Towards Edge Intelligence: Real-Time Driver Safety in Smart Transportation System

Md. Shirajum Munir, Sarder Fakhrul Abedin, Kitae Kim, and Choong Seon Hong
Department of Computer Science and Engineering, Kyung Hee University, South Korea.
{ munir, saab0015, glideslope, cshong }@khu.ac.kr

Abstract

In this research, we introduce an edge intelligence model for real-time driver safety in the smart transportation system to enhance the fifth-generation (5G) networks to the beyond 5G. In order to do this, first, we design an intelligent model for road side unit (RSU) that facilitates driver activity recognition in the edge of the networks, where we adopt the concept of capsule network. Second, utilizing this model, we propose a real-time safety notification algorithm for RSU, where this algorithm is capable of sending real-time safety notification to the vehicle driver as well as to centrally controlled road safety agent. So, the risk of road accident due to distracted driving is minimized. Third, we implement our own environment to validate the proposed model, where the benchmark state farm distracted driver detection dataset is used for the model training. Finally, we show that the higher accuracy in classification of the driver activity justifies the performance of the proposed method with a less computational complexity safety notification algorithm.

1. Introduction

In recent years, smart city enables artificial intelligence (AI) to fulfill smart services [1] under the delay constraint [2] that includes smart transportation, smart health care, emergency services, and so on. Therefore, edge computing [3] is a prominent facilitator for this sustainable growth of smart applications, in which edge intelligence is now growing to evolve the 5G technology. The power of intelligent edge computing is already established in the field of smart energy management [4] in wireless networks, smart home energy management [5] and so on.

The smart transportation system already facilities autonomous vehicles, smart parking, driving assistant and other applications. However, for driver safety, it is essential to introduce real-time road safety model based on a driver's current activities, in which activities can be monitored by a safety agent. In this paper, we propose an edge intelligence model under the smart transportation system. The proposed model is able to provide a real-time safety notification to the both on-vehicle driver and safety agent for road safety. Additionally, this model is one of the first model, which enables the edge-AI in the RSU of the smart transportation system.

2. Smart Transportation Scenario and Methodology

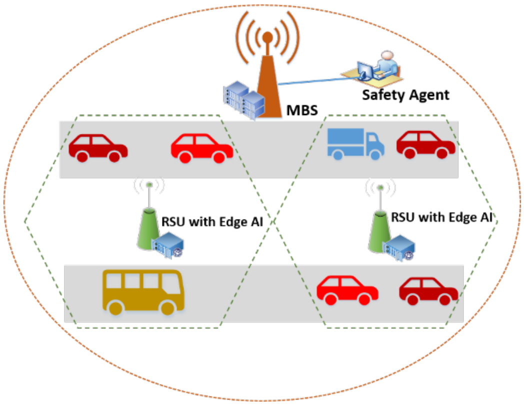

Figure 1: Real-time driver safety in smart transportation scenario

The scenario of smart transportation for real-time driver safety application is presented in Figure 1. In this system model, we consider a set of road side units (RSUs) $R = \{1, \dots, \mathrm{R}\}$ that are deployed under a macro base station (MBS), where each RSU is able to support on edge artificial intelligent (edge-AI) unit with the corresponding edge computing server. This edge-AI unit is capable of serving the driver safety application. Let us consider a set of vehicles $V = \{1, \dots, \mathrm{V}\}$ are associated with RSU r using a given vehicle association indicator θ_{rv}, where $\theta_{rv} = 1$ if vehicle v is associated with RSU r, and 0 otherwise.

A safety agent is responsible for monitoring the entire smart transportation system, while each vehicle v contains the driver safety application on the vehicle dashboard and camera sensor continuously captures real-time driver image for the safety measurement. On one hand, the onboard application notifies the driver safety status using its own application. On other hand, the RSU send the driver activity to the safety agent, where we assume that the vehicle v communicates with RSU r using ultra-reliable low latency communication (uRLLC) and uses the grant free uplink access [6] through the 5G new radio.

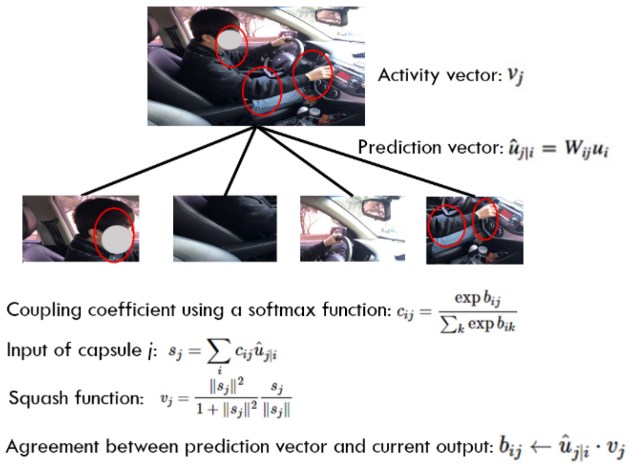

Figure 2: Capsule network [7] for driver activity classification

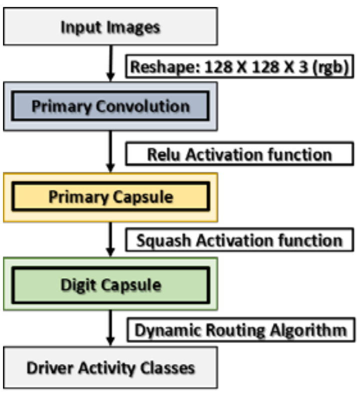

Figure 3: Capsule network training model of RSU edge-AI

In order to provide edge-AI in RSU for driver classification, we adopt capsule network [7] and dynamic routing algorithm (as seen in Figure 2.). This method is capable of handling the different angles of the same object that changes the meaning of the object. In case of driver activity classification, this is one of the important features which cannot be handled by other states of art method (i.e., convolutional neural network (CNN)) due to pooling algorithm.

3. Training Model and Real-Time Driver Safety Algorithm Design

The capsule training model of RSU edge-AI is depicted in figure 3. This model consists of primary convolution (filters=256, kernel =7, strides=1), primary capsule (no. of capsules=32, dimension of capsule=8, kernel=9, strides=2), and digit capsule layer. We train this model in offline and distribute among the RSUs in a smart transportation network.

The proposed real-time safety notification algorithm is as follows:

Algorithm 1: *Real-Time Safety Notification*

1. Input : Camera sensor image
2. Output: Warning/Safe drive
3. session.run(init)
4. saver.restore(session, save_model)
5. *While(True &&* $\theta_{rv} = 1$*)* {
6. image_file = dir+*.jpg
7. Image = misc.imread(image_file)
8. image = misc.imresize()
9. validation_batch_x()
10. pred = argmax(digitCaps_len.eval())
11. NotifyDriver (pred)
12. NotifySafetyAgent (pred)
13. updateCapsuleModel()
14. }

In Algorithm 1, we consider the camera sensor image is already received by RSU from a vehicle through the grant free uplink protocol. This algorithm loads an already trained model (lines 3 to 4), validates the input sensor data (lines 6 to 9), and predict the driver activity in line 10. Finally, notify to the vehicle (line 11), send it to centralized safety agent (line 12), and update the existing model (line 13).

4. Experimental Result

We have implemented our proposed model on python platform, and use the state farm distracted driver detection dataset [8] for model training, which is used in many distracted driver classification problems. This dataset consists of 10 types of driver's activity, which includes safe driving, talking on the phone left, texting left, talking on the phone right, texting right, operating radio, drinking, reaching behind, hair and makeup, and talking to a passenger. Additionally, we have trained the model based on those classifications, in which we have used 14400 training samples, and 8000 samples for validation. Later, we have used this trained model to verify the proof of concept (PoC) of a real-time driver safety application in smart transportation scenario.

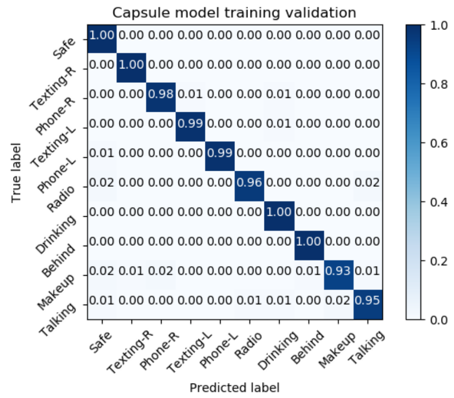

Figure 4: Training validation result using validation dataset

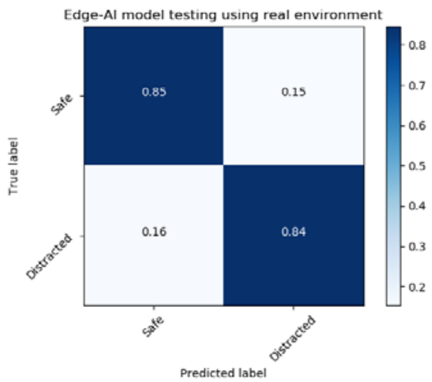

Figure 5: Confusion matrix of edge-AI model testing

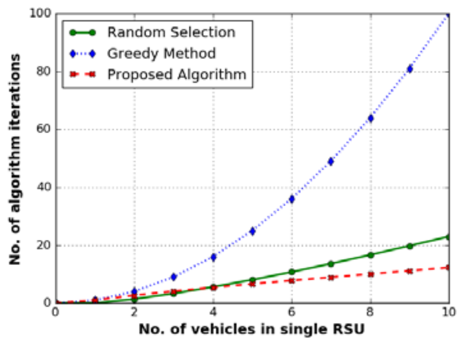

Figure 6: Complexity analysis of real-time safety notification

First, Figure 4 illustrates the training validation, where average accuracy is around 93% for hair and makeup classification. Overall training accuracy is higher since the features of other classes are captured with a higher reliability due to the usages of capsule network that capable of finding a relationship among the features.

Second, we have implemented a real testing environment, where we validate our own generated testing dataset. Figure 5 represents a confusion matrix of test validation result, where accuracy gain up to 85% in the dynamic edge-AI environment.

Finally, Figure 6 illustrates the no. of algorithm iterations of the proposed real-time safety notification (Algorithm 1), where the complexity of proposed algorithm belongs to $O(n + lo\,g(n)) \approx O(n)$. This figure discretized that when the number of vehicles is increasing then the complexity of the proposed algorithm is decreasing. On other hands, the complexity of random selection and greedy methods are $O(n * log(n))$ and $O(n^2)$, respectively.

5. Conclusion

In this paper, we have studied edge-AI based real-time driver safety in the smart transportation system, which is a novel approach that enables the physical safety for the vehicle drivers. The proposed edge-AI model in RSU can recognize driver current activity in real-time and notify the driver as well as to the safety agent. Additionally, the proposed algorithm significantly reduces the computational complexity when the number of vehicles is increased in RSU as compare with two baseline methods.

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