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RESEARCH ARTICLE

Experimental Evaluation of Tire Tread Wear Detection Using Machine Learning in Real-Road Driving Conditions

JUN-YOUNG HAN[1], JI-HOON KWON[1], SUK LEE[1], KYUNG-CHANG LEE[2], (Member, IEEE), AND HYEONG-JUN KIM[3], (Member, IEEE)

[1]School of Mechanical Engineering, Pusan National University, Busan 46241, South Korea
[2]Department of Intelligent Robot Engineering, Pukyong National University, Busan 48513, South Korea
[3]Department of Future Automotive Engineering, Gyeongsang National University, Jinju 52828, South Korea

Corresponding author: Hyeong-Jun Kim (hj.kim@gnu.ac.kr)

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ABSTRACT The accurate detection of tire tread wear plays an important role in preventing tire-related accidents. In previous studies, tire wear detection is performed by interpreting mathematical models and tire characteristics. However, this approach may not accurately reflect the real driving environment. In this study, we propose a tire tread wear detection system that utilizes machine learning to provide accurate results under real-road driving conditions. The proposed system comprises: 1) an intelligent tire that samples the measured acceleration signals and processes them in a dataset; 2) a preprocessing component that extracts features from the collected data according to the degree of wear; and 3) a detection component that uses a deep neural network to classify the degree of wear. To implement the proposed system in a vehicle, we designed an acceleration-based intelligent tire that can transmit data over wireless networks. At speeds between 30 and 80 km/h, the proposed system was experimentally demonstrated to achieve an accuracy of 95.51% for detecting tire tread wear under real-road driving conditions. Moreover, this system uses only preprocessed acceleration signals and machine-learning algorithms, without requiring complex physical models and numerical analyses.

INDEX TERMS Classification, deep neural network, intelligent tire, tire condition monitoring, tire tread wear.

I. INTRODUCTION

With recent advancements, vehicle sensor technologies provide drivers with useful information and improve safety by identifying surrounding vehicles or measuring the states of internal components [1], [2]. Among the various sensors, tire pressure monitoring systems (TPMSs), which measure the pneumatic pressure in tires, have contributed significantly to the prevention of tire-related accidents by ensuring that drivers are aware of the current tire state [3], [4], [5]. Although considerable research has been performed on the prevention of tire-related accidents, these accidents still account for a large portion of traffic accidents. In particular, flat tires, punctured tires, and slipping caused by poor tire conditions can make vehicles uncontrollable and result in serious accidents [6], [7].

The National Highway Traffic Safety Administration (NHTSA) in the United States reported that approximately 11,000 cases of tire-related crashes occur annually [8]. Moreover, the NHTSA presented tire pressure, temperature, and tread depth as factors that could be perceived before a tire-related accident occurred. In particular, the tire tread depth is related to maintaining the appropriate grip force and braking force of a vehicle during driving [9], [10]. If tires are severely worn, handling the vehicle can become difficult because of traction loss during driving on wet or snowy roads, and there

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is a possibility of tire blowouts or fires [11], [12]. In addition, tire wear can cause noise or vibration during driving, affecting the driver's comfort [13]. In general, tires are recommended to be replaced when the tread depth is 1.6 mm; tire-related crashes are 12 times more likely to occur when the tread depth is <1.6 mm [14].

To prevent tire-related accidents, it is important to periodically monitor the tire conditions and alert the driver when they deteriorate. For example, using TPMSs can significantly improve vehicle safety [15]. In contrast, the tire tread wear is typically visually inspected by drivers or measured using a gauge. To automatically detect tire damage or elements, various sensors are installed on tires [16], [17], [18], [19], [20]. Additionally, cameras are used to automatically detect tire wear or damage [21], [22]; this research indicated that more complex sensor systems and algorithms must be used to monitor wear.

Accelerometer-based intelligent tires are sensitive to vibrations [23], [24]; thus, they are frequently used to estimate the roadway conditions [25], [26], [27], [28], tire force [29], [30], [31], [32], and slip angle [33], [34]. In recent years, several studies have been conducted on the estimation of tire wear [35], [36], [37] using intelligent tires. Jeong et al. [35] estimated dimensionless tire dynamics parameters, which were simplified using a flexible ring tire model incorporating the acceleration of intelligent tires, and they analyzed the occurrence of tire wear. Li et al. [36] analyzed the effects of tire pressure and wear on radial acceleration using a finite-element model and estimated the degree of wear using a neural network. However, approaches utilizing physical models have limitations, as it is difficult to create a precise model reflecting the parameters of real road surfaces. Zhang et al. [37] estimated tire wear by extracting signal features such as the peak value of the strain-gauge signal and width of the contact patch. They used an accelerometer for conducting measurements on an indoor treadmill. However, approaches based on indoor experimental environments fail to consider irregular events generated by real driving conditions. In the aforementioned studies, the proposed methods were validated in controlled environments using experimental devices set up indoors. However, in the case of driving on real roads, many variables can significantly affect the assessment of tire wear. In particular, when mathematical models are used, it is difficult to reflect the complex conditions of real road driving.

This paper proposes a tire tread wear detection method using an accelerometer for application in real driving conditions. The proposed method consists of a preprocessing algorithm for acceleration signals and a deep neural network (DNN) for classifying tread wear conditions without using complex physical models and numerical analyses. We verified that the proposed method can classify different tire tread depths by extracting features from accelerometer data acquired while driving on real roads at different speeds. The contributions of this study can be summarized as follows:

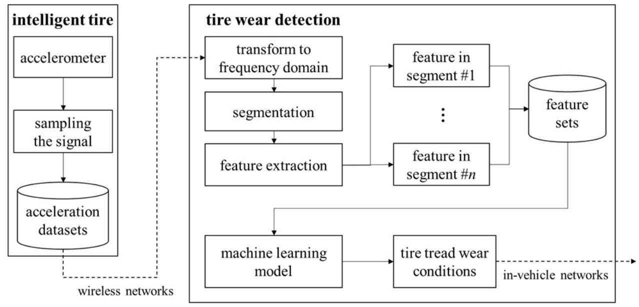

FIGURE 1. Schematic of the proposed tire wear detection system using machine learning.

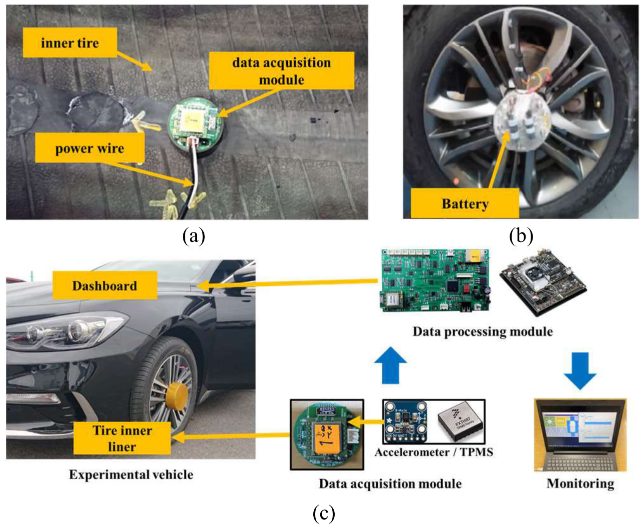

FIGURE 2. Experimental setup for measuring acceleration under real-road driving conditions: (a) data acquisition module; (b) battery setup; (c) entire testing system.

- The proposed method detects tire wear using only accelerometer data, without complex mathematical models or interpretation of tire characteristics.
- A preprocessing method for the accelerometer signal to classify the tire wear state is proposed, and it is shown that the tire wear can be detected using general machine-learning algorithms.
- The feasibility of the proposed method was verified using sensor data obtained under actual vehicle driving conditions.

The remainder of this paper is organized as follows. Section II presents a schematic of the proposed tire wear detection system using machine learning and the field-based experimental setup. Section III explains the features and preprocessing method of the acceleration signals measured during the experiment, as well as the deep learning model to which the features extracted using the proposed preprocessing method are input. Section IV presents an experimental performance evaluation of the proposed tire wear detection method.

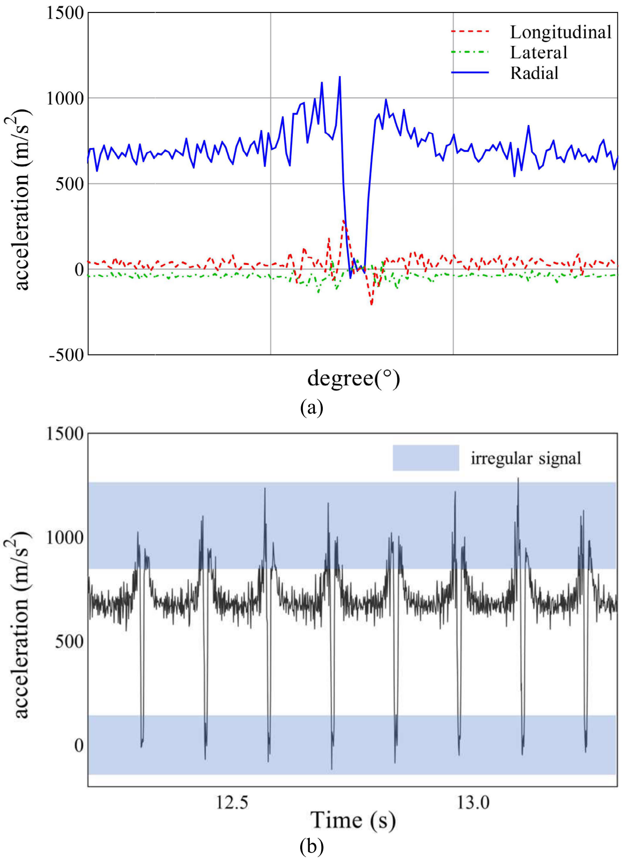

FIGURE 3. Characteristics of the acceleration signal: (a) during one rotation; (b) radial acceleration over several seconds.

Finally, conclusions and future research directions are presented in Section V.

II. TIRE WEAR DETECTION METHOD USING MACHINE LEARNING

A. SCHEMATIC OF TIRE WEAR DETECTION SYSTEM

Fig. 1 shows a schematic of the proposed tire tread wear detection system, which consists of an intelligent tire component and a tire wear detection component. In the intelligent tire component, acceleration signals are sampled and stored in a buffer as a dataset. To detect tire wear using the proposed system in real time, the tire measurement dataset is transmitted to the tire wear detection component through a wireless network such as Bluetooth.

The tire wear detection component converts the acceleration dataset from the time domain to the frequency domain and then segments the entire bandwidth into n parts. Next, the features are calculated as the mean amplitude of all signals within each segment, and a feature set consisting of n features is used as the input to a detection model. The machine-learning model in the proposed system is designed using learning and testing procedures, and the detected tread wear conditions are output according to a feature set. Finally, the detection results are sent to a vehicle electronic control unit or monitoring device through an in-vehicle network such as a controller area network.

B. EXPERIMENTAL SETUP FOR TREAD WEAR DETECTION

In this study, the experimental setup shown in Fig. 2 was used to measure the acceleration applied to tires of a passenger car. The experimental setup consisted of a data acquisition module and a data processing module, and it included functions for detecting the tire tread wear, as shown in Fig. 1. The intelligent tire component runs on the data acquisition module, and the tire wear detection component runs on the data processing module. In this system, the output of the tire wear detection component is monitored on a laptop.

Fig. 2(a) shows the data acquisition module, which collected data from the acceleration sensor. It was inserted into a mold to prevent damage, and the mold was attached to the center of the inner liner of the tire. Fig. 2(b) shows the battery used as a power supply for this system. The lithium-ion battery was attached to a jig mounted on the center cap of the wheel and provided power to the data acquisition board via a cable running through a hole in the wheel. Fig. 2(c) shows the data processing module used to detect tire tread wear. The data processing module in the figure was mounted on the dashboard closest to the tire to permit Bluetooth communication, and it was connected to the monitoring module to provide tire condition information.

The selected accelerometer can measure acceleration values in the range of –500 to 500 g at a 1-kHz sampling rate. In addition, the data processing module has a Bluetooth reception board connected to an NVIDIA TX2 board. A 7.4-V lithium-ion battery with a 2000-mAh capacity is used in this system.

III. PREPROCESSING OF ACCELERATION SIGNAL IN PROPOSED TIRE TREAD WEAR DETECTION METHOD

A. CHARACTERISTICS OF ACCELERATION SIGNALS

Fig. 3(a) shows the signals from each axis of the acceleration sensors of the intelligent tires during a single rotation. The radial acceleration exhibited the largest deviation among the three accelerations because it was affected by the centripetal force applied in the vertical direction to the sensor. Therefore, the radial acceleration appropriately represented the characteristics of the tire tread. For this reason, we selected the radial acceleration as the signal to classify the tire tread wear. In the Fig. 3(a), the contact patch is the area of contact between an accelerometer in a tire and the road surface. The signals measured in this area include several characteristics such as the peak-to-peak, vibration, and duration time. However, the method of using these characteristics generated in a specific section requires distinguishing the section from other sections [25], [31]. In addition, irregular signal patterns shown in Fig. 3(b) that are formed due to noise generated when an actual vehicle is driven must be considered. Therefore, we considered extracting features in the frequency domain instead of using LSTM, which is widely used for processing time-series data, for tire wear detection.

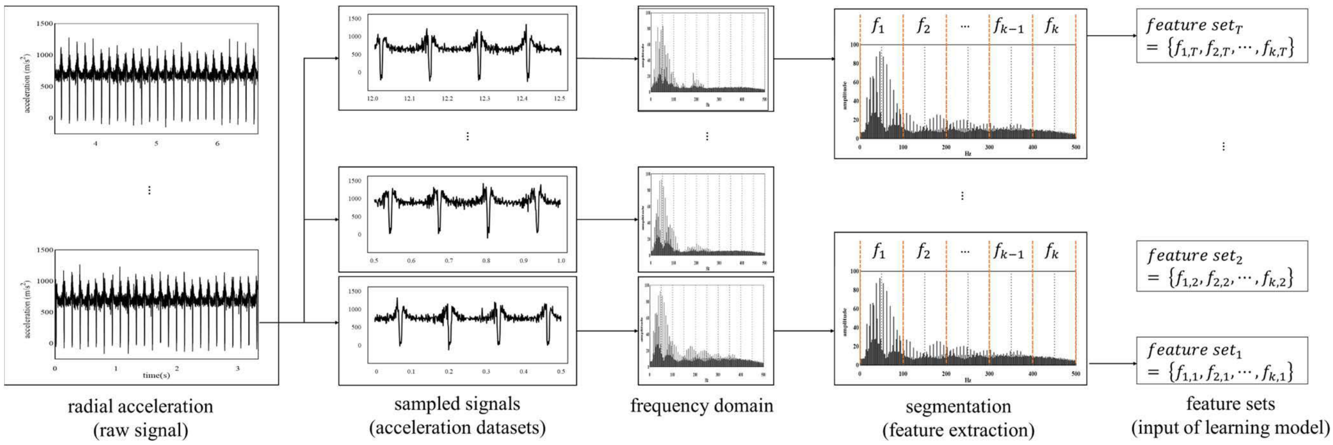

FIGURE 4. Signal preprocessing framework for extraction features.

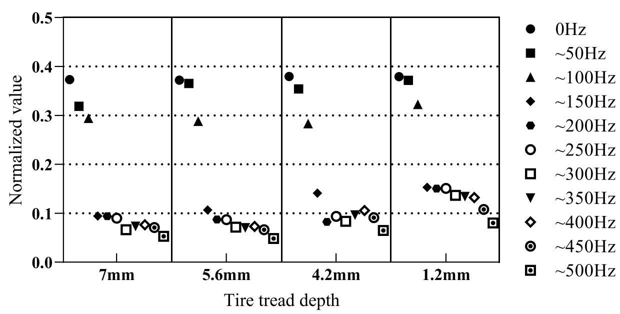

FIGURE 5. Distribution of features for different tire tread wear depths.

B. PREPROCESSING OF ACCELERATION SIGNALS

In this study, the radial acceleration is sampled n times to consider the noise generated during real-road driving conditions. As the tire rotates multiple times while the acceleration signals are sampled, general characteristics reflecting the tire tread wear can be identified; the tire tread wear can be represented in the frequency domain using the identified signal characteristics. Fig. 4 presents the preprocessing method for extracting features from acceleration signals. As shown, the measured acceleration signals are sampled considering the number of specific signals collected and stored in the form of a dataset. In this study, a 500-point accelerometer signal is sampled as one dataset. To achieve this, the signal from the accelerometer sensor is sampled at a period of 0.5 s. After the stored dataset is converted into the frequency domain, the bandwidth is divided into k segments to extract the features of signals in all bandwidths in the frequency domain. Finally, the average amplitude of a signal existing in each segment is calculated to extract statistical features. Here, the feature point $f_{k,T}$ extracted by a segment can be defined as follows:

$$f_{k,T} = \frac{1}{N}\sum_{i=0}^{N-1} a_{amplitude}\left(i^T, k\right), (k = 1, 2, 3, \ldots) \tag{1}$$

where k represents the frequency segment, T represents the order of the sampled datasets, $a_{amplitude}(i^T, k)$ represents the amplitude of the i^{th} signal in the k^{th} segment, and N represents the number of acceleration signals in the segment.

The feature set used as the input for the deep-learning model consists of k features ($f_{k,T}$) and a DC offset, which is denoted as $f_{0,T}$. Fig. 5 shows the distribution of the features that have been normalized between 0 and 1 for use as input values to the proposed model. The 0-Hz features in the figure indicate the DC offset. Furthermore, the 0-Hz features for the different tread wear conditions are similar because they reflect the velocity of the vehicle. For other frequency segments, the average value varies depending on the tire tread wear. The largest value is observed in the low-frequency band.

The features shown in Fig. 5 appear to be easily classifiable using a simple approach. However, this figure represents the results of extracting features from a single dataset under specific conditions to demonstrate the applicability of the extracted features. When extracting features from the entire dataset, the feature patterns can be much more complex and not as straightforward as those shown in the figure. This is evident from the performance evaluation results in section IV, which indicate that it is difficult to accurately judge tire wear using a simple classification method. Therefore, this paper uses a complex deep learning model to classify features and detect tire wear.

C. PROPOSED METHOD FOR TIRE TREAD WEAR DETECTION

In this section, a DNN model for detecting tread wear conditions is designed and a method for increasing the detection accuracy is proposed. Because the tire tread becomes worn from damage accumulated over a long period of time, it is less affected by real-time responses than the tire forces and friction. Therefore, the accuracy of the proposed system is more important than the response time for the detection of tire tread wear. In particular, the use of a sensitive acceleration

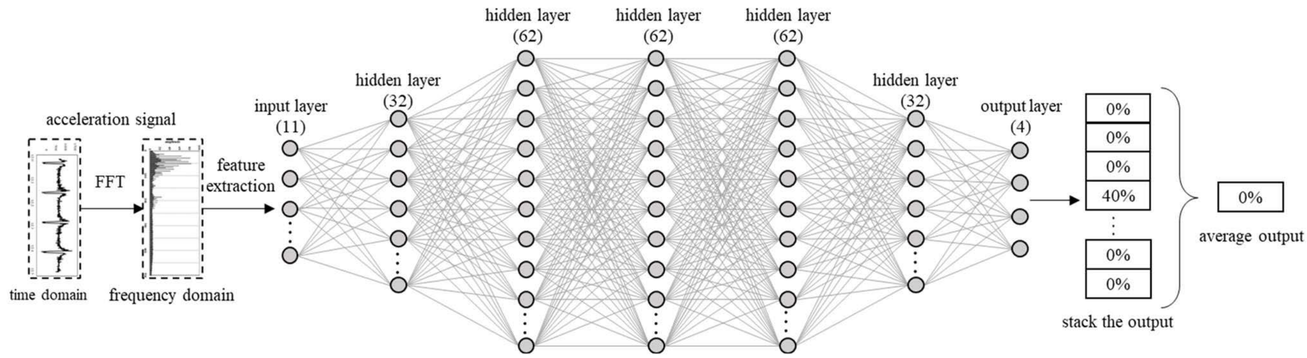

FIGURE 6. DNN model architecture for detecting tire tread wear.

sensor for the detection of wear conditions may reduce the detection accuracy because of the various noises generated under real-world driving conditions.

Fig. 6 illustrates the proposed method for increasing the detection accuracy for tread wear considering such characteristics. The signal characteristics in the frequency domain extracted via the proposed preprocessing method are used as the input of a DNN model. The DNN model outputs the detection results for four tread wear conditions, and the output results are accumulated in a buffer over a certain period of time. Eventually, the output value that has accumulated the most in the buffer is considered to be the current tire tread wear condition.

In Fig. 6, the input layer of the DNN model consists of 11 nodes, i.e., the average amplitude of each segment and the amplitude at 0 Hz. The hidden layer is designed with five layers, each consisting of 32 or 62 nodes, depending on the position. We use rectified linear unit (ReLU) as the activation function for the hidden layers in the DNN to ensure that the input tire wear features are well propagated to deeper layers. We use the softmax function to calculate the final output for estimating each wear class.

We denote the input of the DNN model as x, the output as y, the class to be classified by the DNN model as s, and the number of hidden layers as N_{layer}. The number of classes is equal to the number of tire tread depths we wish to classify. We denote the input of the i^{th} layer as v^i, the weight as w^i, and the bias as b^i. Equation (2) gives the weighted sum of the i^{th} layer. The output of the i^{th} layer of the DNN model is calculated using (3), and the tire tread depth is detected by selecting the class with the highest probability calculated using (4).

$$z^i = w^i v^i + b^i, 0 \le i \le N_{layer} \tag{2}$$

$$v^{i+1} = ReLU\left(z^i\right), 0 \le i < N_{layer} \tag{3}$$

$$(y = s \mid x) = softmax\left(z^{N_{layer}}\right) \tag{4}$$

The DNN model was trained using categorical cross-entropy as the loss function, which is suitable for multi-class classification. Equation (5) gives the loss function, where N_{class} represents the number of classes, and $t_{i,j}$ and $y_{i,j}$ represent the target value and the output of the DNN for the j^{th} class of the i^{th} dataset, respectively. Adaptive Moment Estimation (Adam) was used as the optimizer for training the DNN model.

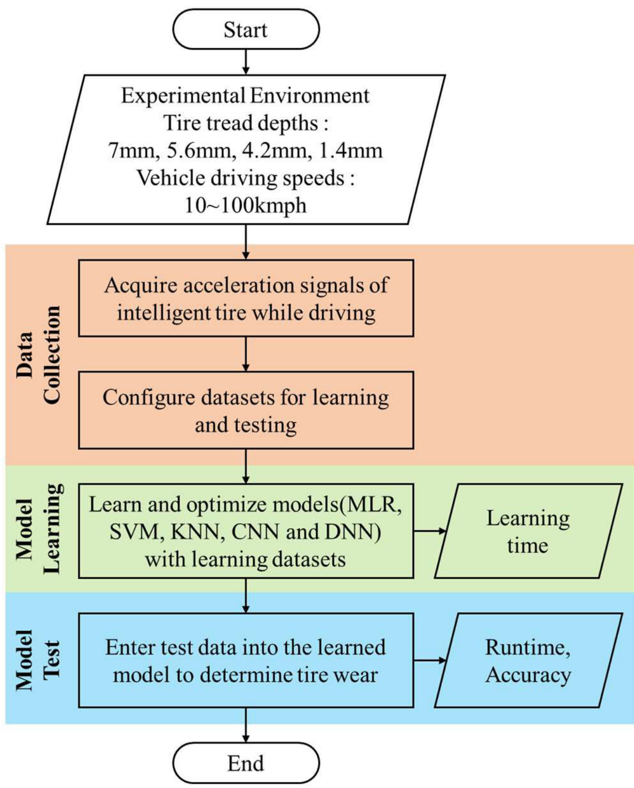

FIGURE 7. Experimental procedure.

$$L = \frac{1}{N_{sample}} \sum_{j=1}^{N_{sample}} \sum_{i=1}^{N_{class}} t_{i,j} \log(y_{i,j}) \tag{5}$$

IV. PERFORMANCE EVALUATION USING VARIOUS MACHINE-LEARNING METHODS

We evaluated the performance of the proposed tire wear detection method via the procedure shown in Fig. 7.

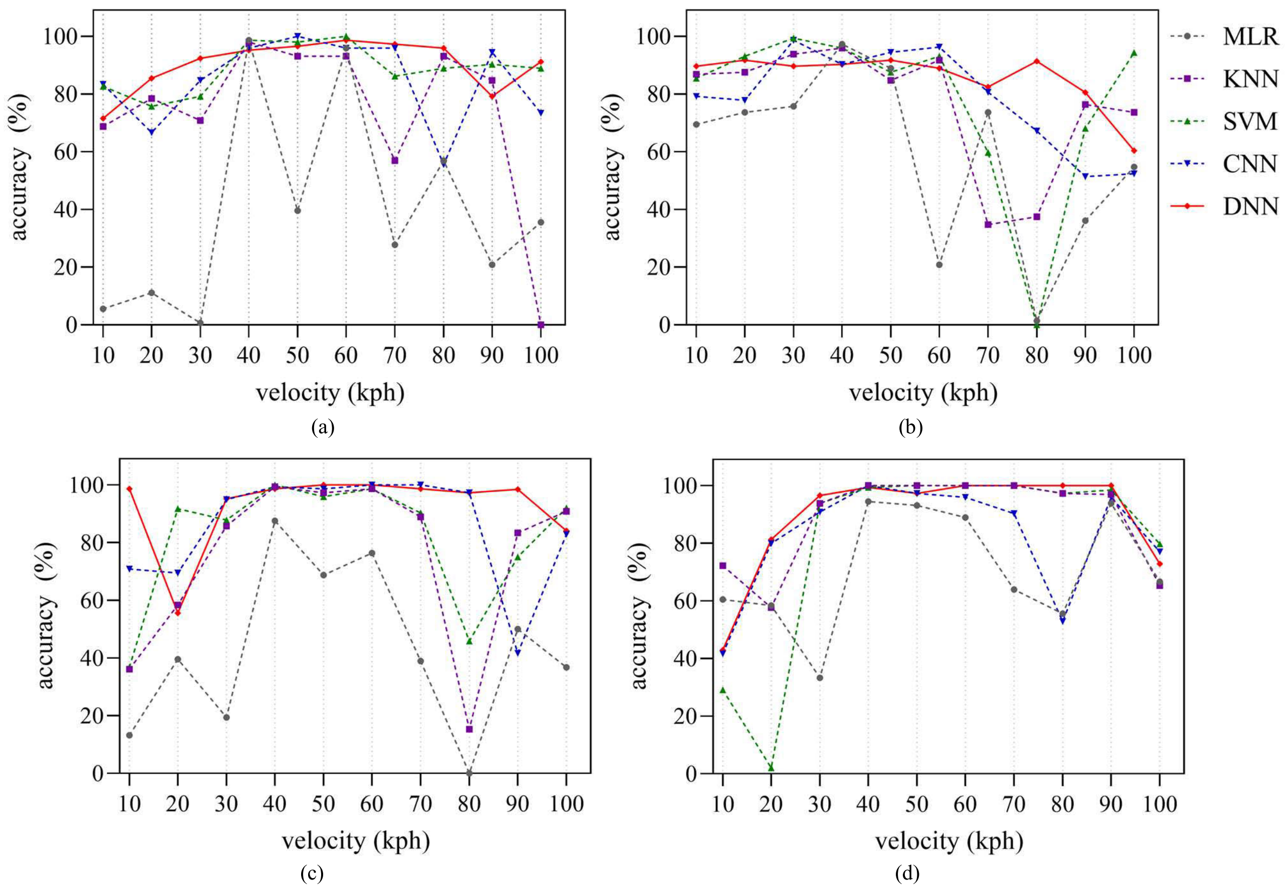

FIGURE 8. Comparison of the tire tread wear detection accuracies of different algorithms: (a) 0%, (b) 20%, (c) 40%, and (d) 80% tire tread wear.

The performance verification was conducted in three stages: experimental data preparation, model training, and performance verification. In the experimental data preparation stage, data were acquired through vehicle driving and divided into verification and training datasets. This process is described in Section IV-A.

In the model training stage, the tire wear judgment model was trained using the training dataset, and the training time was measured. In the model testing stage, the tire wear degree was determined by inputting the test dataset to the trained model. The time required to detect the tire wear and the accuracy of the determination were measured. This process is described in Section IV-B.

A. EXPERIMENTAL ENVIRONMENT

In this section, the experimental environment for verifying the performance of the proposed tire tread wear detection method is described. The data used for performance evaluation were collected by driving a vehicle on a drive proving ground. During the experiment, a vehicle was driven on an asphalt road in a straight line, and the speed was increased from 10 to 100 km/h in increments of 10 km/h, corresponding to 10 different speeds. One 18-in acceleration-based intelligent tire was installed at the front left of the vehicle, and

TABLE 1. Number of datasets for training and testing.

Velocity	0%		20%		40%		80%	
(km/h)	Train	Test	Train	Test	Train	Test	Learn	Test
10	428	642	388	582	347	521	414	621
20	353	530	342	513	347	521	389	584
30	337	506	334	501	347	521	375	563
40	432	648	256	384	212	318	375	563
50	288	432	256	384	232	348	312	468
60	288	432	256	384	254	381	332	498
70	288	432	278	417	254	381	288	432
80	264	396	281	422	217	326	267	401
90	264	396	253	380	247	371	267	401
100	252	378	240	360	226	339	256	384

the tire pressure was maintained at 39 psi. The signals were measured by switching among four different types of tires with tread depths of 7 mm (0% wear, new), 5.6 mm (20% wear, normal), 4.2 mm (40% wear, normal), and 1.4 mm (80% wear, dangerous). The vehicle weight was 1550 kg, and two adults were on board.

The degree of wear and datasets for each speed obtained from the experiment were used for training and testing the classification models. Table 1 presents the number of datasets obtained for each speed and the degree of wear, which were used to create and validate the models. 40% of the datasets collected by speed and tire tread depth were used for training, and the remaining 60% were used for testing. The driving experiments were repeated, as the experimental road had a limited length, and less data were acquired at higher speeds because the driving time was shorter.

B. EVALUATION RESULTS OF PROPOSED METHOD

The proposed DNN model was compared with four widely used machine-learning algorithms to evaluate its performance for using the acceleration characteristics in the frequency domain to detect tread wear. The machine-learning algorithms used for comparison included multiple linear regression (MLR), a support vector machine (SVM), k-nearest neighbors (KNN), and a convolutional neural network (CNN). For KNN, k was set as 4, which exhibited the best performance in the experiment, and for the SVM, the radial basis function [36] was used as the kernel. The CNN model uses the acceleration signal converted to the frequency domain as an input without applying the proposed preprocessing method.

We designed the DNN and CNN models with a sufficiently large capacity to optimize the hyperparameters of each model. Subsequently, we optimized the neural network by reducing the size of the model until performance degradation occurred. The number of epochs was set to 400 and 1000. We evaluated the accuracies, running times, and learning times of all models to compare their performance.

Fig. 8 shows the tread depth classification accuracy for each driving speed and the degree of wear observed when estimated using the DNN with the preprocessing method. Here, the distribution of the dataset samples is not consistent, therefore the accuracy is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{6}$$

where true positive (TP) refers to the case where a positive class is detected as true, true negative (TN) refers to the case where a negative class is detected as true, false positive (FP) refers to the case where a positive class is detected as false, and false negative (FN) refers to the case where a negative class is detected as false.

As shown in Fig. 8, the accuracies of all the models were high at driving speeds between 30–80 km/h but significantly lower outside of this range. This is because at low speeds, sufficient vibrations do not occur for the tire wear conditions to be classified, whereas the vibrations generated at high speeds are stronger than those related to the tire wear condition. Therefore, in this study, we compared the detection accuracies of the models for the tire tread depth considering the driving speeds typically observed in cities.

Table 2 presents the average accuracies of the machine-learning models according to the tread depth at speeds ranging from 30 to 80 km/h. The DNN model applied with the proposed preprocessing method achieved excellent classification results for each tire wear condition, with an overall average accuracy of 95.51%. At a tire tread wear of 80%, at which point tires are recommended to be replaced, the accuracy was 98.84%. This result was obtained when 500 acceleration signals were used as the input and the detection period was approximately 0.5 s. However, because the monitoring of tire wear does not need to be real-time, the detection accuracy can be increased by accumulating the detection results in a buffer, as explained in Section III-C.

TABLE 2. Average accuracy for each machine-learning model from 30 to 80 km/h.

Tire wear	Average accuracy (%)				
	CNN	MLR	KNN	SVM	DNN
	Frequency domain	Proposed preprocessing			
0%	87.96	53.24	84.15	91.78	95.94
20%	87.89	59.61	73.03	72.57	89.03
40%	98.34	48.49	80.84	86.39	98.26
80%	87.82	71.53	98.50	98.38	98.84
Overall	90.5	58.22	84.13	87.28	95.51

TABLE 3. Running and learning times for each machine-learning model.

	MLR	KNN	SVM	CNN	DNN
Running time (ms)	0.99	39.91	19.74	30.92	29.62
Learning time (s)	0.08	0.02	0.22	523.83	118.65

Table 3 presents the running and learning times of the models, which confirm the applicability of the proposed tire tread wear detection method. Deep learning-based classification models, such as DNNs and CNNs, require long running times. However, because the detection of the tire tread depth does not require an extremely fast response time, a machine-learning model with long running time, such as a DNN, is still applicable. For the same reason, the relatively long learning times for CNNs and DNNs may not be a critical factor.

V. CONCLUSION

We propose a method for detecting tire tread wear, which can reduce related accidents by analyzing acceleration signals from an intelligent tire. The proposed method consists of (1) an intelligent tire that samples the measured acceleration values and processes them in a dataset, (2) a preprocessing component that extracts features from the collected data, and (3) a detection component that uses a DNN model. The proposed method was implemented in a real vehicle, and its feasibility was verified using acceleration values measured under real road conditions while driving. Additionally, its detection performance was compared with that of various machine-learning algorithms.

The experimental results indicated that the intelligent tire-based tread wear detection method is capable of detection using only acceleration signals and machine-learning algorithms, without numerical or other complex tire models. In particular, the proposed preprocessing method can adequately extract features according to tread wear conditions regardless of how the acceleration signals are collected under real driving conditions that exhibit irregular noise. The proposed detection method achieved an average accuracy of 95.51% at driving speeds ranging between 30–80 km/h. The accuracy increased when the detection period was increased.

To improve the performance of the proposed tire wear assessment method and ensure its feasibility in various environments, additional research is needed as follows:

- In this study, we collected data by driving at different speeds under actual road conditions, but the evaluation of the proposed method is limited to repeating the same driving scenario under specific conditions. Therefore, the proposed method may exhibit performance changes under various driving scenarios and physical parameters such as the load on the vehicle and internal tire pressure. Consequently, additional performance verification of the proposed method is required under various environments and scenarios.
- To enhance the performance of the proposed system, it is necessary to use approaches such as Kalman filters to remove signal noise in the preprocessing stage and optimize the parameters of the deep learning model. Additionally, it is necessary to supplement and improve the proposed system by comparing and verifying it with mathematical modeling or finite element analysis-based wear estimation algorithms proposed in previous studies.
- The sensor module of the intelligent tire used in this study is powered by a battery. However, this method has the inconvenience of constantly replacing the battery. Therefore, a new idea is needed to provide power to the intelligent tire until its lifespan is exhausted.

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JUN-YOUNG HAN received the B.S. degree in control and instrument engineering from Pukyong National University, in 2016. He is currently pursuing the Ph.D. degree in mechanical engineering with Pusan National University. His research interests include machine learning, in-vehicle networking, and network-based control systems.

JI-HOON KWON received the B.S. degree in computer science and engineering from Pusan National University, in 2016, where he is currently pursuing the Ph.D. degree in mechanical engineering. His research interests include machine learning, in-vehicle networking, and battery electric vehicles.

SUK LEE received the B.S. degree from Seoul National University, Seoul, South Korea, in 1984, and the M.S. and Ph.D. degrees from The Pennsylvania State University, University Park, PA, USA, in 1985 and 1990, respectively. He is currently a Professor with the School of Mechanical Engineering, Pusan National University, Busan, South Korea. His research interests include industrial networks, in-vehicle networks, and home networks.

KYUNG-CHANG LEE (Member, IEEE) received the B.S., M.S., and Ph.D. degrees from Pusan National University, Busan, South Korea, in 1996, 1998, and 2003, respectively. He is currently a Professor with the Department of Control and Instrumentation Engineering, Pukyong National University, Busan. His research interests include embedded network systems, industrial networks, in-vehicle networks, home networks, wireless sensor networks, and networked control systems.

HYEONG-JUN KIM (Member, IEEE) received the B.S. degree in control and instrument engineering from Pukyong National University, Busan, South Korea, in 2013, and the Ph.D. degree in mechanical engineering from Pusan National University, Busan, in 2021. He is currently an Assistant Professor with the Department of Future Automotive Engineering, Gyeongsang National University. His research interests include artificial intelligence and its applications in automotive and industrial robots.