

ENHANCING SAFETY IN RAIL VEHICLE USING IOT AND TINYML

Kiran Bharane, Vaishnavi Shitole, Mayuri Madane , Ashana Shaikh

(UG Students , Information Technology , SVPM's Collage of Engineering , Malegaon (BK) , Baramati)

Emails : kiranbharane02002@gmail.com , vaishnavishitole58@gmail.com , mayurimadane2002@gmail.com , ashanashaikh0305@gmail.com

ABSTRACT

Real- time identification of the running state is one of the crucial technologies for a advance rail vehicle. But, it's a grueling to directly real- time sense the complex handling countries of the rail vehicle on an Internet of effects(IoT) edge device. Traditional systems generally upload a large quantum of real- time data from the vehicle to the pall for identification, which is delicate and hamstrung. In this paper, an advance identification system for rail vehicle running state is proposed grounded on bitsy Machine Learning TinyML) technology, and an IoT system is developed with small size and low energy consumption. The system uses a Micro-Electro-Mechanical System(MEMS) detector to collect acceleration data for machine literacy training. A neural network model for feting the running state of rail vehicles is erected and trained by defining a machine learning running state bracket model. The trained recognition model is stationed to the IoT device at the vehicle side, and an offset time window system is employed for real- time state seeing. In addition, the seeing results are uploaded to the IoT garçon for visualization. The trials on the shelter vehicle showed that the system could identify six complex handling countries in real- time with over 99 delicacy using only one IoT microcontroller. The model with three axes converges faster than the model with one. The model recognition delicacy remained above 98 and 95, under different installation positions on the rail vehicle and the zero- drift miracle of the MEMS acceleration detector, independently. The presented system and system can also be extended to edge-apprehensive operations of outfit similar as motorcars and vessels.

INDEX TERMS *TinyML, IoT, running state, smart rail vehicle, artificial neural network.*

I. INTRODUCTION

Enabling rail vehicles to have tone- mindfulness through detectors with low energy consumption is a challenge as the rail vehicle assiduity is fleetly developing towards intelligence and low carbonization. Real- time identification of the running state is the crucial technology for realizing the tone- mindfulness of smart rail vehicles. still, relating colorful complex handling countries with low energy consumption is a delicate task because the computing power of edge bias at the vehicle side is low and the state data covered by detectors is complex.

Presently, state monitoring is substantially concentrated on the bus 30 motive sphere in the being studies . Most state monitoring systems of these researches are achieved by the real-time acquisition of vehicle-side ECU sensors or GPS data which is sent to the cloud when the vehicle is moving. States results are fed back to the vehicle after using complex algorithms in the cloud to identify the various states of the vehicle. This type of system is not suitable for smart rail vehicles because of its disadvantages and limitations such as high cost, high power consumption, large size, poor real-time performance, and complicated structure. In contrast, the edge state sensing system with small size, low cost, and low power consumption has high practical and economic value for intelligent rail vehicles. For example, the system can record the running states of each vehicle, and provide accurate and quantitative data for structural health monitoring and condition-based maintenance of rail vehicles. In addition, this type of system can provide long-term tracking and monitoring services for rail vehicles (such as rail wagons) only using solar power.

Therefore, carrying out the research on edge identification technology will have important theoretical research and engineering application significance to the design, manufacture, and maintenance of smart rail vehicles.

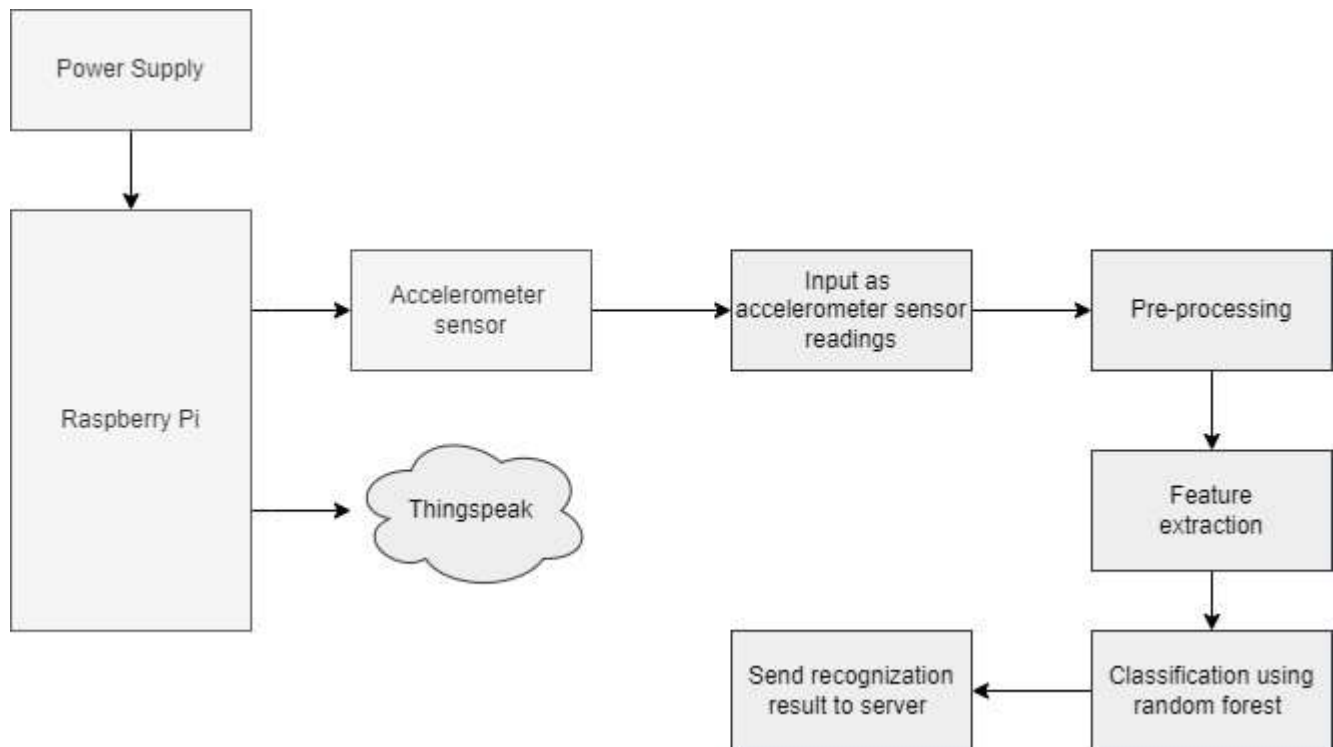


Figure 1 :- Diagram of the Enhancing Safety in Rail Vehicle using TinyML and IoT

With the development of artificial intelligence, some researchers have used machine learning in automobile vehicle intelligence. These studies include autonomous vehicle driving ,intelligent vehicle classification, and intelligent vehicle monitoring . Some researchers considered vehicle running safety on vehicle intelligent classification, which classified and identified the vehicle running states. Some researchers have studied the state recognition methods for various equipment.

II . MODULE

A . Preprocessing

Preprocessing refers to all the transformations on the raw data before it is fed to the machine learning or deep learning algorithm. For instance, training a convolutional neural network on raw images will probably lead to bad classification performances .

B. Feature extraction

Random Forest is primarily used as a machine learning algorithm for classification and regression tasks, rather than feature extraction. However, you can still utilize a Random Forest model to gain insights into feature importance , which indirectly helps with feature selection or extraction.

C . Segmentation

Segmentation is a process of dividing a dataset into distinct groups or segments based on certain characteristics or features. Random Forest is a popular machine learning algorithm that can be used for segmentation tasks. It's typically used for classification and regression tasks, but it can also be adapted for segmentation.

D. Classification

Random Forest is a powerful machine learning algorithm used for classification and regression tasks. It's an ensemble learning method that combines the predictions of multiple decision trees to improve accuracy and reduce overfitting

III . ALGORITHM

Random Forest Algorithm :

Random Forest is an ensemble machine learning algorithm that is used for both classification and regression tasks. It was first introduced by Leo Breiman and Adele Cutler in 2001. The algorithm is particularly popular in the field of data science and has been applied to various domains due to its robustness and versatility. Random Forest is a versatile algorithm that works well in many situations. However, it's not without limitations, such as decreased interpretability compared to a single decision tree and potential difficulties in handling imbalanced datasets. Nonetheless, it remains a popular choice in many machine learning applications due to its excellent performance and ease of use.

RANDOM FOREST IMPLEMENTATION STEPS :

- **Step 1:** Import the necessary libraries, including Random Forest Classifier for the Random Forest model, datasets for loading data, train test split for splitting the dataset, and accuracy score for evaluating the model.
- **Step 2 :** Load a sample dataset and split it into training and testing sets.
- **Step 3:** Create a Random Forest Classifier with the Random Forest Classifier class. You can adjust hyperparameters like the number of trees as needed.
- **Step4 :** Fit the classifier to the training data using the fit method.
- **Step 5 :** Make predictions on the test data using the predict method.
- **Step 6 :** Evaluate the model's performance using accuracy as the metric.

IV. CONCLUSION

Tiny ML technology is an effective way to make rail vehicles intelligent and perceptive. The constructed system is lowcost, small-sized, and low energy consumption. With only one micro IoT edge device on the vehicle side, each carriage can recognize complex running states . The following conclusions are obtained from this paper's research:

- (1) The recognition model and system proposed in this paper can identify multiple complex running states in real time, and the monitoring results are accurate. The recognition model is robust when using the Sigmoid function as the activation function. The subway experiments showed that the system was capable of identify six complex running states in real-time and the identification accuracy was higher than 99%. Moreover, the experiment shows that the acceleration data can be used for monitoring data for identifying the running state of smart rail vehicles.
- (2) Three-axis acceleration data monitoring is better than one-axis monitoring. Using three-axis acceleration data as model input for model training is faster, more accurate, and has lower loss values than using one-axis acceleration data.
- (3) The sensing system can obtain high accuracy in running state recognition regardless of whether it is installed in the front or rear of the carriage. The experiment on the subway revealed that the recognition accuracy of different installation positions was high, reaching more than 98%. The model has good reliability and generalization capability.
- (4) The established model retains some high-running state recognition capability under zero-drift acceleration. The experimental result showed that the recognition accuracy of the model was still high, reaching more than 95%, with out removing zero drift. Furthermore, it indicated that the zero-drift has a certain influence on the recognition accuracy and the zero-drift should be removed during monitoring for obtaining better results.

The method proposed in this paper can identify more complex running states such as turning, collision, rapid acceleration, slow acceleration, emergency braking, etc. In addition, the system is suitable for mass installation on rail vehicles. The identification results can provide essential data support for structural health monitoring and condition based maintenance. The method and system can also be applied to various rail vehicles like high-speed trains, railway wagons, and intercity trains, as well as other equipment with Tiny ML chips such as cars, ships, aircraft, and spacecraft.

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