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ROAD CONDITION RECOGNITION IN SELF-DRIVING CARS BASED ON CLASSIFICATION AND REGRESSION TREE

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Abstract. *With the continuous development of technology, the realization of self-driving cars is getting closer and closer to our life. Obviously, road condition recognition is undoubtedly the premise and component of this technology. In this paper, a new road condition recognition method based on Classification And Regression Tree (CART) technology is realized. First, we process the original Oxbotica data to get a data set consisting of nine sensors information that can describe the vehicle's driving. We then generate a CART model using the training data set. Finally, we test the model and calculate some evaluation indicators to evaluate our model. The results show that our method performs well for the identification of six types of road conditions.*

Keywords: Road condition recognition, Self-driving cars, Oxbotica data, CART

1. **Introduction.** With the continuous development of technology, the practical application of driverless cars is no longer an unreachable dream. More and more companies and organizations have joined the research on self-driving cars. In 2016, Google announced the establishment of Waymo, continuing its in-depth research in the field of unmanned driving, and in 2018, the total test distance of Google's self-driving cars reached 8 million miles. In addition, Baidu, Tesla, Renault, Uber, and Didi companies have also started their own self-driving cars research projects [1-4].

Obviously, for the research of self-driving technology, the first thing that needs to be realized is the identification of different road conditions. In the process of realizing road condition recognition, researchers have adopted different methods [5].

Some researchers extract effective information from images or real-time videos and combine other technologies to achieve road condition recognition. Nugraha et al. used YOLO, a real-time convolutional neural network, to extract traffic information from real-time video [6]. Bi et al. constructed a neural network classifier based on RBF by extracting velocity information and luminance information from traffic video, and achieved good results [7].

However, it can be seen that the above methods have high requirements on the camera, they can be easily affected by the environment, and the computing resources occupied are also large. So some researchers use sensor data for research. Based on the radar sensor, Lee et al. designed the sensor fusion algorithm and solved the road recognition problem under different weather conditions [8]. Therefore, the data set processed and used by us is real-time vehicle driving data collected by multiple sensors.

In this paper, we process and obtain the above mentioned data set, use it to train the CART decision tree model, and finally realize the recognition of road condition. It provides an accurate, efficient and novel solution for road condition recognition in the field of self-driving research.

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The rest of this paper is organized as follows. Section 2 briefly analyzes the principles of CART and describes the data sets used in this paper. In addition, some evaluation criteria are introduced. Section 3 describes the process of the experiment and analyzes the results in detail. Finally, some conclusions are provided in Section 4.

2. Theories and Preliminaries.

2.1. CART. The decision tree is an algorithmic model with a tree structure and classification ability. In terms of structure, the decision tree consists of internal nodes, leaf nodes and directed edges. We can regard the decision tree as a set of if-then rules: the path from the root node to a leaf node constitutes a rule, and the internal nodes it passes correspond to the conditions of that rule, and the leaf node is the result of that rule. Commonly used decision tree algorithms include ID3, C4.5 and CART [9].

Compared with other decision tree algorithms, the CART algorithm used in this paper has some differences in structure and principle. CART is a binary tree structure, that is, each internal node divides the input set into two subsets according to the rules. The schematic diagram of the CART model structure is shown in Figure 1. Letters A, B, and C in that figure are different features of the data, and letters a-e represent different values.

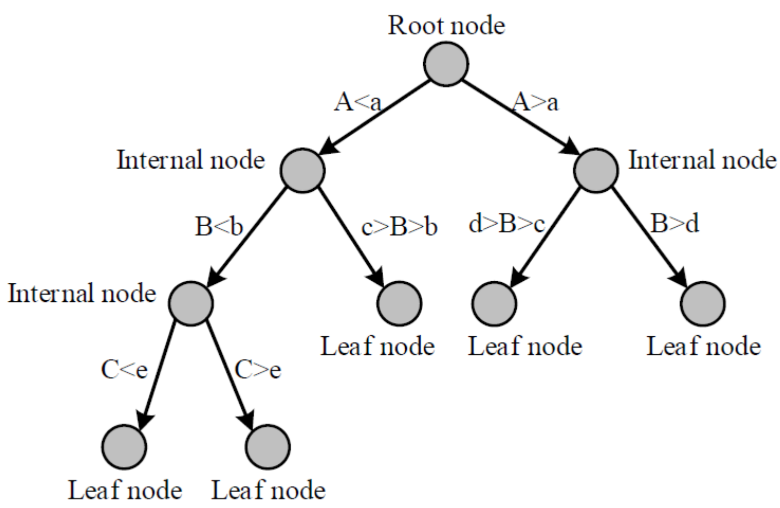

FIGURE 1. Schematic diagram of CART model structure

For the decision tree, the most important thing is the splitting of the nodes. In the case of classification, CART uses the Gini index to select the optimal feature and determines the optimal binary segmentation point of it [10].

The calculation process of the Gini coefficient is as shown in Equation (1):

$$Gini(D) = \sum_{k=1}^{K} p_k(1 - p_k) = 1 - \sum_{k=1}^{K} p_k^2 \tag{1}$$

where D is the data set, and there are K types of data. p_k is the probability that the sample points belong to the kth class. Intuitively, the Gini index reflects the probability that two samples are randomly drawn from the data set with different categories. The smaller the value, the less the different categories of data contained in the data set.

For CART, the calculation process of the Gini index is as shown in Equation (2):

$$Gini(D, A) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2) \tag{2}$$

where D_1 and D_2 are the two subsets of the original data set D that are split according to the value of feature A.

According to the above formula, the CART model is generated by recursive method: calculating the Gini index of each feature in the training set, selecting the optimal feature and the optimal segmentation point, dividing the data into two parts, and then circulating the above process until the stop condition is satisfied.

2.2. **Evaluation criteria.** In evaluating the binary classifier, previous researchers introduced some concepts. First, consider a classification result as "True", and then define several parameters such as True Positive (*TP*), False Negative (*FN*), False Positive (*FP*), and True Negative (*TN*), and these parameters form a binary confusion matrix [11-13]. Then, based on these parameters, some indicators, including Accuracy (*Acc*), Precision Rate (*PR*) and Recall Rate (*RR*), are calculated as shown in (3), (4) and (5):

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$PR = \frac{TP}{TP + FP} \tag{4}$$

$$RR = \frac{TP}{TP + FN} \tag{5}$$

Accuracy calculates the proportion of correctly predicted samples to the total samples, representing the accuracy of the overall prediction. In the samples predicted to be "True", the proportion of the samples whose real value are also "True" is *PR*. Then *RR* calculates the proportion of samples that are predicted to be "true" among the samples that are actually "true". In the application of *PR* and *RR*, the complex impact needs to be considered. Therefore, two indicators are introduced here, namely *F-score* and *G-score*, which can combine *PR* and *RR*, to examine the performance of the classifier. Their calculation formulas are shown in (6) and (7):

$$F\text{-}score = 2 \cdot \frac{PR \cdot RR}{\beta^2 PR + RR} \tag{6}$$

$$G\text{-}score = \sqrt{PR \cdot RR} \tag{7}$$

A multi-classifier can be considered as a combination of multiple binary classifiers. Therefore, when evaluating the multi-classifier performance, we first calculate the confusion matrix and performance indicators of each binary classifier, and then calculate the performance indicators of the multi-classifier based on these results. In addition to calculating the average of *F-score* and *G-score*, this paper also introduces a Kappa Coefficient for evaluating the consistency of each subclass [14].

Suppose the data set has n pieces of data, which are divided into K categories. The actual numbers of each type of samples are $a_1, a_2, \ldots, a_K$, and the predicted numbers are $b_1, b_2, \ldots, b_K$, respectively. Then the calculation of multi-classifier performance indicators is shown in Equations (8) and (9):

$$Avg.F = \sum_{k=1}^{K} \frac{F\text{-}score_k}{K}; \quad Avg.G = \sum_{k=1}^{K} \frac{G\text{-}score_k}{K} \tag{8}$$

$$Kappa = \frac{Acc - \frac{\prod_1^K a_k \cdot b_k}{n \cdot n}}{1 - \frac{\prod_1^K a_k \cdot b_k}{n \cdot n}} \tag{9}$$

2.3. **Data set.** The original data set used in this article is called "2018-2-23-11-47-15-autonomy-long-route-04", which comes from available Oxbotica data. It is a complex data set collected by installing various sensors and cameras on the Nissan experimental vehicle [15].

The data set consists mainly of two parts. The first part is the massive car driving information collected by various types of sensors. The second part is 2d-cost maps (road condition maps) used to indicate the driving status of the car, which are obtained by processing the real-time road condition images.

This paper has processed the original data set to get a new data set suitable for use. First, since the original data set collected too many sensor signals, many of them belonged to meaningless signals, so nine kinds of vehicle travel information from four types of signals were manually selected from them as the characteristics of the data set. The feature details are shown in Table 1.

Table 1. Data set feature

Types	Index	Feature
Steering related signals	1	steering_angle_deg
	2	angl_sensor_deg
Brake related signals	3	pressure_sensor_valve_in_bar
	4	brake_fluid_pressure
Speed related signals	5	wheel_speed_rear_left_rpm
	6	wheel_speed_rear_right_rpm
	8	displayed_speed_kph
	9	speed*2.2369362920544
Acceleration sensor signals	7	yaw_rate_deg_per_sec

Then, using the corresponding cost map data set, the sensor data set of the reselected feature is tagged, and the data set is divided into six types of road conditions. Finally, 50,000 samples were randomly selected from the new tagged data set as the training dataset, and the remaining 7,781 were used as test dataset. The data set details are shown in Table 2.

Table 2. Data set detail

Types	Training dataset	Testing dataset
Straight	30,012	4,573
Crossing	3,926	611
Curve	7,752	1,245
Roundabout	5,165	836
Deceleration	2,457	403
Cars meeting	688	113
Total	50,000	7,781

3. **Experimental Process and Results Analysis.**

3.1. **Workflow.** This paper designs a road condition recognition system based on CART classifier, which can provide decision information for driverless cars. The overall workflow of the system training and testing is shown in Figure 2.

In practical applications, the signals collected are processed according to the data set production process, and can be directly sent to the CART classifier constructed in this paper for classification, realizing the real-time vehicle driving condition detection.

3.2. **Analysis of results.** The CART model is generated using the prepared training data set, and the resulting decision tree model is shown in Figure 3.

It should be noted that since the number of CART model nodes obtained is up to 2767, only a part of the model can be given in the figure. Taking the root node as an example, our model divides the data set into two categories according to the two judgment

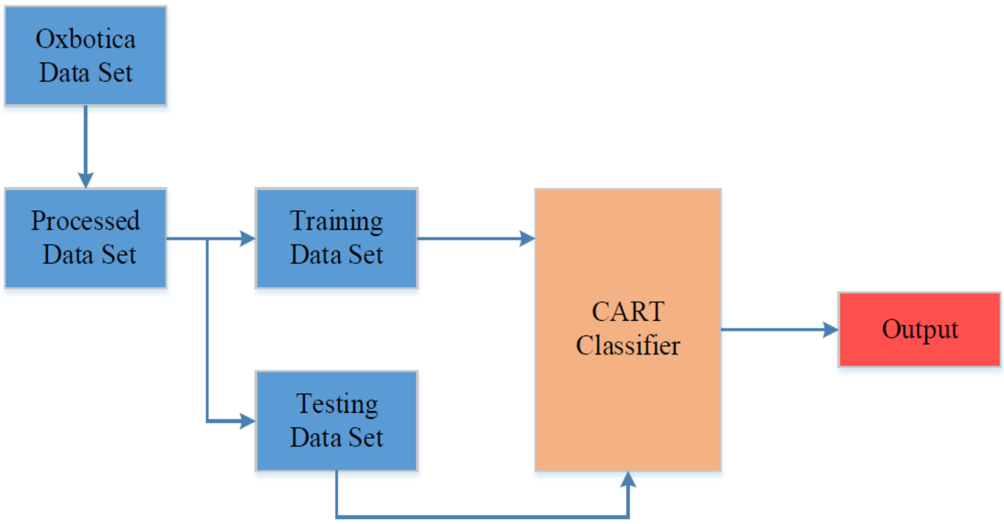

FIGURE 2. The overall workflow of training and testing

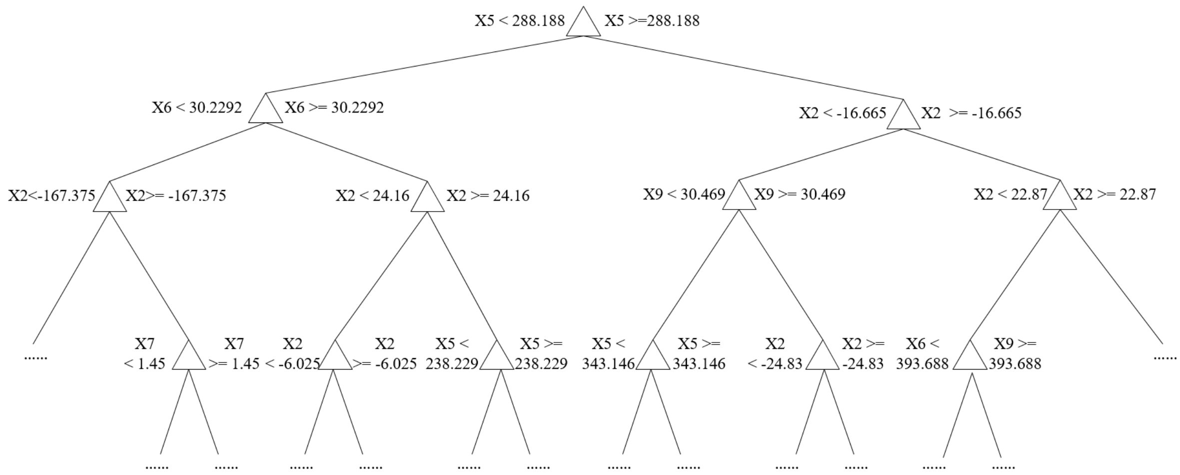

FIGURE 3. Part of the CART model generated in this paper

conditions of 'x5 < 288.188' and 'x5 >= 288.188', that is, the data set is divided into two parts according to the value of the fifth feature. The splitting process of the other nodes is similar.

After generating the CART model through the training data set, input the test data set to get the corresponding results and analyze the performance of the CART model. The corresponding confusion matrix is shown in Figure 4. We can get the relationship between the actual number of six road conditions in the data set and the predicted results from it. Take "Straight" as an example. There are 4573 samples (sum of horizontal axis values) in the dataset, and they are predicted as six types of road conditions. The predicted number of each class is equal to the value corresponding to the horizontal axis, as there are 4487 correctly predicted as "Straight". Then we can get Figure 5, which contains six binary confusion matrices, with similar meanings to the above analysis.

We can calculate the values of *TP*, *TN*, *FP*, and *FN* corresponding to each type of test result from the six sub-confusion matrices in the figure. Then we can calculate the *PR*, *RR*, *F-score*, and *G-score* values for each type of test result, as shown in Figure 6.

We can analyze the recognition performance of each of the six road conditions according to Figure 6. For Straight and Deceleration, the precision is slightly lower than the recall rate; for Crossing, Curve and Cars meetings, the recall rate is slightly lower than

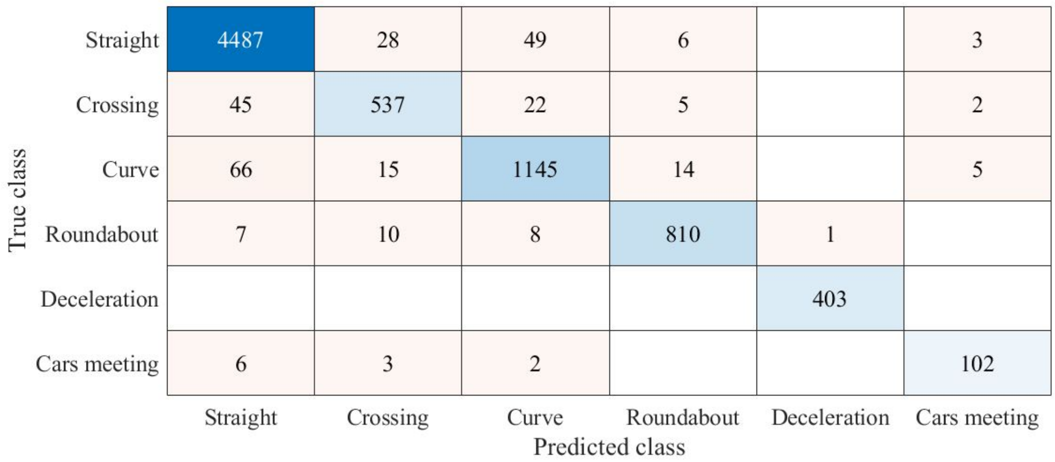

FIGURE 4. Confusion matrix corresponding to the test result

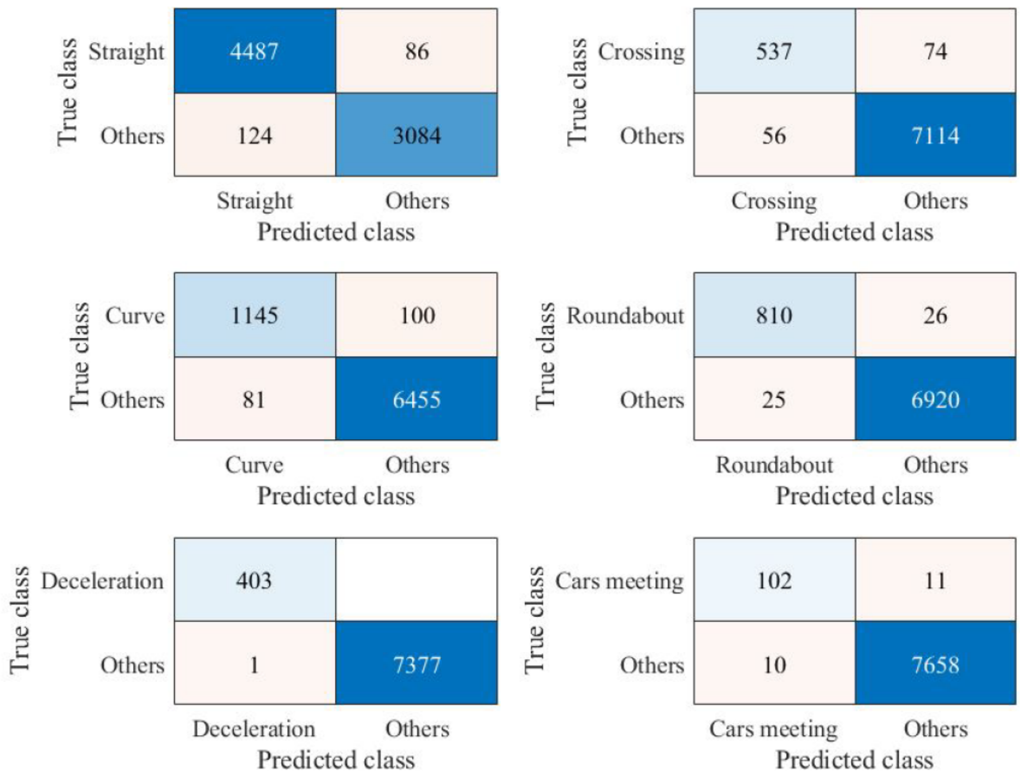

FIGURE 5. Binary confusion matrices obtained by splitting

the precision. For Roundabout, the two indicator parameters are almost identical. Considering *F-score* and *G-score*, except for Crossing, its value is 89.2%, and the values of other five situations are higher than 90%. In general, the recognition of each of the six road conditions is excellent.

From a general perspective, the performance indicators are shown in Table 3.

From the perspective of the entire system, the average value of *F-score* and *G-score* is equal to 0.945, indicating that the system's precision and recall are excellent. The value of *Acc* is 0.9618, which means that the recognition accuracy is high. The Kappa Coefficient has a value of 0.937, representing that the consistency after classification is great, which also indicates that the recognition accuracy is excellent.

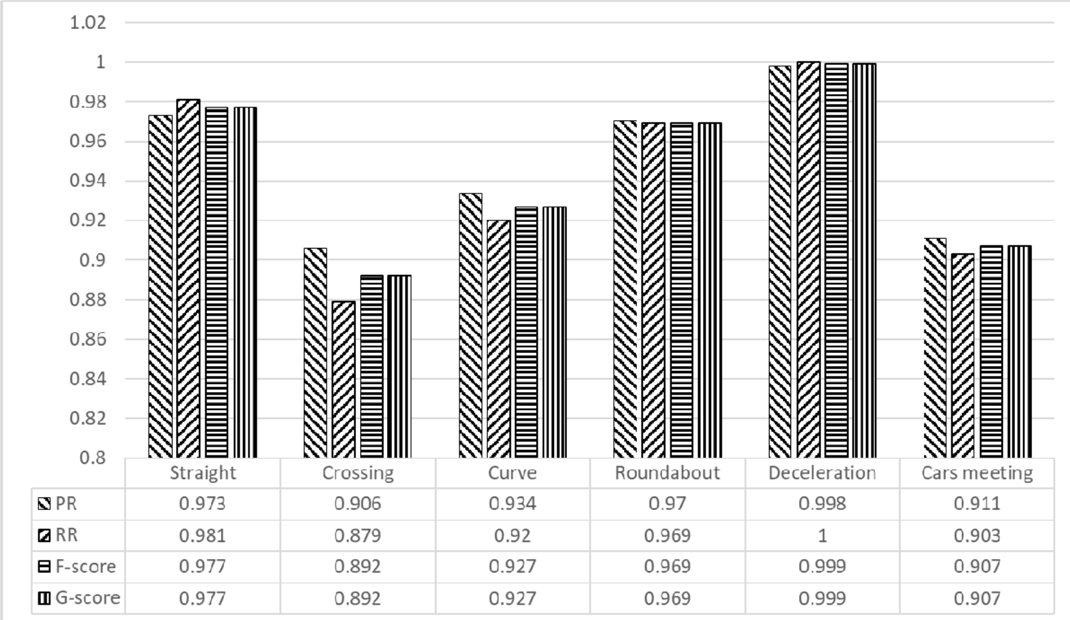

Figure 6. Six types of road condition classification performance indicators

Table 3. Comprehensive performance indicators of multiple classifiers

	$Avg.F$	$Avg.G$	Acc	$Kappa$
Value	0.945	0.945	0.9618	0.937

4. **Conclusions.** In order to provide accurate and effective decision-making information for autonomous vehicles, research on road condition identification is very important. This paper proposes a new road condition recognition method using CART technology, which can accurately identify different road conditions. After some experiments, we can prove that the method does have excellent performance in accurately identifying the six types of road conditions. In future research, we can increase the variety of road conditions and optimize the classifier to improve its accuracy.

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