. The predicted results of the SVM model are presented in Figures 4 to 7, showcasing the predictions of vehicle speed and acceleration under different weather conditions, including sunny, rainy, snowy, and foggy conditions. Figures 8 to 11 denote the results of the EL, which will be compared with other models in the following section. The results show that under snowy and foggy conditions, the vehicle speed fluctuates significantly, with overall lower speeds. In comparison to sunny days, there are more instances of deceleration in rainy conditions. On sunny days, the vehicles exhibit higher acceleration, while under snowy and foggy conditions, the acceleration fluctuates and the average acceleration is lower than that of sunny and rainy conditions.

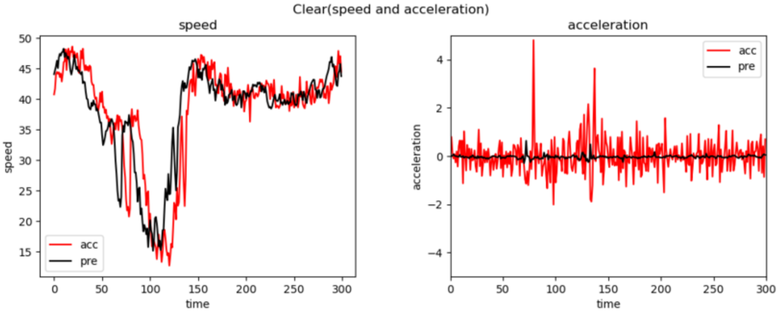

Figure 4. The predicted results of vehicle speed and acceleration under sunny conditions using SVM are shown.

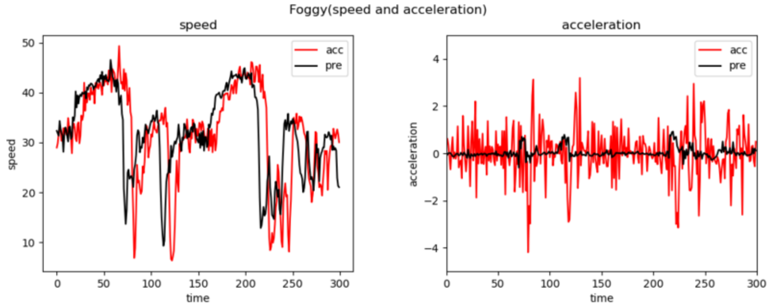

Figure 5. The predicted results of vehicle speed and acceleration under foggy conditions using SVM are shown.

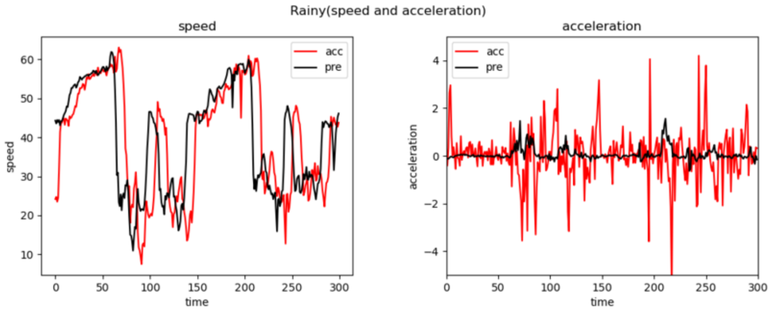

Figure 6. The predicted results of vehicle speed and acceleration under rainy conditions using SVM are shown.

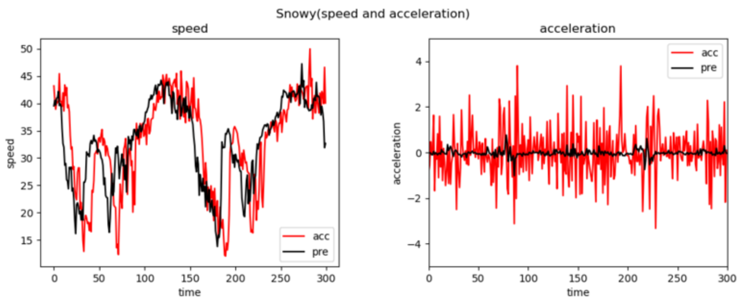

Figure 7. The predicted results of vehicle speed and acceleration under snowy conditions using SVM are shown.

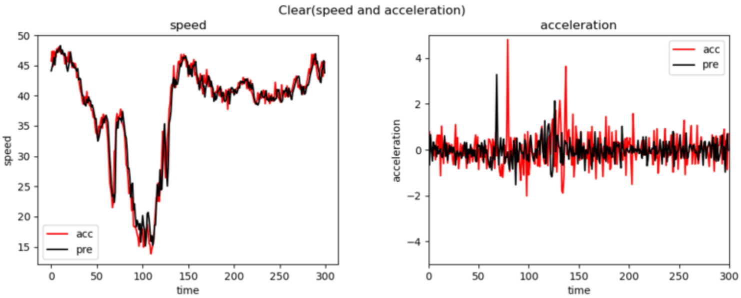

Figure 8. The predicted results of vehicle speed and acceleration under sunny conditions using EL are shown.

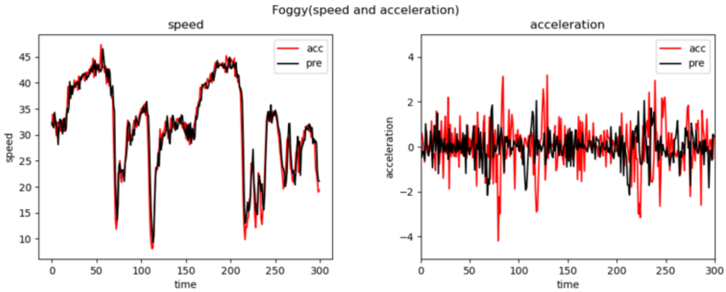

Figure 9. The predicted results of vehicle speed and acceleration under foggy conditions using EL are shown.

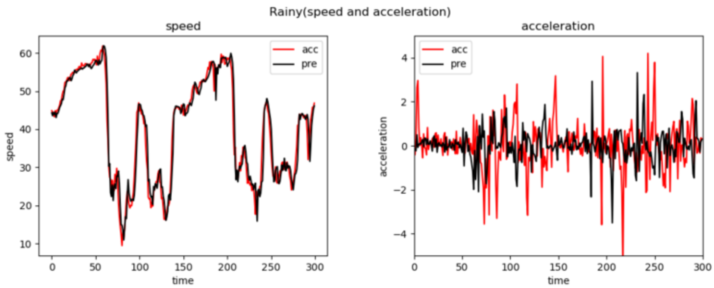

Figure 10. The predicted results of vehicle speed and acceleration under rainy conditions using EL are shown.

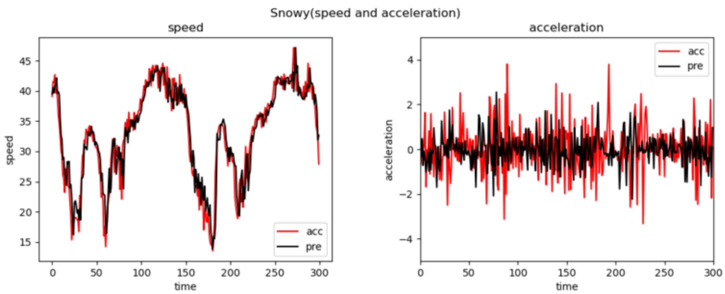

Figure 11. The predicted results of vehicle speed and acceleration under snowy conditions using EL are shown.

Table 2 presents a performance comparison between the Support Vector Machine (SVM) and the proposed model in this paper. Ultimately, this paper identifies the bestfitting ensemble learning model for predicting driving behavior under different weather conditions.

Table 2. Performance comparison between SVM and the proposed model.

Name	RMSE	MAE	R^2
SVM	0.3152	0.06101	0.89
Proposed Model	0.2123	0.05720	0.94

4.2. Analysis

In this section, a comparison was made between the ensemble learning model and other powerful existing models using different evaluation metrics. Table 3 describes the performance of different ML classifiers on the dataset with and without oversampling. From Table 3, it can be concluded that all the learners exhibit high accuracy, i.e., 98%. Therefore, the performance of the classifiers must be further examined on other metrics such as precision, sensitivity, specificity, F1 score, and G-mean.

Table 3. Comparison of various prediction models and ensemble learners' prediction metrics.

	MLP	XGBoost	CatBoost	SVM	RF	EL
	Deg0 0.97	Deg0 0.98	Deg0 0.99	Deg0 0.97	Deg0 0.97	Deg0 0.99
Precision	Deg1 0.52	Deg1 0.69	Deg1 0.53	Deg1 0.56	Deg1 0.51	Deg1 0.70
	Deg2 0.42	Deg2 0.82	Deg2 0.41	Deg2 0.41	Deg2 0.44	Deg2 0.57
	Deg0 0.97	Deg0 0.96	Deg0 0.97	Deg0 0.97	Deg0 0.97	Deg0 0.97
Sensitivity	Deg1 0.56	Deg1 0.61	Deg1 0.56	Deg1 0.56	Deg1 0.59	Deg1 0.71
	Deg2 0.41	Deg2 0.77	Deg2 0.43	Deg2 0.41	Deg2 0.38	Deg2 0.58
	Deg0 0.97	Deg0 0.97	Deg0 0.99	Deg0 0.97	Deg0 0.99	Deg0 0.99
Specificity	Deg1 0.57	Deg1 0.68	Deg1 0.55	Deg1 0.56	Deg1 0.56	Deg1 0.69
	Deg2 0.38	Deg2 0.78	Deg2 0.44	Deg2 0.41	Deg2 0.43	Deg2 0.58
	Deg0 0.97	Deg0 0.95	Deg0 0.98	Deg0 0.97	Deg0 0.98	Deg0 0.98
F1-Score	Deg1 0.56	Deg1 0.71	Deg1 0.59	Deg1 0.56	Deg1 0.52	Deg1 0.74
	Deg2 0.41	Deg2 0.75	Deg2 0.39	Deg2 0.41	Deg2 0.46	Deg2 0.79
	Deg0 0.97	Deg0 0.97	Deg0 0.98	Deg0 0.97	Deg0 0.97	Deg0 0.99
AUC	Deg1 0.58	Deg1 0.56	Deg1 0.57	Deg1 0.56	Deg1 0.61	Deg1 0.63
	Deg2 0.41	Deg2 0.41	Deg2 0.46	Deg2 0.41	Deg2 0.44	Deg2 0.49
Accuracy	0.97	0.98	0.98	0.98	0.98	0.98
G-mean	0.85	0.87	0.86	0.86	0.85	0.88

The results in Table 3 illustrate a trade-off between accuracy and sensitivity. The model proposed in this paper cannot simultaneously achieve high sensitivity and high accuracy. When considering the weather conditions, the performance of the classifier improved by 11% in accuracy, 18% in sensitivity, 6.7% in specificity, 3% in F1 score, and 12.5% in G-mean.

Additionally, in this paper, a booster was added to the first layer of the stacked ensemble model. Figure 12 shows a comparison of the model with and without boosters. This confirms that the use of the booster resulted in improved performance.

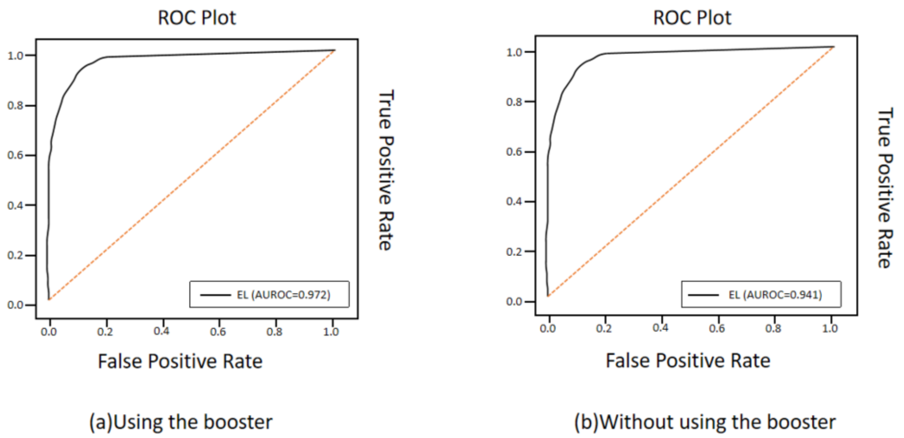

Figure 12. The ROC curves of the EL model are shown in Figure (a) with the booster and (b) without the booster. The AUC value of (b) is 0.941 and the AUC value of (a) is 0.972.

5. Conclusion

An effective artificial intelligence solution for predicting driver behavior considering road weather conditions was developed in this study, based on the theoretical foundation of ensemble learning using adaptive networks. This paper uses heterogeneous integration strategies to reduce complexity, address the limitations of individual machine-learning models, and leverage the most efficient models.

This paper realizes driving behavior prediction based on different weather conditions. This research has significant theoretical implications for enhancing road traffic safety. The adaptive framework fulfills the requirements of real-time and effectiveness for the model. As road conditions vary with different weather conditions, corresponding driving behaviors also change. When performing maneuvers such as lane changing or overtaking, vehicles can rely on the predicted model to predict the driving behaviors of adjacent vehicles, thus meeting the needs of their vehicles.

Future studies need to consider more factors, such as the level of road service and traffic flow.

Acknowledgments

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