

Claims:

1. A driving model training method, comprising:
 - acquiring training behavior data of a user wherein the training behavior data are associated with a user identifier;
 - acquiring training driving data associated with the user identifier based on the training behavior data;
 - acquiring positive and negative samples from the training driving data based on the user identifier, and dividing the positive and negative samples into a training set and a test set;
 - training the training set using a bagging algorithm, wherein the bagging algorithm is used to sample the positive and negative samples from the training set by inputting the positive and negative samples in the training set into at least two classification models for training, each of the classification models being a model for solving classification problems, and each classification model being a predication function in the bagging algorithm, and acquiring an original driving model; and
 - testing the original driving model using the test set, and acquiring a target driving model.
2. The driving model training method according to claim 1, wherein the step of acquiring the training driving data associated with the user identifier based on the training behavior data comprises:
 - acquiring a behavior type corresponding to the training behavior data based on the training behavior data wherein the behavior type is associated with the user identifier; and
 - taking the training behavior data that the behavior type is the driving type as the training driving data.
3. The driving model training method according to claim 1, wherein the step of training the training set using the bagging algorithm and acquiring the original driving model comprises:
 - inputting the positive and negative samples of the training set into at least two classification models for training, and acquiring a single driving model; and
 - fusing at least two single driving models, and acquiring the original driving model.

4. The driving model training method according to claim 3, wherein the classification models comprise a long short-term memory model;

the step of inputting the positive and negative samples in the training set into the at least two classification models for training and acquiring the single driving model comprises:

training the positive and negative samples in the training set by adopting a forward propagation algorithm in the long short-term memory model, and acquiring the original single driving model, wherein the computation formulas of the forward propagation algorithm comprise $S_t = \tanh(U_{x_t} + W_{s_{t-1}})$ and $\hat{o}_t = \text{softmax}(V_{s_t})$, wherein S_t indicates an output of a hidden layer at a current moment; U_{x_t} indicates a weight of the hidden layer from a previous moment to the current moment; $W_{s_{t-1}}$ indicates a weight from the input layer to the output layer; $\hat{o}_t$ indicates a predicted output of the current moment; and V_{s_t} indicates a weight from the hidden layer to the output layer; and

carrying out error calculation on the original single driving model by adopting a back propagation algorithm in the long short-term memory model, and acquiring the single driving model, wherein the computation formula of the back propagation

algorithm comprises $E_t = -\sum_t o_t \log \hat{o}_t$, wherein $\hat{o}_t$ indicates a predicted output of a moment t; and o_t indicates a true value corresponding to $\hat{o}_t$ at the moment t.

5. The driving model training method according to claim 3 or 4, wherein the classification models comprise a logistic regression model;

the step of inputting the positive and negative samples of the training set into the at least two classification models for training and acquiring the single driving model comprises:

training the positive and negative samples in the training set using a logistic regression algorithm in the logistic regression model, and acquiring an original single driving model, wherein the computation formulas of the logistic regression algorithm

comprise
$$h_\theta(x) = \frac{1}{1 + e^{-\theta^m x}}$$
 and

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_\theta(x^{(i)})) - (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)})) \right]$$
, wherein $h_\theta(x)$ indicates

a probability density function of the positive and negative samples; $x^{(i)}$ indicates an input of the positive and negative samples; $y^{(i)}$ indicates an output result corresponding to the input of the positive and negative samples; and m indicates quantities of the positive and negative samples; and

carrying out the error calculation on the original single driving model using a gradient descent algorithm in the logistic regression model, and acquiring the single driving model, wherein the computation formulas of the gradient descent algorithm

comprise $\frac{\partial}{\partial \theta_j} J(\theta) = (h_\theta(x) - y)x_j$ and $\theta_j = \theta_j - \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$,

wherein θ_j indicates θ value obtained by each iteration; $h_\theta(x)$ indicates a probability density function of the positive and negative samples; x_j indicates the positive and negative samples of the j -th iteration; and $J(\theta)$ indicates the original single driving model.

6. The driving model training method according to claim 3, wherein the step of fusing at least two single driving models comprises a majority voting fusion way;

the step of fusing at least two single driving models and acquiring the original driving model comprises:

acquiring the target probability based on the ratio of the positive samples to the negative samples in the test set;

inputting the positive and negative samples of the test set into the at least two single driving models for testing, and acquiring the at least two classification probabilities; and

selecting the single driving model corresponding to the classification probability which is closest to the target probability, and acquiring the original driving model.

7. The driving model training method according to claim 3, wherein the step of fusing at least two single driving models comprises a weighting fusion way;

the step of fusing at least two single driving models and acquiring the original driving model comprises:

configuring the positive and negative samples in the test set according to different ratios, and acquiring at least two target probabilities;

inputting the positive and negative samples in the test set into the at least two single driving models according to the different ratios for processing, and acquiring the classification probability corresponding to the single driving model;

normalizing the model weight of each single driving model using a computational method $P = \sum P_i W_i$, to determine the final model weight, wherein P indicates the target probability, P_i indicates a test probability of the i-th single driving model; and W_i indicates the model weight of the i-th single driving model; and

acquiring the original driving model based on the model parameter and the model weight of the at least two single driving models.

8. The driving model training method according to claim 1, wherein the step of acquiring the positive and negative samples from the training driving data based on the user identifier comprises:

selecting the training driving data corresponding to the preset time period from the training driving data corresponding to the target user identifier as the positive sample;

selecting the training driving data corresponding to the same time period as the preset time period from the training driving data corresponding to a non-target user identifier as the negative sample; and

configuring quantities of the positive samples and the negative samples according to a preset ratio.

9. A driver identification method, comprising:

acquiring to-be-identified behavior data of a user wherein the to-be-identified behavior data are associated with a user identifier;

querying a database based on the user identifier, and acquiring a target driving model corresponding to the user identifier, wherein the target driving model is a model acquired by the driving model training method of any one of claims 1-9;

identifying the to-be-identified behavior data by using the target driving model and acquiring an identification probability; and

judging whether the identification probability is greater than a preset probability, and determining that a driver herself/himself drives if the identification probability is

greater than the preset probability.

10. A driving model training apparatus, comprising:

- a training behavior data acquisition module, configured to acquire training behavior data of a user wherein the training behavior data are associated with a user identifier;

- a training driving data acquisition module, configured to acquire training driving data associated with the user identifier based on the training behavior data;

- a positive and negative samples acquisition module, configured to acquire positive and negative samples from the training driving data based on the user identifier, and divide the positive and negative samples into a training set and a test set;

- an original driving model acquisition module, configured to train the training set using a bagging algorithm, wherein the bagging algorithm is used to sample the positive and negative samples from the training set by inputting the positive and negative samples in the training set into at least two classification models for training, each of the classification models being a model for solving classification problems, and each classification model being a prediction function in the bagging algorithm, and acquire an original driving model; and

- a target driving model acquisition module, configured to test the original driving model using the test set, and acquire a target driving model.

11. A terminal device, comprising a memory, a processor and a computer readable instruction stored in the memory and operated on the processor, wherein the following steps are achieved when the processor executes the computer readable instruction:

- acquiring training behavior data of a user wherein the training behavior data are associated with a user identifier;

- acquiring training driving data associated with the user identifier based on the training behavior data;

- acquiring positive and negative samples from the training driving data based on the user identifier, and dividing the positive and negative samples into a training set and a test set;

- training the training set using a bagging algorithm, wherein the bagging

algorithm is used to sample the positive and negative samples from the training set by inputting the positive and negative samples in the training set into at least two classification models for training, each of the classification models being a model for solving classification problems, and acquiring an original driving model; and

testing the original driving model using the test set, and acquiring a target driving model.

12. The terminal device according to claim 11, wherein the step of acquiring the training driving data associated with the user identifier based on the training behavior data comprises:

acquiring a behavior type corresponding to the training behavior data based on the training behavior data wherein the behavior type is associated with the user identifier; and

taking the training behavior data that the behavior type is the driving type as the training driving data.

13. The terminal device according to claim 11, wherein the step of training the training set using a bagging algorithm and acquiring an original driving model comprises:

inputting the positive and negative samples in the training set into at least two classification models for training, and acquiring a single driving model; and

fusing at least two single driving models, and acquiring the original driving model.

14. The terminal device according to claim 13, wherein the classification models comprise a long short-term memory model;

the step of inputting the positive and negative samples in the training set into the at least two classification models for training and acquiring the single driving model comprises:

training the positive and negative samples in the training set by adopting a forward propagation algorithm in the long short-term memory model, and acquiring the original single driving model, wherein the computation formulas of the forward

propagation algorithm comprise $S_t = \tanh(U_{x_t} + W_{s_{t-1}})$ and

$\hat{o}_t = \text{softmax}(V_{s_t})$, wherein S_t indicates an output of a hidden layer at a current moment; U_{x_t} indicates a weight of the hidden layer from a previous moment to the current moment; $W_{s_{t-1}}$ indicates a weight from the input layer to the output layer; $\hat{o}_t$ indicates a predicted output of the current moment; and V_{s_t} indicates a weight from the hidden layer to the output layer; and

carrying out error calculation on the original single driving model by adopting a back propagation algorithm in the long short-term memory model, and acquiring the single driving model, wherein the computation formula of the back propagation

algorithm comprises $E_t = -\sum_t o_t \log \hat{o}_t$, wherein $\hat{o}_t$ indicates a predicted output of a moment t ; and o_t indicates a true value corresponding to $\hat{o}_t$ at the moment t .

15. The terminal device according to claim 13 or 14, wherein the classification models comprise a logistic regression model;

the step of inputting the positive and negative samples of the training set into the at least two classification models for training and acquiring the single driving model comprises:

training the positive and negative samples in the training set using a logistic regression algorithm in the logistic regression model, and acquiring an original single driving model, wherein the computation formulas of the logistic regression algorithm

comprise
$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$
 and

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) - (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)})) \right]$$
, wherein $h_{\theta}(x)$ indicates a probability density function of the positive and negative samples; $x^{(i)}$ indicates an input of the positive and negative samples; $y^{(i)}$ indicates an output result corresponding to the input of the positive and negative samples; and m indicates quantities of the positive and negative samples; and

carrying out the error calculation on the original single driving model using a gradient descent algorithm in the logistic regression model, and acquiring the single

driving model, wherein the computation formulas of the gradient descent algorithm

comprise $\frac{\partial}{\partial \theta_j} J(\theta) = (h_{\theta}(x) - y)x_j$ and $\theta_j = \theta_j - \partial \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})x_j^{(i)}$,

wherein θ_j indicates θ value obtained by each iteration; $h_{\theta}(x)$ indicates a probability density function of the positive and negative samples; x_j indicates the positive and negative samples of the j-th iteration; and $J(\theta)$ indicates the original single driving model.

16. The terminal device according to claim 13, wherein the step of fusing at least two single driving models comprises a majority voting fusion way;

the step of fusing at least two single driving models and acquiring the original driving model comprises:

acquiring the ratio of the positive samples to the negative samples in the test set;

acquiring the target probability based on the ratio of the positive samples to the negative samples in the test set;

inputting the positive and negative samples of the test set into the at least two single driving models for testing, and acquiring the at least two classification probabilities; and

selecting the single driving model corresponding to the classification probability which is closest to the target probability, and acquiring the original driving model.

17. The terminal device according to claim 13, wherein the step of fusing at least two single driving models comprises a weighting fusion way;

the step of fusing at least two single driving models and acquiring the original driving model comprises:

configuring the positive and negative samples in the test set according to different ratios, and acquiring at least two target probabilities;

inputting the positive and negative samples in the test set into the at least two single driving models according to the different ratios for processing, and acquiring the classification probability corresponding to the single driving model;

normalizing the model weight of each single driving model using a computational method $P = \sum P_i W_i$, to determine the final model weight, wherein P

indicates the target probability, P_i indicates a test probability of the i-th single driving model; and W_i indicates the model weight of the i-th single driving model; and

acquiring the original driving model based on the model parameter and the model weight of the at least two single driving models.

18. The terminal device according to claim 11, wherein the step of acquiring the positive and negative samples from the training driving data based on the user identifier comprises:

selecting the training driving data corresponding to a preset time period from the training driving data corresponding to the target user identifier as the positive sample;

selecting the training driving data corresponding to the same time period as the preset time period from the training driving data corresponding to a non-target user identifier as the negative sample; and

configuring quantities of the positive samples and the negative samples according to a preset ratio.

19. A terminal device, comprising a memory, a processor and a computer readable instruction stored in the memory and operated on the processor, wherein the following steps are achieved when the processor executes the computer readable instruction:

acquiring to-be-identified behavior data of a user wherein the to-be-identified behavior data are associated with a user identifier;

querying a database based on the user identifier, and acquiring a target driving model corresponding to the user identifier, wherein the target driving model is a model acquired by the driving model training method of any one of claims 1-9;

identifying the to-be-identified behavior data by using the target driving model and acquiring an identification probability; and

judging whether the identification probability is greater than a preset probability, and determining that a driver herself/himself drives if the identification probability is greater than the preset probability.