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Using Convolution Neural Networks for Improving Customer Requirements Classification Performance of Autonomous Vehicle

Hao Wang[1], Asrul Adam[1] and Fengrong Han[2]

[1]*College of Engineering, University Malaysia Pahang, Kuantan, Malaysia*
[2]*Faculty of Electrical & Electronics Engineering, University Malaysia Pahang, Pekan, Malaysia*

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Abstract: Customer requirements are vital information prior to the early stage of autonomous vehicle (AV) development processes. In the development process of AV many decisions have been made concerning customer requirements at the first stage. The development of AV that meets customer requirements will increase the global consumer and remain competitive. Safety and regulation are one of crucial aspect for customers that requires to be concerned and evaluated at the early stage of AV development. If safety and regulation related requirements did not well identified, AV developer could not develop the safest vehicles due to the huge compensation of accidents. To efficiently classify customer requirements, this study proposed an approach based on natural language processing method. For classification purpose, the customer requirements are divided into six categories that the concept are come from the quality management system (QMS) standard. These categories will be as input for the next process development in making the best decision. Most of conventional algorithms, such as, Naive Bayes, MAXENT, and support vector machine (SVM), only use limited human engineered features and their accuracy for customized corpus in sentences classification are proven low which is less than 50 percent. However, in literature, convolution neural networks (CNN) have been described efficiently to overcome the customized corpus of sentence classification problems. Therefore, this study implements CNN architecture in customized corpus classification operations. As the results, the accuracy of CNN classification has improved at least 6 percent compared to the conventional algorithms.

Keywords: Convolution Neural Network, Autonomous Vehicle, Natural Language Processing, Quality Management, Sentence Classification, Customer Requirements

1. INTRODUCTION

Autonomous vehicles (AV) is the future of transportation that it is driverless, fully automated, and coming to roadways around the world [1]. Several pioneer AV's industries, for example, Tesla, Uber, and Waymo are most of them under trial stage in developing AV and need for more road testing. This technology is forecasted profoundly impact the transportation system of the world in this decade [2]. Therefore, it gains more attention from government agencies, universities, and as well as many automotive industries.

The hazards of autonomous vehicles should be considered according to functional safety standards in automotive and AV industries. Quality management method is a systematically approach to add value on the process development of AV that needs more consideration on safety and regulations. In general, customer requirements on safety and regulations have to be identified at the early stage, and then classify them accordingly for further procedures [3]. Incorporating artificial intelligence (AI) in innovative way on the process development of AV are crucially needed to assist facilitate the complex and sophisticated of conventional AV's process development. A review on the existing methods that integrated between AI and process development and the proposed of the processes specifically for AV can be found in our previous study [3]. However, it may difficult and a challenge to find ways to effectively integrate AI that fit for every process and to make it satisfy with the classification performance. Therefore, in preliminary research, this study focuses on the process of collecting customer requirements that incorporating with AI.

Customer requirements can be divided into six categories according to the information extracted from literature [3]. Those categories are 1) environment, energy, and costs, 2) function, 3) perception, 4) privacy and security, 5) safety, and 6) social, legal, and ethics. Development of the AV technology should be based on quality management frame-

E-mail address: PFD19002@stdmail.ump.edu.my, asrul@ump.edu.my, PEG18005@stdmail.ump.edu.my

work to ensure the safety of the AV's service and system [3][4]. All of these are required to focus on the analyzing the customer requirements and experiences on AV because most of the customers have perception that AV are not safe. Many researchers contribute a lot on customer concerns that related with autonomous vehicles. They contribute on the area of the motivation, demand, and perception on autonomous vehicles. Comparing to previous research works [1][2][5][6][7][8][9], this study comprehensively covers the wide area of research field on development of AV. Some existing research works focus in dedicate area, for example, safety [4][10][11][12][13][14][15][16][17][18], privacy and security [19][20][21][22][23], energy consuming and costs [24][25][26][27], legal and regulatory [28][29][30][31][32][33][34][35][36][37][38][39][40]. Our previous study has collected the most of the latest research works on specific area and make the database on customer requirements more comprehensive including almost all of the aspects [41]. Therefore, investigating the customer's opinions on AV become more and more important to ensure the highest quality of service and system for AV that will be developed and delivered to customers [8].

AI is well developed and used in automotive industries recent years. Although our previous research work introduced different kind of algorithms, for example, Naive Bayes, MAXENT, and support vector machine (SVM) to improve the efficiency of customer requirements classification via natural language processing (NLP) [41], the accuracy has maintained in the low level that lower than 44 percent. Some researchers have introduced convolution neural networks (CNN) to text classification to improve the accuracy recent years [41][42][43][44][45]. Several researchers have introduced CNN and optimized CNN in fake news and offensive language identification [46][47][48]. CNN is not only useful for traditional data classification, however it is also used in sentence classification, recently [49][50][51][52][53][54][55]. Most of the researches focus on question classification and the corpus in which have been published on websites for many years. A new hybrid approach of spotted hyena optimization integrated with quadratic approximation developed for training wavelet neural network [56]. The latest deep multi-model CNN developed for multi-instance multi-label image classification [57]. A combined loss-based multiscale fully convolutional network created for high-resolution remote sensing image change detection recently [58]. Many higher-level methods developed for optimize the algorithms also created recently [59][60][61]. There is only a few evidence that this kind of method works well on customer defined corpus. In this study, the customer defined corpus is created based on our previous research work [41]. This study introduces the implementation of CNN algorithm to classify the customer requirements on AV. The hyperparameters are optimized to improve the accuracy of the results.

The remaining part is organized as follows: Objectives are presented in Section 2. CNN models, materials and method are presented in Section 3. The results are shown in Section 4. The discussion for the research is shown in Section 5. Finally, the conclusion is summarized and discussed in Section 6.

2. OBJECTIVES

Different from other research work that more focused on open-source database, this study creates a specific corpus that elaborate the customs demands on AV. This kind of corpus is named as customized corpus. The objectives of this research are focus on improving the accuracy of the customer requirements on autonomous vehicle that based on customized corpus.

A. *Getting Comparison of Different Algorithms*

Previous research provides results of classification for customer requirements on autonomous vehicles. This paper aimed to compare the result with former research on the accuracy under specific training set ratio.

B. *Improving the Accuracy of the Classification*

Another objective is aimed to improve the accuracy of customer requirements classification by introducing CNN method.

3. METHOD

Nowadays, data is increasing quickly and many of them are archived in textual format. Such as webpage, email, documents. NLP could help people for their daily works. CNN has reached a level that higher than human performance in some NLP tasks. The CNN has already shown the advantages than other conventional machine learning because they learn more features from raw data. CNN have achieved excellent performance in computer vision and NLP [55]. CNN can learn from two-dimensional data. It is a powerful deep model that could leverage the spatial structure of an input to learn from data, for example CNN can process images in a two-dimensional form. In this research we will investigate how to employ the CNN method to classify customer requirements related sentences for AV. CNN is made up of layers, for example convolution layers, pooling layers, and fully connected layers. Then CNN allows people to create deeper models and obtain a better performance. In this research, we use CNN via NLP approach to classify customer requirements of AV into six groups and then improve the accuracy by optimizing the hyperparameters.

A. *Customer Requirements Classification Flow Chart*

To ensure the quality of automotive development, it should follow the predefined procedures of work according to the quality management system (QMS). Our previous study provides a systematic procedure for customer requirements classification, in which under the proposed autonomous vehicle development process [3]. Referring to Figure 1, it starts from collect customer requirements, via text file preparation, set training data, create custom corpus, and classify all of them. Finally, we exhibit the result via qualitative analysis.

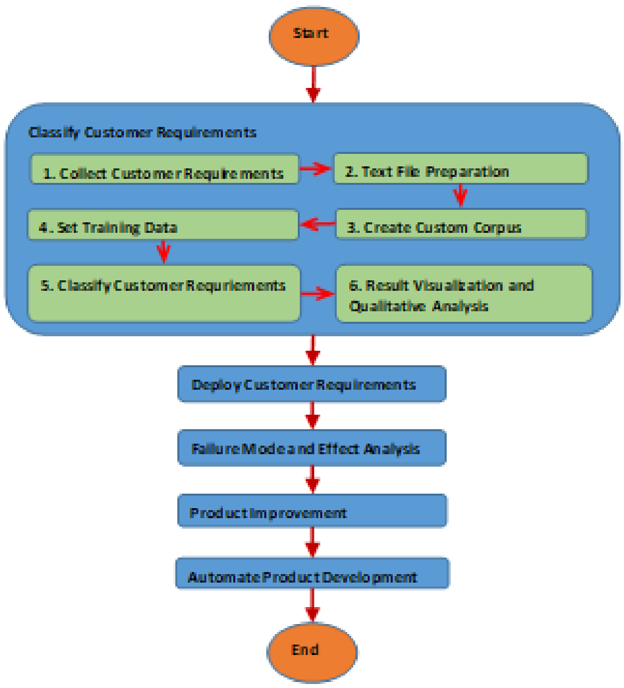

Figure 1. Customer Requirements Classification Flow Chart within the Proposed Autonomous Vehicle Development Process

B. CNN Architectures for Sentence Classification

The CNN for sentence classification is different from image classification because it is with only one dimension. In this Section, we introduce data structure, convolution operation, pooling operation first and then connect all above together.

All customer requirements are collected with the format of sentence. We assume that a sentence has t words, If the length of the sentence less than m, we set the length of the sentence to m words. Here m¿t. Then we use a vector of size f to represent the word in the sentence. Next, we put the sentences in to a batch with size d. Then the batch of sentences is represented by a d×m×f matrix. For example, the three sentences of customer requirements in this research:

- Cost savings.
- Getting on at designated places.
- Getting off at designated places.

Here d=3, the maximum number of words of the three sentences is 5, then we get m=5, The three sentences have totally eight distinct words, so we put f=8. Now we get a 3×5×8 matrix shown in Figure 2.

Then we define convolution weight matrix with size $n \times f$, here n is the filter size for one-dimensional convolution operation. Now we have a $n \times f$ size weight matrix.

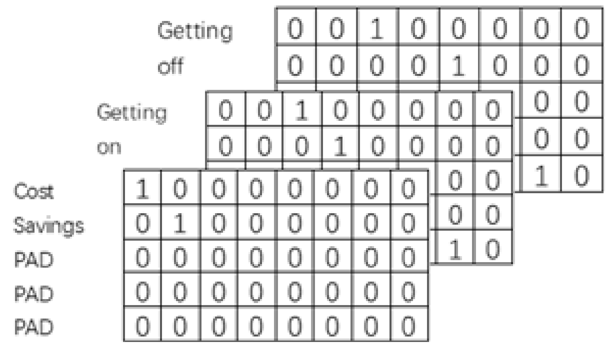

Figure 2. Sentence Matrix

Consume the input x with size $m \times f$. Next we create an output named h with $1 \times m$ size by convolving x. We define w_{ij} as the $(i, j)^{th}$ element of W, ij is the number of row and column of the element. Then we pad x with zeros. Now we have:

$$\sum_{j=1}^{n}\sum_{l=1}^{f} w_{j,l}x_{i+j-1,l}$$

and

$$h = W * x + b$$

Next, we define d as the bias, q as the number of parallel layers. Then we can go into the pooling operation. The output of the last convolution layer with size $q \times m$, the pooling layer could create an output h' with $q \times 1$ size. The formula is shown as below:

$$h' = \{max(h^{(i)}, 1 \leq i \leq q\}$$

and

$$h^i = W^i * x + b$$

Here, $h^{(i)}$ created by the $i^{(th)}$ convolution layer. $W^{(i)}$ are the weights of correspondence layer. Therefore, the maximum element of the convolution layers is transferred to vectors accordingly. The whole convolution neural network architecture is created by combining all these operations. It is shown in Figure 3.

C. Source Preparation

Different from our previous study [41], we put all corpus in one file with the labels of each categories. The label's name are abbreviations of the categories, they are 'ENV', 'FUN', 'PER', 'PRI', 'SAF', and 'SOC'. Then, we split them into two sets one is training set, another one is test set.

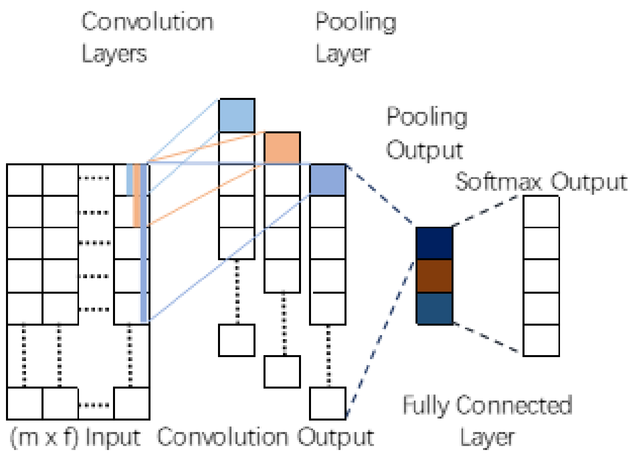

Figure 3. CNN Architecture for Customer Requirements Classification

PER:Perceived restriction in travel behaviour.
PER:Fun.
PER:Freedom.
PER:A self-driving car could cause the loss of the pleas
PRI:recording of all routes and destinations.
PRI:possible leakage of private information.
PRI:software hacking and other forms of abuse.
PRI:Prone to hackers.
PRI:Others can take over control.
PRI:A self-driving car could lead to privacy issues caus
PRI:Data abuse.
SAF:automatically braking in the cases of danger.
SAF:reducing traffic accidents due to human errors.
SAF:increase safety.

Figure 4. Data Format for Customer Requirements Classification

The training set ratio in this research is 75%. The training set format is shown in Figure 4.

D. Software for Calculation

TensorFlow is a powerful tool for artificial intelligence related calculation. It is an open source distributed numerical computation framework which released by Google. It is mainly intended to reduce the complicated details when implementing a neural network. The computation in TensorFlow mostly in dot product method through many matrices and vectors. We call a tensor that in the format of one-dimensional or a two-dimensional matrix or vector. In this research, we select Python as the basic environment and select TensorFlow as the technical tool. The results will be compared with former research under traditional method with NLTK.

4. RESULT

At the beginning, the CNN did not show the better results. After optimizing the super parameters, we finally get the results that shows the advantages of the Convolution Neural Networks. Please see the classification results in Figure 5 and Table I. Under training set 0.5, the result calculated by CNN is not better than other algorithms such as Naive Bayes, Maxent-gis, SVM-LinearSVC. When we add the training set ratio to 0.75. The accuracy result from CNN become more higher than other traditional algorithms. At least 6% better than SVM-LinearSVC, 12% better than Naive Bayes and Maxent-gis.

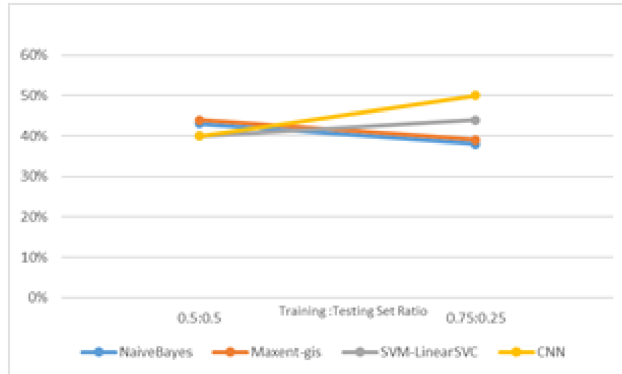

Figure 5. Comparison of Accuracy by Different Algorithms

TABLE I. COMPARISON OF ACCURACY BY DIFFERENT ALGORITHMS

Algorithm	Training set ratio 0.5	Training set ratio 0.75
NaiveBayes	0.43	0.38
Maxent-gis	0.43	0.38
SVM-LinearSVC	0.40	0.44
CNN	0.40	0.50

5. DISCUSSION

The training set ratio is an important factor that impact the accuracy of the calculation. Normally the accuracy increases along with the training set ratio. From Table I we can see that the result from SVM and CNN, when training set ratio increase from 50% to 75%, the accuracy improved 4% and 10% respectively. But the accuracy results from NaiveBayes and Maxent all decrease 5%. It proves that the unsupervised learning from CNN provide better result than other algorithms. The better results from CNN because it is made up of layers that allows people create deeper models. SVM also show better result because it equipped with loss function to deal with the data that not linearly separable. The disadvantage of NaiveBayes and Maxent is they are more suitable for linear data. But the results should be improved even from NaiveBayes and Maxent along with the training set increasing. The decrease caused by limited dataset. The corpus used in this study is unique due to no previous research that focus on creating a comprehensive customer requirements corpus for autonomous vehicle. Therefore, it is difficult to create a large database in this area in a short time.

TABLE II. TESTING ACCURACY FROM DIFFERENT BATCH SIZE

Batch Size	Accuracy
6	0.37
12	0.46
18	0.50
24	0.38
30	0.30

Optimization are necessary for the Convolution Neural Networks because many hyperparameters exist. Here author provide the example of how batch size impact on the accuracy. Please refer to Table II.

The batch size defines the number of samples that will be propagated through the network. The advantage of using a batch size smaller than number of all samples is that it requires less memory and quicker. However, the disadvantage of using smaller batch size is low accuracy. So, we must find a best batch size value to obtain the best accuracy. From Table II we can see that the accuracy reaches top value 50% at batch size 18. Increasing and decreasing batch are all led to lower accuracy. That means hyperparameters such as batch size, filter size, number of steps are impact heavily on the accuracy results.

The results show advantage of Convolution Neural Networks, but there are many works need to be done in the future. The accuracy still not good enough for a customer defined corpus about customer requirements on autonomous vehicle. It is only with 50% of accuracy. That means people still could not relay on computer for this task. Even no clear standard for accuracy in our system, we still need to set a target to improve the result in future research. Hyperparameters such as batch size, filter size, number of steps are impact heavily on the accuracy results. We still need further study on how to automatic detect the best hyperparameters. Furthermore, the calculation results not stable, more works need to be done in the future to investigate stability of the CNN calculation. The volume of corpus(dataset) should be expanded in the future to provide enough training set as well as obtain better accuracy.

6. CONCLUSION

This study proposes a CNN method for classifying customer requirements of autonomous vehicle. The unique customized corpus is adjusted to feed into CNN in TensorFlow. The results of the CNN and traditional NLP method are compared. Even 3% lower than traditional algorithms under 0.5 training set ratio, CNN shows advantage under 0.75 training set ratio in this study. This research illustrates that the accuracy of sentence classification by CNN at least 6% higher than traditional algorithms in NLTK when deal with the customized corpus under specific training set ratio. The limited training data sets is the key impact on the accuracy. The stability of the calculation needs to be improved. The accuracy value should be improved in the future research to meet industry requirement. Although the results in this research are not good enough, it could be a useful reference for the AV problems.

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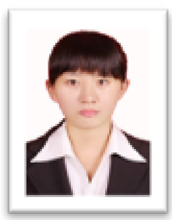
Hao Wang is currently a PHD candidate in College of Engineering, University Malaysia Pahang. His research interests include Autonomous Vehicle, Quality Management, Natural Language Processing, and Machine Learning. He has 11 years quality management experience in automotive industry and 6 years R&D and research experience.

Dr. Asrul Adam received the B.Eng. and M.Eng. degrees in Electrical-Mechatronics and Electrical Engineering from Universiti Teknologi Malaysia (UTM), Malaysia, in 2009 and 2012, respectively. He completed his Ph.D. in Signal and System from Faculty of Engineering, University of Malaya in 2017. He currently works as senior lecturer at College of Engineering, Universiti Malaysia Pahang, Malaysia. His research interests include biomedical signals processing, artificial intelligent, machine learning, and optimization.



Fengrong Han is currently working toward the Ph.D. degree in faculty of electrical & electronics engineering, University Malaysia Pahang, Malaysia. Her research interests include Localization in wireless sensor networks, Routing protocols, Multi-objective optimization, Signal processing, Intelligent system, Deep learning for Image and Signal classification. She has 3 years of software developing experience and 3 years of research experience.