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Road Surface Data Collection and Analysis using A2B Communication in Vehicles from Bearings and Deep Learning Research*

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Abstract

This paper discusses a deep learning-based road surface analysis system that collects data by installing vibration sensors on the 4-axis wheel bearings of a vehicle, analyzes the data, and appropriately classifies the characteristics of the current driving road surface for use in the vehicle's control system. The data used for road surface analysis is real-time large-capacity data, with 48K samples per second, and the A2B protocol, which is used for large-capacity real-time data communication in modern vehicles, was used to collect the data.

CAN and CAN-FD commonly used in vehicle communication, are unable to perform real-time road surface analysis due to bandwidth limitations. By using A2B communication, data was collected at a maximum bandwidth for real-time analysis, requiring a minimum of 24K samples/sec for evaluation. Based on the data collected for real-time analysis, performance was assessed using deep learning models such as LSTM, GRU, and RNN. The results showed similar road surface classification performance across all models. It was also observed that the quality of data used during the training process had an impact on the performance of each model.

Keywords : Deep learning-based road surface analysis, Data collection, A2B, Real-time analysis system, Vibration sensoror

JEL Classification Code : L62, L86, Q32

1. Introduction[1]

Recently, innovative changes such as the introduction of autonomous driving technology have been taking place in vehicles, and the importance of technology to intelligently control and manage vehicles by installing various sensors in them is increasing. In order for such technology to be effective, it must combine the development of sensors that acquire precise data, the advancement of communication protocols that collect acquired data, and data analysis technologies that analyze collected data and immediately derive results to enable real-time feedback.

This paper briefly reviews each of these foundational technologies and demonstrates the effectiveness of real-time collection and analysis of large-volume data in vehicles by integrating these technologies and tentatively applying them to a system that conducts road surface analysis as an application.

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The organization of this paper is as follows. In Chapter 2, we introduce the background technologies related to the proposed system.

We discuss the vehicle's internal communication system and the deep learning model. In Chapter 3, we describe the proposed system. The overall structure and details of the vibration sensor, the in-vehicle communication module, the data collection system, and the analysis system are each described. In Chapter 4, we present the results of analyzing actual data using the proposed system. The results obtained from actual vehicle operation are presented, and it was confirmed that the road surface analysis model has the necessary predictive performance. Finally, in Chapter 5, we present our conclusions and future research tasks.as managers from both for profit and not for profit corporations.

2. Literature Review

2.1. Vehicle Data Collection

To measure vibrations occurring from the vehicle's wheels, a vibration sensor and a communication system capable of collecting sensor data are essential. While there are ICP (Integrated Circuit Piezoelectric) sensors for vibration sensing, these are large and expensive, making them unsuitable for application in our system. Using smaller, lower-specification MEMS (Micro Electro Mechanical Systems) sensors is appropriate, and we chose a sensor from multiple MEMS sensors that has characteristics usable in the data communication system mentioned below (Jung et al., 2019).

Traditionally, CAN (Controller Area Network)/CAN FD(Controller Area Network Flexible Data) has been used as the in-vehicle communication system to transmit data generated from vibration sensors. However, even CAN FD has a limited maximum data transmission rate of 100Kbit/s ~ 5Mbit/s, and separate wiring needs to be reinforced considering collisions with the in-vehicle control signal delivery system. When using CAN FD, it is typically possible to transmit and collect data at around 6400 samples/sec or 8K samples/sec (De Andrade et al., 2018).

However, for data analysis using deep learning models, more precise resolution vibration data is needed, so we adopted the A2B (Automotive Audio Bus) communication system capable of collecting data at 48K samples/sec. The A2B communication system is becoming increasingly adopted in high-end vehicles and electric cars for purposes like the recent vehicle's RANC (Road-noise Active Noise Control) functions. The Figure 1 shows the A2B communication architecture, where each of the four wheels of a vehicle can have a slave node and a single A2B master node can control them (Triggs, 2020).

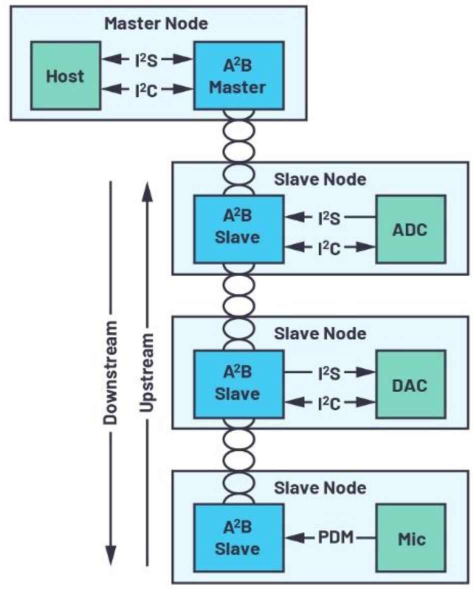


Figure 1: A2B architecture

Figure 2: Sensor Module (MEMS and A2B transceiver)

The Figure 2 represents the sensor data acquisition module using A2B communication implemented in this paper. We used Analog Devices' AD2328 chip as the A2B transceiver and adopted their ADXL317 as the MEMS sensor. We installed these sensor modules on all 4-wheel bearings of the vehicle and simultaneously collected data for the x/y/z axes. Each axis's data is composed of 14 bits, which are transmitted on each 2 Byte Word. The A2B communication system used in this sensor module simultaneously transmitted the data of each of the 4 wheels x 3 axes through a single line.

2.1. Deep Learning-Based Model

In the proposed system, we considered LSTM (Long Short-Term Memory), GRU(Gated Recurrent Unit), and RNN(Recurrent Neural Network) as deep learning-based models and verified the effectiveness of road surface analysis using these three models, each exhibiting different characteristics (Baskar et al., 2013; Zargar, 2021).

LSTM has an architecture that can remember words from long ago or recently, possessing long-term dependencies that can remember information from a long time ago. LSTMs have the advantage of being able to control each memory and result, but they also have the drawback of the possibility of overwriting memory and slower calculation speed. The LSTM structure is like a chain, as shown in the Figure 3, but the repeating module is structured for four layers to exchange information, not a single tanh layer.

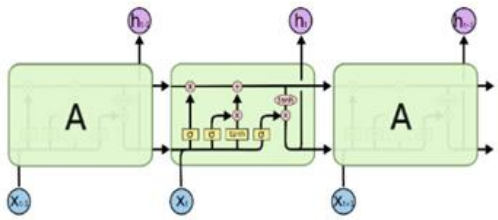


Figure 3: LSTM structure

GRU simplifies the computation for updating the hidden state in the model with a pinhole connection to LSTM. It has the advantage of faster computation speed and no possibility of memory being overwritten like LSTM. However, it has the disadvantage that it is impossible to control memory and results. The GRU structure, as shown in the Figure 4, is similar to the LSTM structure, but instead of a cell and an output gate, it adds a Reset Gate and Update Gate to decide how to reflect past information.

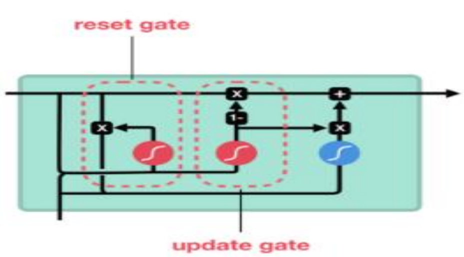


Figure 4: GRU structure

Simple RNN is the simplest form of RNN, and it has the advantage of being useful when you want to quickly create a model. However, it has the problem of Long-Term Dependency, and as the length between the input and output data increases, the correlation decreases. In other words, it depends on past information to obtain the current prediction, but if the past point is too far away, it is difficult to solve the problem. The Simple RNN structure, as shown in the Figure 5, looks like a structure where simple networks are connected in series.

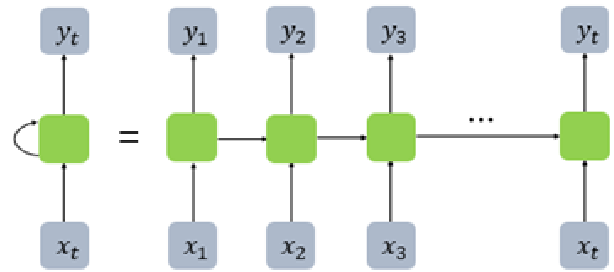


Figure 5: Simple RNN structure

As mentioned earlier, in order to analyze the road surface in real-time during driving, it is necessary to have a deep learning model that can handle high-resolution data. These three models were selected considering these points, and by analyzing the trends and variations of data over time, they can analyze the vibration values of the road surface and effectively extract the characteristics of the current driving road surface.

2.1. Related Research

So far, there have been studies using vibration or noise data from vehicles. In particular, development of diagnostic technology using vibration data has taken place (Noh et al., 2023). In this paper, an artificial intelligence-based diagnostic technology was developed using the noise/vibration data of the automobile powertrain, expecting cost savings in quality and work efficiency of the service. Also, there has been research using relative vibration data for durability reliability evaluation, (Pentachloride, N. METALLURGICAL ABSTRACTS) which can also be considered a type of diagnostic technology.

In the research on the braking force calculation system for autonomous vehicles (Son & Jeong, 2022), a system was developed that classifies the condition of the road using data other than the visual information of the vehicle and calculates the optimal braking force during driving. There is also a case where a method for road surface estimation and CDC control was studied by installing an accelerometer on the wheel bearing, like this paper, and in this paper, real-time FFT analysis technology was used (Jung & Koo, 2019).

This research is similar in that they can provide safety and convenience of driving by using vehicle data analysis, but in this paper, it can be said that it proposes example technology that can systematically collect large amount of real-time precise data using the latest A2B communication protocol and utilize it.

3. Research Methods

3.1. Overall Structure

Figure 6 shows the overall structure of the system. Each of the four wheels of the vehicle is equipped with an A2B slave and sensor module, and the A2B Master retrieves data from the slave via A2B communication. The Data Acquisition S/W module can collect vibration data through audio channels from the A2B Master, and the collected data is forwarded to the Data Analysis module. The Data Analysis module contains a deep learning model and classifies the characteristics of the currently driving road surface in real time based on the results learned in advance.

The Data Acquisition module also incorporates a preprocessing function. In the simple data collection phase, the current data being collected is tagged and stored with the road surface value specified in the GUI (Graphic User Interface) subsystem. This tagged data is later used by the Data Analysis module for training the deep learning model.

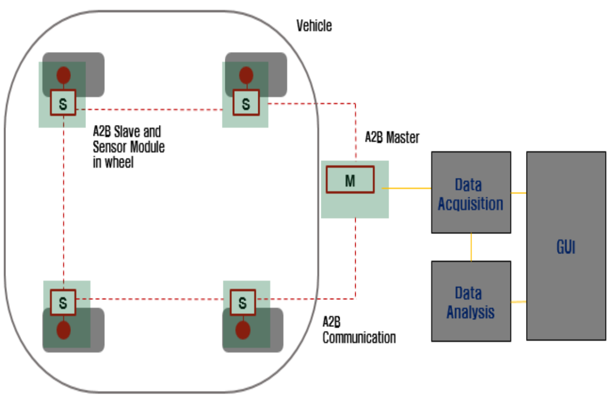


Figure 6: Overall System structure

The Figure 7 shows the deep learning modeling structure of the Data Analysis module. At the top layer, there are LSTM, GRU, and Simple RNN neural network layers, and below that, there is a dropout layer to prevent overfitting. Ultimately, the current road surface is inferred after passing through two layers of dense layers.

In Figures 7 each field denotes the output shape as 256 at the optimal stage and the dropout stage. The dense stage is conducted in two steps: the first step is 128, and the second step represents the final results of Asphalt, Cement, and Gravel with a total of 3 output shapes. The third item, "Param #", refers to the number of parameters at each modeling stage.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 256)               266240

 dropout (Dropout)           (None, 256)               0

 dense (Dense)               (None, 128)               32896

 dense_1 (Dense)             (None, 3)                 387

=================================================================
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru (GRU)                   (None, 256)               200448

 dropout (Dropout)           (None, 256)               0

 dense (Dense)               (None, 128)               32896

 dense_1 (Dense)             (None, 3)                 387

=================================================================
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn (SimpleRNN)      (None, 256)               66560

 dropout (Dropout)           (None, 256)               0

 dense (Dense)               (None, 128)               32896

 dense_1 (Dense)             (None, 3)                 387

=================================================================
```

Figure 7: LSTM, GRU, Simple RNN Result

3.2. Data Receiving Program

The Figure 8 shows the data collection program used in this paper. The data collection program displays vibration data in real-time on the screen, showing the shape of the vibration, and depending on the state of the road currently being driven, it tags the data with user-specified tag values and saves the data. This is then preprocessed into a data format that can be used for later learning.

The data collection program was written using Python. By collecting data and preprocessing it at the same time through this program, the efficiency of the system was improved. In supervised learning, data needs to be classified in advance by the user according to the characteristics of the data. By using a data collection program with built-in preprocessing functionality, it was possible to collect and classify large amounts of real-time data, like sensor data.

Figure 8: Data receiving program

3.3. Data Collection Process

The data collection for actual deep learning model training took place on the following roads. Firstly, the asphalt was from Doan-dong road in Seo-gu, Daejeon, the gravel road was from Jungri-dong in Daedeok-gu, Daejeon, and the cement road was from Sanseo-ro in Jung-gu, Daejeon.

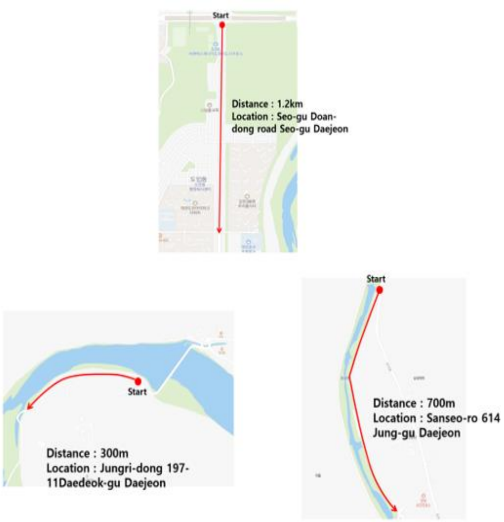


Figure 9: Raw data receiving map

The collected data is approximately 700MB, and a total of about 30 minutes of data has been collected. Each data went through a preprocessing step at the time of collection and was stored along with tags indicating from which road the data was collected, and the collection time information. The Figure 10 shows a sample of the raw data collected.

By conducting this preprocessing in real-time, we reduced the traditional two-step process of manually classifying each data and performing deep learning training into a single step, confirming the time-saving effect.

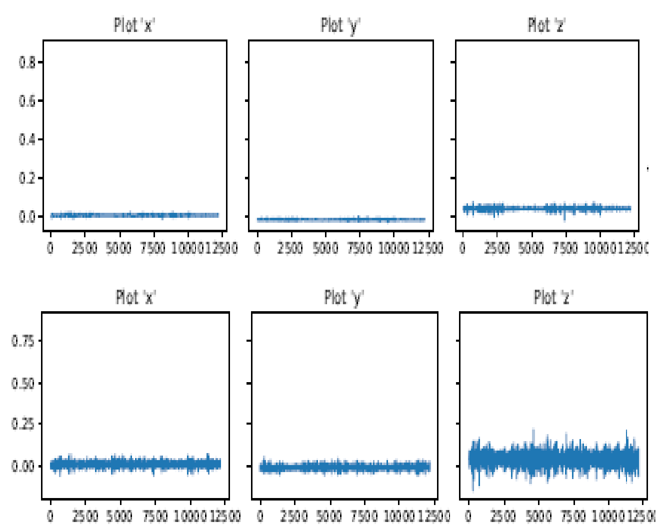
The Figure 11 visualizes the vibration data seen from asphalt, cement, and gravel roads, respectively.

The first field represents the data acquisition time, the 2~4 fields represent the vibration data of the x/y/z axes respectively, and the last field indicates the road surface type of the acquired data.

It can be confirmed that a lot of vibration is applied in the direction of the z-axis, and it can be seen that there are significant changes in the vibration values depending on the characteristics of each road surface.

20220927_094949	0.000249	9.99E-05	0.000516	cement
20220927_094950	0.00053	0.000165	0.000725	cement
20220927_094951	0.00031	0.000112	0.000639	cement
20220927_094952	0.000231	0.000106	0.000479	cement
20220927_094953	0.000188	9.03E-05	0.000432	cement
20220927_094954	0.000253	7.76E-05	0.00038	cement
20220927_094955	4.45E-05	3.80E-05	9.14E-05	asphalt
20220927_094956	6.55E-05	3.98E-05	8.48E-05	asphalt
20220927_094957	3.14E-05	3.11E-05	5.20E-05	asphalt
20220927_094958	4.17E-05	4.05E-05	0.000111	asphalt
20220927_094959	3.30E-05	3.39E-05	6.55E-05	asphalt
20220927_095000	5.29E-05	3.71E-05	8.23E-05	asphalt
20220927_095001	4.59E-05	3.81E-05	5.31E-05	asphalt
20220927_095002	5.16E-05	3.61E-05	7.18E-05	asphalt
20220927_095003	8.37E-05	4.55E-05	0.000126	asphalt
20220927_095004	0.000136	6.14E-05	0.000237	cement
20220927_095005	0.000334	0.000104	0.000405	cement
20220927_095006	0.000102	5.01E-05	0.000168	asphalt
20220927_095007	3.36E-05	3.27E-05	5.48E-05	asphalt
20220927_095008	2.77E-05	3.12E-05	5.00E-05	asphalt
20220927_095009	2.75E-05	3.10E-05	5.08E-05	asphalt
20220927_095010	2.80E-05	3.15E-05	5.05E-05	asphalt
20220927_095011	2.79E-05	3.14E-05	5.15E-05	asphalt
20220927_095012	3.47E-05	3.33E-05	5.40E-05	asphalt
20220927_095013	3.07E-05	3.16E-05	5.10E-05	asphalt

Figure 10: Raw data



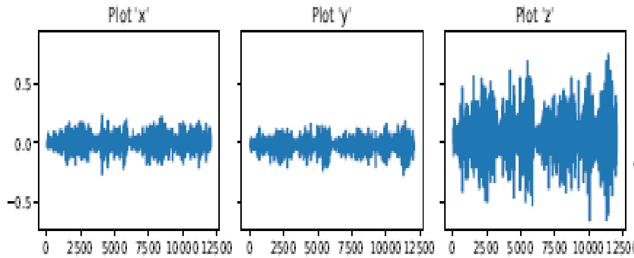


Figure 11: Asphalt, Cement and Gravel data

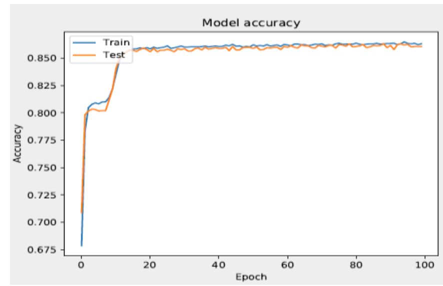


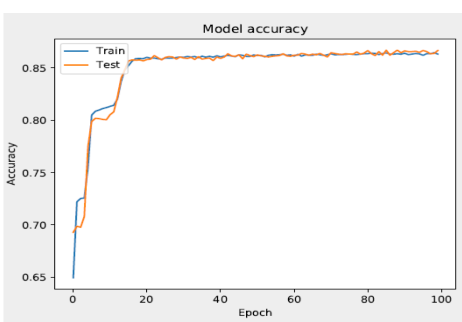
Figure 12: Asphalt, Cement and Gravel road result

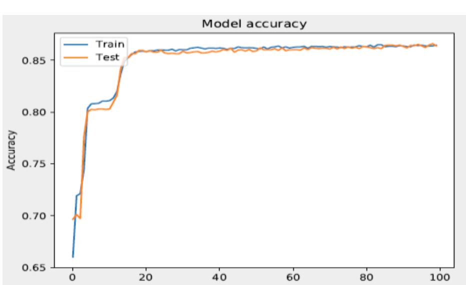
4. Results and Discussion

4.1. Results

The results of the actual application of the pavement analysis system proposed in this paper are presented. The accuracy of each model showed similar results after training, and similar results were also shown in actual environmental tests. Although the accuracy of the model is about 80-90%, when determining the condition of a specific pavement every second, it would be possible to derive the accurate pavement condition by applying methods such as deciding based on the mode value for a 10-second interval. In this case, the final accuracy of the model rose to a level of 90~95%, resulting in 5~12% performance improvement.

The Figure 12 below is a screenshot of the results from the pavement analysis program that shows the condition of the pavement every second, demonstrating the process of analyzing actual data to derive results.





The performance produced by driving on an actual road through the above process is as shown in the table below. Each row represents the actual pavement value, and each column represents the result derived by the pavement analysis system. Roughly, the probability of correctly identifying asphalt roads as asphalt was the highest, followed by gravel roads, and the probability of correctly identifying cement roads was the lowest. As seen in the data collection process, the cement road has intermediate characteristics between asphalt and gravel roads, so there was a high rate of mistakenly identifying cement roads as either asphalt or gravel roads.

Also, among the deep learning models, LSTM showed the best performance. However, the difference was not that significant, with a discernment difference of about 0.1% to 1%.

Table 1: LSTM, GRU and Simple RNN Result

Road	Model	Asphalt Detect	Cement Detect	Gravel Detect	Average
Asphalt	LSTM	670	75	0	0.8993
	GRU	663	82	0	0.8899
	Simple RNN	663	82	0	0.8899
Cement	LSTM	75	582	59	0.8128
	GRU	74	581	61	0.8114
	Simple RNN	77	581	58	0.8114
Gravel	LSTM	1	105	623	0.8545
	GRU	1	106	622	0.8532
	Simple RNN	1	113	615	0.8436

4.2. Discussion

The fact that can be learned from experimental results so far is that while the way a deep learning model is constructed does affect prediction accuracy, the quality of the collected data, specifically the data sampling rate, has an even more significant impact.

When the collected data had a resolution so low that it could not properly reflect the characteristics of the road surface, the learning process and the results did not satisfy the desired level.

However, CAN and CAN-FD, which are currently used in automobile communication, are unable to perform real-time road surface analysis due to bandwidth limitations. We overcame this by using the proposed A2B communication and confirmed that real-time road surface analysis was possible by collecting data at the maximum bandwidth supported by A2B.

When the data collected from A2B was down-sampled to enable real-time road surface analysis, the minimum down-sampling rate required to maintain the current analysis performance is 24K samples/sec.

The experimental results and methodology used in this paper differ from previous research (Varona & Teyseyre, 2020), which utilized sensors embedded in multiple vehicles' smart phones. In contrast, our work directly analyzes data from precise sensors mounted on a single vehicle. If the real-time data collection system proposed in this paper could be applied to such crowdsensing efforts, it would likely enable more accurate road surface analysis.

5. Conclusions

We propose a system that analyzes vehicle vibration data in real-time to inform the current surface condition of the road being driven on. Accurate road surface analysis requires high-resolution vibration data. However, we applied an analysis of data collected using an affordable compact MEMS sensor and an A2B communication system, and a learning model based on deep learning, in our proposed system.

We confirmed that LSTM, GRU, RNN, etc., used in the deep learning model, all showed similar road surface classification performance, and the quality of data used in the learning process of the model affected the performance of the model.

In the future, we plan to develop a model that can distinguish even if the same road becomes slippery when it rains, and such distinction will have various potential uses (Shang et al., 2021).

. The distinction of slippery roads can be used in controlling the vehicle's braking system. Also, we will plan to increase the types of classified road surfaces to distinguish more finely the roads that are ambiguous due to surface aging, thereby expanding the applicability of the model.

The vehicle vibration data collection system implemented in this paper is expected to increase its utility by enabling the collection and use of high-resolution real-time vehicle vibration data, and the road surface analysis used in this paper will be an example of this.

References

Baskar, P., Joseph, M. A., Narayanan, N., & Loya, R. B. (2013, April). Experimental investigation of oxygen enrichment on performance of twin cylinder diesel engine with variation of injection pressure. In *2013 International Conference on Energy Efficient Technologies for Sustainability* (pp. 682-687). IEEE.

De Andrade, R., Hodel, K. N., Justo, J. F., Laganá, A. M., Santos, M. M., & Gu, Z. (2018). Analytical and experimental performance evaluations of CAN-FD bus. *IEEE Access*, *6*, 21287-21295.

Jung, D. Y., & Koo, B. Y. (2019). Comparative e study of piezoelectric and MEMS accelerometers for vibrational measurements. *Journal of the Korean Society for Nondestructive Testing*, *39*(3), 168-175.

Noh, K. J, Lee, D. C, Jin, J. M, Jung, I. S, & Chang, J. H. (2023) Development of Deep Learning-based Vehicle Diagnosis Technology Using Noise Data. *Trans. Korean Soc. Noise Vib. Eng., 33*(3), 306~312, 2023.

Pentachloride, N. METALLURGICAL ABSTRACTS.

Shang, R., Zhang, Y., & Shen, Z. J. M. (2021). Analyzing the effects of road type and rainy weather on fuel consumption and emissions: A mesoscopic model based on big traffic data. *IEEE Access*, *9*, 62298-62315.

Son, S. R., & Jeong, Y. N. (2022). The Road condition-based Braking Strength Calculation System for a fully autonomous driving vehicle. *Journal of Internet Computing and Services*, *23*(2), 53-59.

Triggs, J. (2020). The A to Z of A2B Applications. *Analog Dialogue*, *54*(3), 1-4.

Varona, B., Monteserin, A. & Teyseyre, A. A deep learning approach to automatic road surface monitoring and pothole detection. *Pers Ubiquit Comput* 24, 519–534 (2020). https://doi.org/10.1007/s00779-019-01234-z

Zargar, S. (2021). Introduction to sequence learning models: RNN, LSTM, GRU. *Department of Mechanical and Aerospace Engineering, North Carolina State University, Raleigh, North Carolina*, *27606*.